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# The Automation of Financial Statement Fraud Detection: A Framework Using Process Mining

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## 1. Introduction

Process mining is an analytical methodology that is used to analyze an entity's business processes based on event logs that have been automatically recorded in the accounting information systems prior to the analysis. In order to analyze event logs, five characteristics need to be extracted from the accounting information system (Jans et al., 2014; Chiu and Jans, 2019): 1) activity: business activities in an event (e.g., "invoice receipt" in the procure-to-pay process); 2) process instance: the process instance of an event (e.g., a purchase order number in the procure-to-pay process); 3) resource: individual or party who conducted the activity (e.g., if Vincent signs purchase order A, then he is the "resource" of the activity "sign" in purchase order A); and 4) timestamp: the timestamp of an event (e.g., year, month, date, and time of the event: 2018-01-01 12:09:00). For example, if Vincent signs purchase order 0001 on 2017-12-31 at 12:00 pm, then for this event log, the activity is "Sign", the process instance for this activity is "0001," the resource for this activity is "Vincent," and the timestamp for this activity is "2017-12-31 at 12:00 pm." The example event log for purchase order 0001 is shown in Table 1 (including the aforementioned example). [see Table 1, pg 96]

Process mining of event logs has been adopted in a variety of areas, such as computer science, engineering, and management (Schimm, 2003; van der Aalst and Weijters, 2004; Rozinat et al., 2008; Wen et al., 2009). Moreover, in recent years, process mining has also been applied to the auditing field, both in practice and in academia. AICPA's Guide to Audit Data Analytics shows that process mining allows auditors to understand their client's internal control process and detect potential risks (AICPA, 2017). The application of process mining in auditing could add value and provide a new perspective of auditing because auditors could access the full population of event logs and these are recorded human-independently (Jans et al., 2010; Bukhsh and Weigand, 2012). Previous studies on using process mining in internal audit indicated that process mining could improve the performance of auditing and the evaluation of internal control effectiveness (Kopp and O'Donnell, 2005; Jans, 2009; Jans et al., 2011; Jans et al., 2013; Chiu and Jans, 2019). In addition, process mining can be used to detect fraudulent transactions that traditional audit methods fail to discover (Yang and Hwang, 2006; Jans et al., 2014). For example, Yang and Hwang (2006) applied process mining techniques to detect potential fraudulent and abusive cases in healthcare service. Their results indicated that the proposed detection model is capable of identifying several fraudulent and abusive cases which have not been detected by traditional methods (i.e., a manually constructed detection model).

Sarbanes–Oxley Act (SOX) Section 404 mandates that publicly traded companies in the United States need to ensure the effectiveness of their internal control procedures and the auditors are required to attest to the management's internal control assessment. The purpose of the SOX is to enhance the strictness of procedures for financial reporting so that the occurrence of financial statement fraud can be reduced. Although the main objective of an audit is to obtain sufficient and appropriate audit evidence to express an opinion on the truth and fairness of financial statements, Statement on Auditing Standards No. 99 (SAS 99) requires auditors to perform necessary procedures to identify and assess fraud risk.

Fraud is gaining an unfair advantage over another person, which can be classified into corruption, assets misappropriation, and financial statement fraud (ACFE, 2018). Specifically, the financial statement fraud is intentional or reckless conduct, whether by act or omission, that results in the materially misleading financial statement to influence stock performance (ACFE, 2018). There are several common financial statement fraud schemes, such as "side agreements" and "channel stuffing"[1] etc., which will lead to an overstatement of revenue or understatement of expense (Arens et al., 2017). A large number of prior studies have applied financial information to predict potential financial statement fraud risks

[1] "Side agreement fraud" refers to that sales terms and conditions may be modified, revoked, or otherwise amended outside of the recognized sales process or reporting channels and may impact revenue recognition. "Channel stuffing" refers to a deceptive business practice used by a company to inflate its sales and earnings figures by deliberately sending retailers along its distribution channel more products than they are able to sell to the public.



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(Dechow et al., 2011; Cecchini et al., 2010; Perols, 2011; Perols et al., 2016; Wang and Vasarhelyi, 2017). Moreover, apart from financial information, non-financial information can also be used in the prediction of financial statement fraud (Brazel et al., 2009; Dechow et al., 2011). Brazel et al. (2009) examined non-financial measures (e.g., facilities growth) and suggested that these measures could be used to predict financial statement fraud. Dechow et al. (2011) used employee numbers and order backlog data to predict material accounting misstatement.

Since process mining analyzes the event logs of an ERP system and information stored in the event log does not contain a dollar amount, it can be applied as non-financial information in the prediction of financial statement fraud. Process mining analysis also enables the examination on the whole population of event logs, which has the potential of adding value to auditing in the era of big data (Moffitt and Vasarhelyi, 2013). The purpose of this article is to provide a framework on how process mining can be applied to automatically identify fraud schemes. Specifically, the proposed framework captures how suspicious patterns in process mining can be used to detect potentially fraudulent transactions.

The contribution of this article is two-fold. First, the study proposes a framework that links non-standard variants/activities in process mining with corresponding fraud schemes to detect potential fraudulent transactions. Second, the proposed framework can be applied to build a continuous fraud monitoring system that uses suspicious patterns as filters to detect financial statement fraud. The remainder of the study is organized as follows: Section 2 reviews the prior studies, Section 3 proposes a framework of applying process mining to detect and prevent potential financial statement fraud, and Section 4 concludes the article and discusses future studies.

## 2. Literature Review

### 2.1 Process Mining and the Applications

The idea of mining business processes was first proposed by Agrawal et al. (1998) where they developed an approach to identify business processes occurred in the system by evaluating existing logs. Cook and Wolf (1998) proposed the term, process discovery, and introduced a technique that develops process models by capturing current business processes. Specifically, their process discovery tool evolves over time based on the organization's business process evolution.

A large body of academic research analyzed business processes using event logs and proposed either new types of process mining techniques or a case study to evaluate or improve these techniques (van der Aalst et al., 2007; Bozkaya et al., 2009; Werner, 2017). van der Aalst et al. (2007) demonstrated how process mining could be applied in practice by using various process mining techniques to analyze invoice process in a provincial office of the Dutch National Public Works Department. The analysis focused on three aspects: process, organization, and case perspectives. Bozkaya et al. (2009) proposed a process diagnostics method using process mining to help organizations understand three perspectives, namely: "how the process model actually looks like," "how well does the system perform," and "who is involved in the process and how." Werner (2017) proposed a novel process mining approach which identifies control flow based on data dependencies in the accounting structure rather than the timestamp dependent used by most of the contemporary process mining algorithms.

Process mining techniques can be applied to analyze control flows, authorization rules, business data models, organizational models, and business rules (van der Aalst et al., 2003; van der Aalst et al., 2007; Rozinat and van der Aalst, 2006; Rozinat and van der Aalst, 2008; Bukhsh and Weigand, 2012). According to Fahland and van der Aalst (2015), process discovery and conformance checking are the two major analyses of process mining. Process discovery aims at constructing process models that describe event log behaviors while conformance checking compares the designed process models with real-life logs (Fahland and van der Aalst, 2015). For example, Gunther and van der Aalst (2007) proposed a process discovery technique called fuzzy mining. They used the concept of a roadmap to show how process models can be designed based on significance and correlation. The proposed technique could add value to capturing "spaghetti-like" real-life business processes.[2] Rozinat and van der Aalst (2008) proposed a novel conformance checking approach to examine the differences between the observed business process and the designed process model.[3]

Process mining techniques enable new forms of auditing (van der Aalst et al., 2010). For example, process mining allows the auditors to have an unbiased view of what has happened in the company by concisely models behavior in the event log (van der Aalst et al., 2010). Process mining can provide new audit evidence in that it provides auditors with the whole population of data instead of selected samples. Moreover, Bukhsh and Weigand (2012) indicated that process mining techniques could be applied to detect bottlenecks, examine conformance of processes, predict execution problems, and monitor deviations (e.g., comparing the observed events with predefined models or business rules). Process Mining is closely related to Business Activity Monitoring (BAM), Business Operations Management (BOM), Business Process Intelligence (BPI), and Data/Workflow Mining (van der Aalst, 2011). Process mining techniques could assist users in understanding an organization's business process as the patterns and rules are available in the event log. (Bukhsh and Weigand, 2012). For example, users will be able to know the activity and resource related to all the purchase orders."

Process mining of event logs can add value to auditing in the following four aspects (Jans et al., 2013): 1) process mining examines the entire population of data; 2) the event logs have been automatically recorded by the system rather than entered by the auditees; 3) process mining allows auditors to conduct audit procedures that are not possible with current audit tools, e.g., discovering the way that business processes are actually being carried out in practice, and identifying social relationships between individuals; and 4) process mining enables auditors to implement the audit risk model more effectively by providing effective ways of conducting the required walkthroughs of processes and conducting analytical procedures.

Process mining can provide new audit evidence as the analysis of event logs focuses on the transactional processes rather than the value of transactions and its aggregation (Jans et al., 2014). Process mining techniques are capable of objectively extracting a model out of transactional logs. Therefore, the model is not biased towards any expectations the researcher may have. Jans et al. (2013) indicated that process mining could add value to audit by the continuous monitoring nature of event logs. The prevention of audit fraud will be more effective if auditees realize the existence of event logs. The reason is that event logs may indicate that all events have been continuously monitored by auditors for anomalies and subject to tests of analytical procedures. They also proposed that process mining is not only capable of identifying fraud risk but also able to assist auditors in understating the client's business process and evaluating internal control risk.

The application of process mining to internal auditing could improve the effectiveness of internal control (Kopp and Donnell, 2005; Jans et al., 2011, 2014). Compared with using control objective information, using business process focused information in the internal control framework could improve the effectiveness of internal control evaluation (Kopp and Donnell, 2005). Jans et al. (2011) applied process mining techniques to detect internal transaction fraud. Their results showed that process mining enables auditing not only by providing theory and algorithms to check compliance but also by providing tools that help the auditor to detect fraud or other errors in a much earlier stage. Applying process mining in auditing analytical procedures can successfully detect anomalous transactions which traditional auditing analytical procedure fail to discover. Process mining techniques enable the identification of numerous transactions that are audit-relevant, including payments without the approval process, violations of segregation of duty controls and internal procedures (Jans et al., 2014).

In addition, Chiu and Jans (2019) indicated that by adopting process mining to evaluate the effectiveness of internal control, auditors would be able to utilize the results from process mining analysis in the audit procedure. For example, auditors could focus on the non-standard variants, process instances that have process duration over the acceptable range, and employees that violate segregation of duty controls or involved in multiple control violations. As a result, process mining could assist auditors in evaluating the effectiveness of internal control and serve as new audit evidence that ultimately changes the way of audit (Chiu and Jans, 2019). Process mining has been used by industry for real-time fraud detection. For

[2] "Spaghetti-like" real-life business process refers to unstructured business processes directly extracted from real-life event log data (i.e., real-life event log data captures all the business activities occurred in an organization and it could include anything happens in the firm; therefore, the process map would look "spaghetti-like").

[3] Rozinat and van der Aalst (2008) proposed a conformance checking tool that helps with understanding real-life business process by comparing it with the firm's designed process model (i.e., what the business processes are expected to look like) and pointing out the differences.

example, ING bank (a European bank) applied process mining to analyze a user's click path on a distributed stream computing platform (Bruin and Hendriksen, 2016).

### 2.2 Financial Statements Fraud and Fraud Types

Accounting research on financial statement fraud and Accounting and Auditing Enforcement Releases (AAERs) includes testing hypotheses grounded in the literature of earnings management (Summers and Sweeney, 1998; Beneish, 1999; Sharma, 2004) and corporate governance (e.g., Beasley, 1996). The early research of financial statement fraud dates back to 1980s (Elliott and Willingham, 1980). Feroz et al. (1991) documented the AAERs affecting the stock price. Beasley (1996) examined the association between the board of the director composition and financial statement fraud. With fewer proportions of outside members on the board of directors supervising a firm's management (Beasley, 1996), it is more likely that the management uses discretion to manage the firm's accruals and earnings, or even aggressively commits to financial statement fraud.

Therefore, numerous measures for earnings management are created to indicate the risk of financial misstatement and fraud, such as earnings persistence (e.g., Richardson et al., 2005), abnormal accruals and accruals models (e.g., Jones, 1991; Dechow et al., 1995; Dechow and Dichev, 2002; Kothari et al., 2005), and earnings smoothness (e.g., McInnis, 2010). Beneish (1999) matched the sample of fraud to non-fraud by SIC code and year and created an index consisting of seven ratios to indicate the likelihood of an earnings overstatement. Green and Choi (1997) used neural network technology to assess the risk of management fraud (i.e., financial statement fraud), which was one of the first applications of a machine learning technology for predicting financial statement fraud. Dechow et al. (2011) applied predictors identified in the prior literature (e.g., accrual quality variables, financial ratios, employment and order backlog, and stock price related variables) and developed a measure, the *F*-score, to assess the risk of financial misstatement and corporate fraud. To add more information for predicting fraud risk, Brazel et al. (2009) examined nonfinancial measures (e.g., facilities growth) and suggested that these measures could be used to predict financial statement fraud.

However, most of the non-financial variables are available for only limited samples, which could result in the loss of generality of the prediction models. In order to evaluate the predictive power of the extent accrual-based earnings management measures to detect financial statement fraud, Jones et al. (2008) conducted an empirical analysis comparing ten measures (e.g., discretionary accruals, accrual quality) derived from popular accrual models and found that only the accrual estimation errors (Dechow and Dichev, 2002) and their modifications have the ability to predict fraud and non-fraudulent restatements of earnings.

## 3. Framework: Applying Process Mining for Potential Financial Statement Fraud Detection[4]

To detect financial statement fraud using process mining, it is necessary to understand the standard business process for accounting cycles. The two accounting cycles applied in this proposed framework for potential fraud detection are "order-to-cash" cycle and "procure-to-pay" cycle. The standard business process[5] for each cycle is: 1) order-to-cash cycle: "Order Created -> Goods Issued -> Invoice Created -> Invoice Posted: Accounts Receivable -> Invoice Cleared"; and 2) procure-to-pay cycle: "Create Purchase Order -> Sign -> Release -> Goods Receipt -> Invoice Receipt -> Payment." It is important to note that for both order-to-cash and procure-to-pay cycle the approval process (i.e., signature) is required either manually or in the accounting information system. For example, the order-to-cash event log data has a manual approval process and therefore there is no "signature" in the log, while procure-to-pay event log data has an approval process in the system and therefore the activity "sign" shows in the log. The standard business processes for the two accounting cycles are presented in Figure 1. [see Figure 1, pg 104]

A "variant" in process mining refers to a group of process instances that have the same process pattern. For example, if process patterns for process instance A and process instance B are both 'Create Purchase Order -> Sign -> Release -> Goods Receipt -> Invoice Receipt -> Payment,' then these two process instances can be grouped into the same variant. In other words, process instances within a variant share exactly the same process pattern while those between variants have different process patterns. Any type of deviation from the standard business process will be considered as a non-standard

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[4] The proposed framework used full population of event logs to detect financial statement fraud.

[5] The standard business process is discovered from two real-world datasets (one in order-to-cash cycle and another in procure-to-pay cycle). The sub-categories of non-standard variants in order-to-cash cycle and the detailed descriptions of the data are presented in Table 1 and Table 2. The standard and non-standard business processes for procure-to-pay cycle are extracted from Chiu and Jans (2019), as presented in Appendix A.

variant (Chiu and Jans, 2019). Appendix A shows non-standard variant categories (i.e., variants that do not conform to standard business processes) for the procure-to-pay cycle, which is extracted from Chiu and Jans (2019). This study extends their non-standard variant categories to the order-to-cash process, as shown in Table 2. [see Table 2, pg 97]

The data used in Table 2 for categorizing non-standard variants is a real-life event log of an order-to-cash process from an instant food solutions wholesaler in the Netherlands. The company is a producer of instant food solutions, primarily focused on milk creamers, for the consumer market. Their customers are retailers (supermarkets), and their revenue is around €100 million, staff about 100 FTE. Table 3 shows the detailed information of this data. Following Chiu and Jans (2019), the sub-categories of the non-standard variant are defined and established by experts in the field based on the standard business processes of the business cycle, and Table 2 has been reviewed by auditors from the major accounting firms in the United States. [see Table 3, pg 99]

Based on the most common occurred financial statement fraud schemes and the activities and variants in the event logs of an ERP system, this study identifies suspicious patterns or activities for each fraud scheme. The frequency and percentage of accounting fraud schemes from 1994–2016 are presented in Table 4. The fraudulent financial statement sample is collected from the WRDS Restatement Database that contains 279 restatements related to fraud. After dropping the fraud observations with short period restatement (less than 350 days) and merging with Compustat data from 1994 to 2016, there are 202 fraud firms and 470 fraud firm-year observations. Then, the fraud firm-year sample is partitioned into fraud categories. As shown in Table 4, revenue recognition issues, related party transaction issues, and accrual estimate failures are the top three fraud schemes with 174, 150, and 114 instances during 1994 and 2016. The total number of fraud instances by categories is 1,271, which is 270.43% of the 470 fraudulent financial statements. It indicates that one fraudulent financial statement could contain more than one fraud categories. After understanding the frequency and percentage of different fraud categories, we will link the non-standard variants to fraud categories for preparing the framework of using process mining to detect potential financial statement fraud. [see Table 4, pg 100]

### 3.1 Mapping from Non-standard Variants to Fraud Categories

An overview of mapping from non-standard variants to fraud categories is presented in Figure 2. The items on the left are non-standard variants in process mining (e.g., Missing Goods Issued, Missing/Redundant Goods Receipt, Missing Invoice Cleared and Invoices Adjusted without Sign) and items on the right are fraud categories (e.g., Accounts Receivable Issues, Revenue Recognition Issues, and Inventory Issues). Based on the identified non-standard variants in process mining, Figure 2 shows how several fraud categories can be noted by examining the organization's non-standard variants. We can build the association rules that link non-standard variants to fraud categories in an automatic process mining fraud detection system. If any non-standard transaction triggers the association rules, the system will send an alarm to the auditors for further investigation. [see Figure 2, pg 105]

For example, if one finds a sales order does not have "Goods Issued" and "Invoice Cleared" activities, there is a risk that this order/transaction could turn out to be fictitious or involve in a "bill-and-hold" fraud scheme, which will ultimately result in revenue recognition issues. Therefore, the "Missing Goods Issued" and "Missing Invoice Cleared" bubbles are linked to the "Revenue Recognition Issues" bubble on the right. If a sales order does not have "Goods Issued" activity, then it is possible that this order has potential inventory issue such as "fictitious inventory" fraud scheme. Therefore, the "Missing Goods Issued" is linked to the "Inventory Issues" bubble on the right. In addition, if the "Invoice Adjusted" activities frequently occur in sales orders without an appropriate approval process (i.e., signature), it could represent high risks that Accounts Receivable is manipulated or a "refresh receivables" fraud is perpetrated, which will ultimately result in accounts receivable issues. Therefore, the "Invoices Adjusted Without Sign" bubble is linked to the "Accounts Receivable Issues" bubble on the right.

In a procure-to-pay cycle, if a purchase order does not have "Goods Receipt" or has too many redundant "Goods Receipt" activities, then the risk of having inventory related fraud is high. Therefore, the "Missing/Redundant Goods Receipt" bubble is linked to the "Inventory Issues" bubble on the right. However, not every fraud scheme can be detected by process mining. Only the fraud schemes that are related to activities performed in the organization's accounting information systems can potentially be detected by process mining non-standard variants.

After mapping non-standard variants into fraud categories, the fraud categories are broken into the specific fraud schemes. For example, the revenue recognition issues could include many specific fraud schemes, such as bill and hold, channel stuffing and up-front fees. The inventory issues could include inflating the value of inventory and off-site or fictitious inventory. Moreover, some other issues could include failure to record sale allowances and promotional allowance manipulation schemes. In addition, we identify non-standard activities based on corresponding non-standard variant categories and fraud schemes and provide suspicious pattern examples that capture accounting cycles, fraud schemes, and non-standard activities.

Table 5 presents fraud schemes, non-standard variants/activities, and their corresponding suspicious patterns. In the category of improper revenue recognition, the sales orders that are missing "goods issued" or "invoice cleared" activities could be a bill-and-holding fraud, which might need the auditor to do further investigation. If many "order adjusted: order return" or "invoice adjusted: invoice credit note" occurs immediately after a firm's fiscal year-end, it could be an indication of channel stuffing or side agreement fraud. A high frequency of "order adjusted" or "invoice adjusted" activities occur without approval process during fiscal-year-end period increases the possibility of altering sales documentation fraud.

Auditors should also look into the transactions have "invoice cleared" occurs before "goods issued" in order to prevent up-front fees fraud. In the category of inventory schemes, if the "order adjusted: net price" activity occurs without a proper approval process, then this order should be sent to the auditor as this activity could be used as a tool to inflate the value of inventory. Moreover, "goods receipt" activity of "procure-to-pay" cycle should be examined in the prevention of fictitious inventory fraud. For example, if the process mining fraud detection system identifies that goods receipt occurs more than once or missing goods receipt document, it will send an alarm to auditors. The auditors will determine whether the identified transaction is a fraud. All activities and the corresponding variants could also be used as evidence in audit confirmation. For example, the auditors can match the trading partners' event logs to confirm the transaction's occurrence, accuracy, and completeness. [see Table 5, pg 102]

### 3.2 An Example of Detecting Potential Fraud Scheme Using Process Mining

This section provides an example of detecting potential fraud scheme using a non-standard variant. As shown in Figure 3, when auditors perform analytical procedures on a client using process mining, they notice that a large number of process instances have activities "Order Adjusted: Order Return" and "Invoice Adjusted: Invoice Credit Note" during January.[6] Then, the auditors perform substantive tests on these sales orders using the event log. If they find a large portion of the returned goods are associated with the sales orders created and processed by the same manager at the end of December, there could be a high risk that this manager has been involved in a "channel stuffing" fraud scheme.

Assume this firm has a business rule that during the holiday season (i.e., from November to December), all the sales orders can be created and processed by only one employee because the firm usually has limited personnel at work during the holiday season. The auditors could then investigate this incident in cooperation with the firm's audit committee and internal auditors. The investigation team finds that the sales manager tried to send a large amount of inventory to the customers before the fiscal year end to increase the sales revenue. Moreover, the customers do not need these goods, and therefore all the goods have been sent back to the firm's warehouse at the beginning of January. This situation an example of examining non-standard variant to detect potential fraud scheme "channel stuffing." The details of a non-standard variant for channel stuffing are presented in Figure 3. [see Figure 3, pg 106]

## 4. Conclusions

The application of process mining in financial statement fraud detection can assist auditors in detecting potential fraud by examining the potential fraudulent process patterns. The framework proposed in this study indicates that process mining can be an automatic tool for the detection of the abnormal transaction and potential fraud if a process mining fraud detection system is embedded with the association rules that link fraud schemes with non-standard variants. This article contributes to the current research by proposing a framework that links non-standard variants/activities in process mining with corresponding fraud schemes; therefore, auditors could use process mining as an analytical tool in fraud detection.

The limitation of this study is that we only include non-standard variants/activities in two accounting cycles and several most commonly occurred fraud schemes in our framework. It is important to note that not all fraudulent transactions could be automatically detected by the process mining of event logs. Only the transactions in procure-to-pay or order-to-cash cycles or those follow standard business processes in other business cycles can be evaluated. Future research could extend the current framework by incorporating more fraud schemes and other accounting cycles when discussing how

[6] Assume the fiscal year end for this firm is on 12/31.

process mining can be used in fraud detection. Furthermore, validation can be performed to simulate the application of the proposed framework to detect certain types of fraud schemes.

## References

Agrawal, R., D. Gunopulos, and F. Leymann. 1998. Mining process models from workflow logs. *EDBT '98 Proceedings of the 6th* International *Conference on Extending Database Technology: Advances in Database Technology*: 469–483.

AICPA. 2017. Guide to Audit Data Analytics. *American Institute of Certified Public Accountants, Inc. New York, NY 10036-8775.*

Arens, A. A, Randal J. Elder, Mark S. Beasley, and Chris E. Hogan. 2017. Auditing and Assurance Services, 16th Edition. Published by Pearson.

Association of Certified Fraud Examiner (ACFE). 2018. Report to the Nations – 2018 Global Study on Occupational Fraud and Abuse. Available at: https://s3-us-west-2.amazonaws.com/acfepublic/2018-report-to-the-nations.pdf

Beasley, M. S. 1996. An empirical analysis of the relation between the board of director composition and financial statement fraud. *The Accounting Review* 71 (4): 443–465.

Beneish, M. D. 1999. Incentives and penalties related to earnings overstatements that violate GAAP. *The Accounting Review* 74 (4): 425–457.

Bozkaya, M., J. Gabriels, and J. van der Werf. 2009. Process diagnostics: A method based on process mining. *Paper read at the International Conference on Information, Process, and Knowledge Management (eKNOW), February 1–7, Cancun, Mexico*.

Brazel, J. F., K. L. Jones, and M. F. Zimbelman. 2009. Using nonfinancial measures to assess fraud risk. *Journal of Accounting Research* 47 (5): 1135–1166.

Bruin, B. and H. Hendriksen. 2016. Real-time fraud detection using process mining with Spark Streaming. *Data Science & Advanced Analytics conference*.

Bukhsh, F.A. and H. Weigand. 2012. REA & process mining: How to combine them for auditing? *6th International Workshop on Value Modeling and Business Ontology, Vienna Austria*.

Cecchini, M., H. Aytug, G. J. Koehler, and P. Pathak. 2010. Detecting management fraud in public companies. *Management Science* 56 (7): 1146–1160.

Chiu, T. and M. Jans. 2019. Process mining of event logs: a case study evaluating internal control effectiveness. *Working paper, Rutgers University*.

Cook, J. E., and A. L. Wolf. 1998. Discovering models of software processes from event-based data. *ACM Transactions on Software Engineering and Methodology (TOSEM)* 7 (3):215–249.

Dechow, P. M. and I. D. Dichev. 2002. The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review* 77 (1): 35–59.

Dechow, P. M., W. Ge, C. R. Larson, and R. G. Sloan. 2011. Predicting material accounting misstatements. *Contemporary Accounting Research* 28 (1): 17–82.

Dechow, P. M., R. G. Sloan, and A. P. Sweeney. 1995. Detecting earnings management. *The Accounting Review* 70 (2): 193–225.

Elliott, R. K. and J. J. Willingham. 1980. Management fraud: Detection and deterrence. *Petrocelli Books New York, NY.*

Fahland, D., and W. M. P. van der Aalst. 2015. Model repair - aligning process models to reality. *Information Systems* 47: 220–243.

Feroz, E. H., K. Park, and V. S. Pastena. 1991. The financial and market effects of the SEC's accounting and auditing enforcement releases. *Journal of Accounting Research* 29:107–142.

Green, B. P. and Choi, J. H., 1997. Assessing the risk of management fraud through neural network technology. *Auditing A Journal of Practice & Theory* 16: 14–28.

Gunther, C. W., and W. M. P. van der Aalst. 2007. Fuzzy mining—Adaptive process simplification based on multi-perspective metrics. *In Business Process Management, Proceedings, edited by G. Alonso, P. Dadam, and M. Rosemann. Berlin, Germany: Springer-Verlag.*

Jans, M. 2009. Internal fraud risk reduction by data mining and process mining: framework and case study. *Diepenbeek: Hasselt University (PhD Thesis)*.

Jans, M., M. Alles, and M. A. Vasarhelyi. 2010. Process mining of event logs in auditing: Opportunities and challenges. *Available at SSRN:* https://ssrn.com/abstract=2488737 *or* http://dx.doi.org/10.2139/ssrn.2488737

Jans, M., J. M. van Der Werf, N. Lybaert, and K. Vanhoof. 2011. A business process mining application for internal transaction fraud mitigation. *Expert Systems with Applications* 38 (10): 13351–13359.

Jans, M., M. Alles, and M. A. Vasarhelyi. 2013. The case for process mining in auditing: sources of value added and areas of application. *International Journal of Accounting Information Systems* 14 (1): 1–20.

Jans, M., M. Alles, and M. A. Vasarhelyi. 2014. A field study on the use of process mining of event logs as an analytical procedure in auditing. *The Accounting Review* 89 (5): 1751–1773.

Jones, J. J. 1991. Earnings management during import relief investigations, *Journal of Accounting Research* 29 (2): 193–228.

Jones, K. L., G. V. Krishnan, and K. D. Melendrez. 2008. Do models of discretionary accruals detect actual cases of fraudulent and restated earnings? An empirical analysis. *Contemporary Accounting Research* 25 (2): 499–531.

Kopp, L. S. and E. O'Donnell. 2005. The influence of a business-process focus on category knowledge and internal control evaluation. *Accounting, Organizations and Society* 30 (5): 423–434.

Kothari, S. P., A. J. Leone, and C. E. Wasley. 2005 Performance matched discretionary accrual measures. *Journal of Accounting and Economics* 39 (1): 163–197.

McInnis, J. 2010. Earnings smoothness, average returns, and implied cost of equity capital. *The Accounting Review* 85 (1): 315–341.

Moffitt, C. K. and Vasarhelyi, M. A. 2013. AIS in an Age of Big Data. *Journal of Information Systems* 27 (2): 1–19.

Perols, J. 2011. Financial statement fraud detection: An analysis of statistical and machine learning algorithms. *Auditing: A Journal of Practice & Theory* 30 (2): 19–50.

Perols, J. L., R. M. Bowen, C. Zimmermann, and B. Samba. 2016. Finding needles in a haystack: Using data analytics to improve fraud prediction. *The Accounting Review* 92 (2): 221–245.

Richardson, S. A., R. G. Sloan, M.T. Soliman, and I. Tuna. 2005. Accrual reliability, earnings persistence and stock prices. *Journal of Accounting and Economics* 39 (3): 437–485.

Rozinat, A. and W. M. P. van der Aalst. 2006. Conformance testing: Measuring the fit and appropriateness of event logs and process models. *Business Process Management Workshops* (3812): 163–176.

Rozinat, A., A. K. A. de Medeiros, C. W. Günther, A.J.M.M. Weijters, and W.M.P. van der Aalst. 2008. The need for a process mining evaluation framework in research and practice. *Business Process Management Workshops, Springer* 4928: 84–89.

Rozinat, A. and W. M. P. van der Aalst. 2008. Conformance checking of processes based on monitoring real behavior. *Information Systems* 33 (1): 64–95.

Schimm, G. 2003. Mining most specific workflow models from event-based data. *Business Process Management*: 1021–1021.

Sharma, V. D. 2004. Board of director characteristics, institutional ownership, and fraud: Evidence from Australia. *Auditing: A Journal of Practice & Theory* 23 (2): 105–117.

Summers, S. L. and J. T. Sweeney. 1998 Fraudulently misstated financial statements and insider trading: An empirical analysis. *The Accounting Review* 73 (1): 131–146.

U.S. House of Representatives. 2002. The Sarbanes–Oxley Act of 2002. Public Law 107–204 [H. R. 3763]. Washington, D.C.: Government Printing Office.

van der Aalst, W. M. P, B. F. van Dongen, J. Herbst, L. Maruster, G. Schimm, and A.J.M.M. Weijters. 2003. Workflow mining: A survey of issues and approaches. *Data & Knowledge Engineering* 47 (2): 237–267.

van der Aalst, W. M. P. and A. J. M. M Weijters. 2004. Process Mining: A Research Agenda. *Computers in Industry* 53: 231–244.

van der Aalst W. M. P., H. A. Reijers, A. J. M. M. Weijters, B. F. van Dongen, A. K. Alves de Medeiros, M. Song M, and H. M. W. Verbeek. 2007. Business process mining: An industrial application. *Information Systems* 32 (5): 713–32.

van der Aalst, W. M. P. 2010. Process discovery: capturing the invisible. *Computational Intelligence Magazine IEEE* 5 (1): 28–41.

van der Aalst, W. M. P., K. M. van Hee, J. M. van Werf, and M. Verdonk. 2010. Auditing 2.0: using process mining to support tomorrow's auditor. *Computer* 43(3).

van der Aalst, W. M. P. 2011. Process mining: Discovery, Conformance and Enhancement of Business Processes. *Springer Verlag, Berlin (ISBN 978-3-642-19344-6).*

Wang, Y. and M. A. Vasarhelyi. 2017. Adding an accounting layer to deep neural network: Designing a deep learning-based continuous fraud detection system. *Working paper*, *Rutgers University*.

Wen, L., J. Wang, W. M. P. van der Aalst, B. Huang, and J. Sun. 2009. A novel approach for process mining based on event types. *Journal of Intelligent Information Systems* 32 (2): 163–190.

Werner, M. 2017. Financial process mining - Accounting data structure dependent control flow inference. *International Journal of Accounting Information Systems* 25:57–80.

Yang, W. and S. Hwang. 2006. A process-mining framework for the detection of healthcare fraud and abuse. *Expert Systems with Applications* 31 (1): 56–68.

**Table 1: Example Event Log: Purchase order 0001**

| Process Instance | Activity | Resource | Timestamp |
|---|---|---|---|
| **0001** | Create Purchase Order | Peter | 2017-12-31 11:00am |
| **0001** | Sign | Vincent | 2017-12-31 12:00pm |
| **0001** | Release | Ben | 2017-12-31 12:05pm |
| **0001** | Goods Receipt | Josh | 2017-12-31 3:00pm |
| **0001** | Invoice Receipt | John | 2017-12-31 4:00pm |
| **0001** | Payment | Mary | 2017-12-31 5:00pm |

## Table 2: Non-Standard Variants for Order-to-Cash Cycle

**Panel A: Missing Activity**

| Sub-category | Description |
|---|---|
| Missing order created | Missing activity "Order Created" in the business process.<br>• For example: Sign-Goods Issued-Invoice Created-Invoice Posted: Accounts Receivable-Invoice Cleared |
| Missing sign | Missing activity "Sign" in the business process.<br>• For example: Order Created-Goods Issued-Invoice Created-Invoice Posted: Accounts Receivable-Invoice Cleared |
| Missing goods issued | Missing activity "Goods Issued" in the business process.<br>• For example: Order Created-Sign-Invoice Created-Invoice Posted: Accounts Receivable- Invoice Cleared |
| Missing invoice created | Missing activity "Invoice Created" in the business process.<br>• For example: Order Created-Sign-Goods Issued-Invoice Posted: Accounts Receivable- Invoice Cleared |
| Missing invoice posted: accounts receivable | Missing activity "Invoice Posted: Accounts Receivable" in the business process.<br>• For example: Order Created-Sign-Goods Issued-Invoice Created-Invoice Cleared |
| Missing invoice cleared | Missing activity "Invoice Cleared" in the business process.<br>• For example: Order Created-Sign-Goods Issued-Invoice Created-Invoice Posted: Accounts Receivable |
| Order adjusted without sign | In the business process, there is no “Sign” after “Order Adjusted.”<br>• For example: Order Created-Sign-Order Adjusted-Goods Issued-Invoice Created-Invoice Posted: Accounts Receivable-Invoice Cleared |
| Invoice adjusted without sign | In the business process, there is no “Sign” after “Invoice Adjusted.”<br>• For example: Order Created-Sign-Invoice Adjusted-Goods Issued-Invoice Created-Invoice Posted: Accounts Receivable-Invoice Cleared |

**Panel B: Activity NOT in right order**

| Sub-category | Description |
|---|---|
| Goods issued occurs before sign | “Goods Issued” occurs before “Sign” in the business process.<br>• For example: Order Created-Goods Issued-Sign-Invoice Created-Invoice Posted: Accounts Receivable-Invoice Cleared |
| Invoice created occurs before sign | “Invoice Created” occurs before “Sign” in the business process.<br>• For example: Order Created-Invoice Created-Sign-Invoice Posted: Accounts Receivable- Invoice Cleared |
| Invoice posted: accounts receivable occurs before sign | “Invoice Posted: Accounts Receivable” occurs before “Sign” in the business process.<br>• For example: Order Created-Goods Issued-Invoice Created-Invoice Posted: Accounts Receivable-Sign-Invoice Cleared |
| Invoice posted: accounts receivable occurs before invoice created | “Invoice Posted: Accounts Receivable” occurs before “invoice Created” in the business process.<br>• For example: Order Created-Sign-Goods Issued-Invoice Posted: Accounts Receivable-Invoice Created-Invoice Cleared |
| Invoice cleared occurs before Sign | “Invoice Cleared” occurs before “Sign” in the business process.<br>• For example: Order Created-Goods Issued-Invoice Created-Invoice Posted: Accounts Receivable-Invoice Cleared-Sign |
| Invoice cleared occurs before invoice created | “Invoice Cleared” occurs before “Invoice Created” in the business process. |

| | |
|---|---|
| | • For example: Order Created-Sign-Goods Issued-Invoice Cleared-Invoice Created-Invoice Posted: Accounts Receivable |
| Invoice cleared occurs before invoice posted: accounts receivable | "Invoice Cleared" occurs before "Invoice Posted: Accounts Receivable" in the business process.<br>• For example: Order Created-Sign-Goods Issued-Invoice Created-Invoice Cleared-Invoice Posted: Accounts Receivable |

**Panel C: Redundant Activity**

| Sub-category | Description |
|---|---|
| Redundant order created | More than one "Order Created" occurs in the business process.<br>• For example: Order Created-Order Created-Sign-Goods Issued-Invoice Created-Invoice Posted: Accounts Receivable-Invoice Cleared |
| Redundant sign | More than one "Sign" occurs in the business process.<br>• For example: Order Created-Sign-Sign-Goods Issued-Invoice Created-Invoice Posted: Accounts Receivable-Invoice Cleared |
| Redundant goods issued | More than one "Goods Issued" occurs in the business process.<br>• For example: Order Created-Sign-Goods Issued-Goods Issued-Invoice Created-Invoice Posted: Accounts Receivable-Invoice Cleared |
| Redundant invoice created | More than one "Invoice Created" occurs in the business process.<br>• For example: Order Created-Sign-Goods Issued-Invoice Created-Invoice Created -Invoice Posted: Accounts Receivable-Invoice Cleared |
| Redundant invoice posted: accounts receivable | More than one "Invoice Posted: Accounts Receivable" occurs in the business process.<br>• For example: Order Created-Sign-Goods Issued-Invoice Created-Invoice Posted: Accounts Receivable -Invoice Posted: Accounts Receivable-Invoice Cleared |
| Redundant invoice cleared | More than one "Invoice Cleared" occurs in the business process.<br>• For example: Order Created-Sign-Goods Issued-Invoice Created-Invoice Posted: Accounts Receivable-Invoice Cleared-Invoice Cleared |

**Table 3: Order-to-Cash Process from an Instant Food Solutions Wholesaler**

| | |
|---|---|
| Process Instance | 17,196 |
| Resource | 23 |
| Variant | 1,375 |
| Mean Process Instance Duration | 58 Day |
| Start | 01/02/2014 |
| End | 01/29/2016 |

**Table 4: Fraud Types and Fraud Category**

| Fraud Category | Frequency | Percentage |
|---|---|---|
| Revenue recognition issues | 174 | 37.02% |
| Foreign, related party, affiliated, or subsidiary issues | 150 | 31.91% |
| Liabilities, payables, reserves and accrual estimate failures | 114 | 24.26% |
| Accounts/loans receivable, investments & cash issues | 107 | 22.77% |
| Inventory, vendor and/or cost of sales issues | 107 | 22.77% |
| Foreign, subsidiary only issues (subcategory) | 97 | 20.64% |
| Expense (payroll, SGA, other) recording issues | 90 | 19.15% |
| PPE intangible or fixed asset (value/diminution) issues | 44 | 9.36% |
| Deferred, stock-based and/or executive comp issues | 35 | 7.45% |
| Acquisitions, mergers, disposals, re-org acct issues | 34 | 7.23% |
| Tax expense/benefit/deferral/other (FAS 109) issues | 31 | 6.60% |
| Intercompany, investment in subs./affiliate issues | 30 | 6.38% |
| Fin Statement, footnote & segment disclosure issues | 30 | 6.38% |
| Debt, quasi-debt, warrants & equity (BCF) security issues | 25 | 5.32% |
| Lease, SFAS 5, legal, contingency and commitment issues | 24 | 5.11% |
| Capitalization of expenditures issues | 21 | 4.47% |
| Unspecified (amounts or accounts) restatement adjustments | 21 | 4.47% |
| Acquisitions, mergers, only (subcategory) acct issues | 16 | 3.40% |
| PPE issues - Intangible assets, goodwill only (subcategory) | 15 | 3.19% |
| Consolidation issues included Fin 46 variable interest & off-B/S | 13 | 2.77% |
| Intercompany, only, (subcategory) - accounting issues | 13 | 2.77% |
| Cash flow statement (SFAS 95) classification errors | 8 | 1.70% |
| Gain or loss recognition issues | 8 | 1.70% |
| Financial derivatives/hedging (FAS 133) acct issues | 7 | 1.49% |
| EPS, ratio, and classification of income statement issues | 7 | 1.49% |
| Depreciation, depletion or amortization errors | 6 | 1.28% |
| Lease, leasehold and FAS 13 (98) only (subcategory) | 6 | 1.28% |
| Deferred, stock-based options backdating only (subcategory) | 6 | 1.28% |
| Y - Registration/security (included debt) issuance issues | 5 | 1.06% |
| X - Audit or auditor related restatements or nonreliance | 5 | 1.06% |
| X – Audit (or) consent re opinion in f/s issues (subcategory) | 4 | 0.85% |
| Comprehensive income issues | 4 | 0.85% |

| | | |
|---|---|---|
| Balance sheet classification of assets issues | 3 | 0.64% |
| Debt and/or equity classification issues | 2 | 0.43% |
| Y - Loan covenant violations/issues | 2 | 0.43% |
| X – Audit (or) inability to rely on Co reps (subcategory) | 2 | 0.43% |
| Consolidation, foreign currency/inflation (subcategory) issue | 2 | 0.43% |
| Restatements made while in bankruptcy/receivership | 1 | 0.21% |
| Pension and other post-retirement benefit issues | 1 | 0.21% |
| Asset retirement issues | 1 | 0.21% |
| Total Fraud Sample = 470 | 1271 | 270.43% |

**Table 5: Accounting Fraud Schemes and Suspicious Process Patterns**

| Accounting Cycle | Fraud Scheme | Non-standard Variant/Activity | Suspicion Pattern Example |
|---|---|---|---|
| Order-to-Cash | Altering Documentation | • Order Adjusted: Goods Issued Date<br>• Invoice Adjusted | Frequent occurrence of order adjusted and/or invoice adjusted activities without approval process during the fiscal year-end period. |
| Order-to-Cash | Bill and Hold | • Goods Issued<br>• Invoice Cleared | Missing goods issued and/or invoice cleared . |
| Order-to-Cash | Channel Stuffing | • Order Adjusted: Order Return<br>• Invoice Adjusted: Invoice Credit Note | Frequent occurrence of order return or invoice credit note immediately after fiscal year end without an approval process. |
| Order-to-Cash | Failure to Record Sales Allowances | • Invoice Cleared | Missing invoice cleared or incomplete payment |
| Order-to-Cash | Inflating the Value of Inventory | • Order Adjusted: Net Price | Order adjusted without an approval process<br>Putting in improper price comparing to the market value |
| Order-to-Cash | Promotional Allowance Manipulation | • Invoice Adjusted: Cash Discount | Many Invoice Adjusted: Cash Discount activities are entered. |
| Order-to-Cash | Up-Front Fees | • Invoice Cleared<br>• Goods Issued<br>• Order Adjusted: Change Goods Issued Date | invoice cleared occurs before goods issued or invoice created. |

| | | | |
|---|---|---|---|
| Procure-to-Pay | Off-site or Fictitious Inventory | • Goods Receipt | Abnormal goods receipt records: missing goods receipt and/or have duplicate or more than one goods receipt in one purchase order |
| Others | Fraudulent Audit Confirmation | • All Activities | Matching trading partners corresponding event logs |
| Others | Refresh Receivables | • Invoice Adjusted | Invoices adjusted occurs for many transactions without an approval process |
| Others | Bribery and Corruption | • All Activities | Using resource information in event logs to identify a potential violation of segregation of duty controls |

**Figure 1: Standard Order-to-Cash and Procure-to-Pay Business Processes**

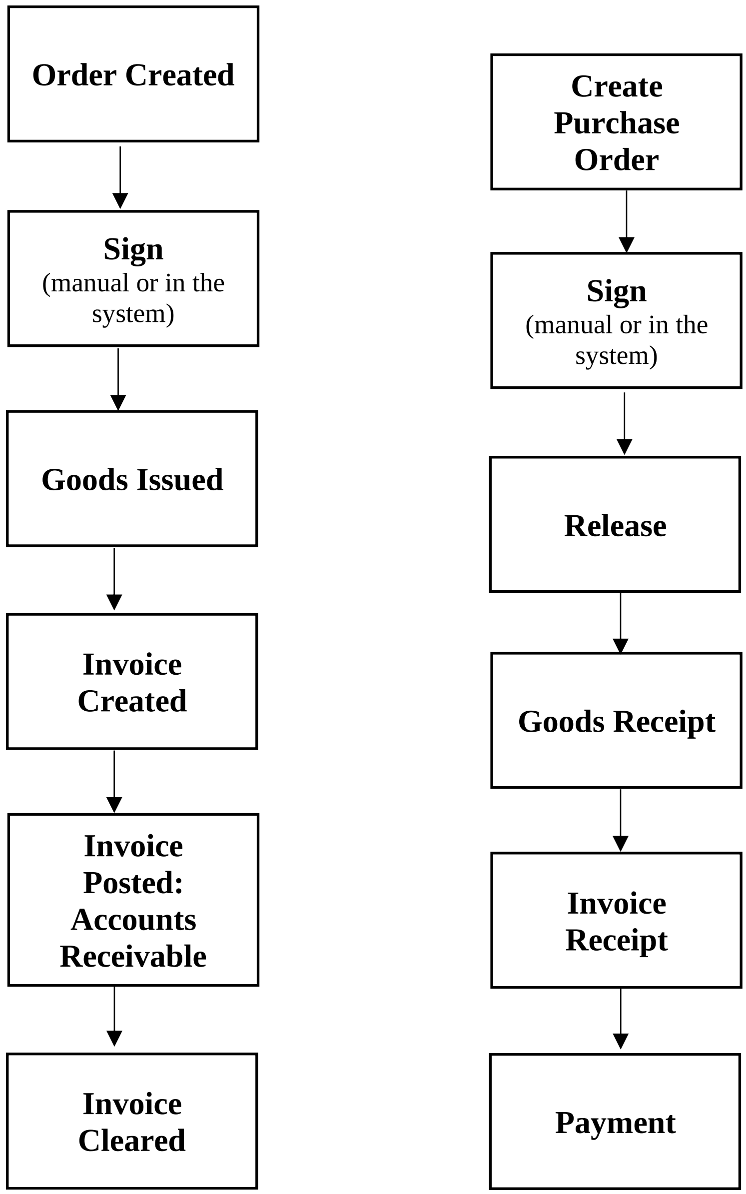


**Figure 2: Mapping Non-Standard Variants into Financial Statement Fraud Categories**

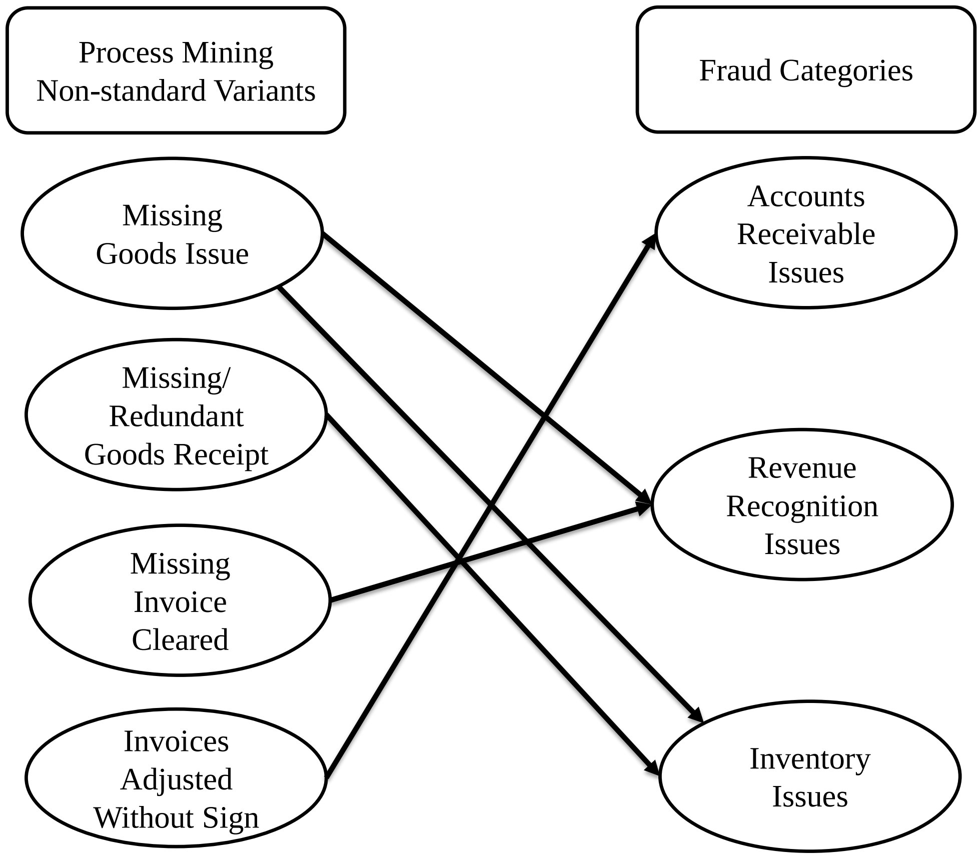
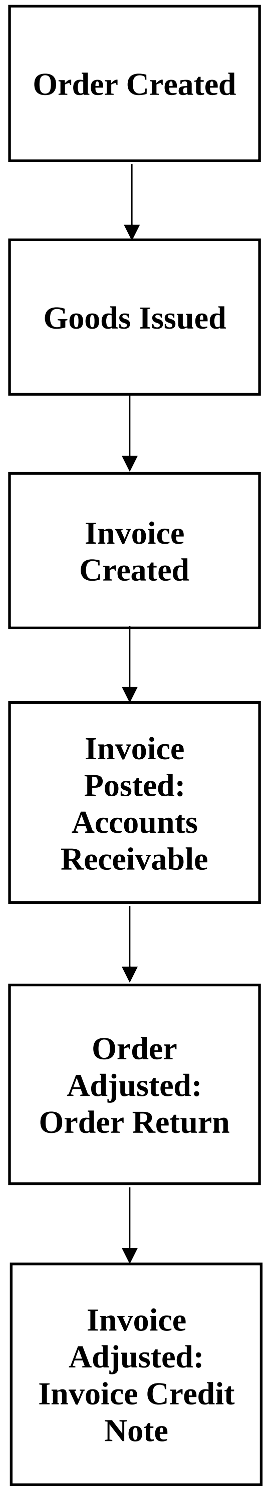


**Figure 3: Non-Standard Variant for Channel Stuffing**



## Appendix A: Non-Standard Variants for Procure-to-Pay Cycle (Chiu and Jans, 2019)

**Panel A: Missing Activity**

| Sub-category | Description |
|---|---|
| Missing purchase order (PO) | Missing activity "PO" in the business process.<br>• For example: Sign-Release-GR-IR-Pay |
| Missing sign | Missing activity "Sign" in the business process.<br>• For example: PO-Release-GR-IR-Pay |
| Missing release | Missing activity "Release" in the business process.<br>• For example: PO-Sign-GR-IR-Pay |
| Missing goods receipt (GR) | Missing activity "GR" in the business process.<br>• For example: PO-Sign-Release-IR-Pay |
| Missing invoice receipt (IR) | Missing activity "IR" in the business process.<br>• For example: PO-Sign-Release-GR-Pay |
| Missing payment (Pay) | Missing activity "Pay" in the business process.<br>• For example: PO-Sign-Release-GR-IR |
| Change line without sign | In the business process, there is no “Sign” after changing line.<br>• For example: PO-Sign-Release-Change Line-Release-GR-IR-Pay |
| Change line without sign nor release | In the business process, there is no “Sign” nor “Release” after changing line.<br>• For example: PO-Sign-Release-Change Line-GR-IR-Pay |

**Panel B: Activity NOT in right order**

| Sub-category | Description |
|---|---|
| Goods receipt (GR) occurs before sign | “GR” occurs before “Sign” in the business process.<br>• For example: PO-GR-Sign-Release-IR-Pay |
| Goods receipt (GR) occurs before release | “GR” occurs before “Release” in the business process.<br>• For example: PO-Sign-GR-Release-IR-Pay |
| Invoice receipt (IR) occurs before sign | “IR” occurs before “Sign” in the business process.<br>• For example: PO-IR-Sign-Release-GR-Pay |
| Invoice receipt (IR) occurs before release | “IR” occurs before “Release” in the business process.<br>• For example: PO-IR-Release-GR-Pay |
| Payment (Pay) occurs before sign | “Pay” occurs before “Sign” in the business process.<br>• For example: PO-Pay-Sign-Release-GR-IR-Pay |
| Payment (Pay) occurs before release | “Pay” occurs before “Release” in the business process.<br>• For example: PO-Pay-Release-GR-IR |
| Payment (Pay) occurs before goods receipt (GR) | “Pay” occurs before “GR” in the business process.<br>• For example: PO-Sign-Release-IR-Pay-GR |
| Payment (Pay) occurs before invoice receipt (IR) | “Pay” occurs before “IR” in the business process.<br>• For example: PO-Sign-Release-GR-Pay-IR |

**Panel C: Redundant Activity**

| Sub-category | Description |
|---|---|
| Redundant purchase order (PO) | More than one “PO” occurs in the business process.<br>• For example: PO-PO-Sign-Release-GR-IR-Pay |

| | |
|---|---|
| Redundant sign | More than one "Sign" occurs in the business process.<br>• For example: PO-Sign-Sign-Release-GR-IR-Pay |
| Redundant release | More than one "Release" occurs in the business process.<br>• For example: PO-Sign-Release-Release-GR-IR-Pay |
| Redundant goods receipt (GR) | More than one "GR" occurs in the business process.<br>• For example: PO-Sign-Release-GR-GR-IR-Pay |
| Redundant invoice receipt (IR) | More than one "IR" occurs in the business process.<br>• For example: PO-Sign-Release-GR-IR-IR-Pay |
| Redundant payment (Pay) | More than one "Pay" occurs in the business process.<br>• For example: PO-Sign-Release-GR-IR-Pay-Pay |