EXPLORING NEW AUDIT EVIDENCE: THE APPLICATION OF PROCESS MINING IN AUDITING

by

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ABSTRACT OF THE DISSERTATION

Exploring New Audit Evidence: The Application of Process Mining in Auditing

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Process mining refers to analyzing business processes using the event log information from the accounting information systems. Process mining techniques have been widely applied in many research domains; however, the application of process mining in auditing has just emerged. Motivated by the potential benefits of applying process mining to auditing, this dissertation consists of three essays that examine how process mining can serve as new audit evidence to evaluate internal control effectiveness, assist auditors in audit risk assessment, and identify fraud schemes.

The first essay aims at adopting process mining to evaluate the effectiveness of internal control using a real-life event log. Specifically, the evaluation is based on the full population of an event log and contains four analyses: (1) variant analysis that identifies standard and non-standard variants, (2) segregation of duty analysis that examines process instances and employees that violate segregation of duty controls, (3) personnel analysis that investigates employees who are involved in multiple potential control violations, and (4) timestamp analysis that detects time related issues such as the process instances that have lengthy process duration.

The second essay aims at building a framework on how auditors can utilize both routing and transaction value information when using process mining as a new type of audit evidence. Specifically, this framework is based on auditor's risk assessment. The application of the proposed risk assessment framework on an event log from a not for profit organization shows that auditors could benefit from the prioritized process mining results as they could focus on process instances with material transaction values and have higher risk scores.

The third essay aims at providing a framework on how process mining can be applied to identify corporate fraud schemes and assessing the riskiness of business processes. Specifically, the proposed framework captures how the patterns in process mining can be used to detect potentially fraudulent transactions. This essay contributes to the existing literature by associating non-standard variants/activities with potential fraud schemes and then assigning risk levels, which could be used as an automatic tool to test the fraud risk of every transaction.

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CHAPTER 1: INTRODUCTION

This dissertation incorporates three essays on examining how process mining can serve as a new type of audit evidence. Among the five chapters of the thesis, chapter one introduces the motivation and main research issues of this thesis. The three essays are included in chapter two, three and four, respectively. Essay one evaluates the effectiveness of internal control using process mining, essay two identifies how process mining can be integrated into the risk assessment procedure, and essay three applies process mining to detect fraud schemes. The last chapter concludes the dissertation by providing a summary of findings and future research implications.

Process mining is a technique that extracts information from event logs in order to allow users to discover and improve business processes through the analysis of event logs (van der Aalst 2011; Alles et al. 2011). The Federation of American Scientists (FAS) defined an event log as *"a chronological record of computer system activities which are saved to a file on the system. The file can later be reviewed by the system administrator to identify users' actions on the system or processes which occurred on the system."*

Process mining has been widely applied in computer science, engineering and management research domains (Schimm 2003; van der Aalst and Weijters 2004; Rozinat et al. 2008; Wen et al. 2009). However, the application of process mining in auditing and other accounting sub-fields has just emerged. Process mining provides a new aspect for auditing in the way that it analyzes the routing of the entire event log data. Traditional analytical procedure highly depends on the integrity and competence of the auditee who prepares the audit data, while event logs in process mining automatically record every

event that gave rise to each transaction. Jans et al. (2013) indicated that process mining could add value to audit by the continuous monitoring nature of event logs. The prevention of fraud will be more effective if auditee realizes the existence of event logs. The reason is that event logs may indicate all events have been continuously monitored by auditors for anomalies and subject to tests of analytical procedures.

Unlike traditional audit techniques, process mining of event logs provides a new aspect for auditing by tracking and capturing every single routing in the dataset. The first essay aims at applying process mining to evaluate the effectiveness of internal control. Specifically, the evaluation is based on the entire population of a real-life event log and contains four analyses: (1) variant analysis that identifies standard and non-standard business processes, (2) segregation of duty analysis that examines process instances and employees that violate segregation of duty controls, (3) personnel analysis that investigates employees who are involved in potential control violations, and (4) timestamp analysis that detects process instances that have lengthy process duration.

The results from essay one indicate that process mining could assist auditors in identifying several control related issues. By classifying variants into standard and non-standard categories based on the path of the business processes, it is possible for process mining to detect potential risks, the ineffectiveness of controls and inefficient processes. U.S. Auditing Standard (AS) 1105 (AS 1105, PCAOB 2010a) defines audit evidence as "*all the information, whether obtained from audit procedures or other sources, that is used by the auditor in arriving at the conclusions on which the auditor's opinion is based. Audit evidence consists of both information that supports and corroborates management's*

assertions regarding the financial statements or internal control over financial reporting and information that contradicts such assertions." Process mining could be a new type of audit evidence as process mining results could be an important part of audit work. For example, auditors could focus on the purchase orders that are classified as non-standard variants, violate segregation of duty controls or have very long process duration, and they could also examine personnel that is involved in multiple potential violations. Therefore, process mining of event logs generates a new type of audit evidence and could potentially revolutionize the traditional audit procedure.

Previous studies on the application of process mining in auditing indicated that process mining could add value to auditing and could be applied to evaluate the effectiveness of internal control (Yang and Hwang 2006; Jans et al. 2009, 2010, 2011, 2013, 2014; Chiu and Jans 2017). Most of the existing studies did not link event log information with the transaction amount when demonstrating why process mining can be a new form of audit evidence. This is mainly due to the lack of available process mining log data and the nature of the information provided in the event logs (i.e., does not include transaction values). The application of process mining in auditing has just evolved, and therefore there is no or little real-life data available for related research, especially in accounting and auditing fields. Examining the information from event logs enables auditors to analyze their clients' data in terms of activities, variants, timestamps, and resources. Nonetheless, it is also critical for auditors to consider transaction amounts when making audit judgments on the exceptions found in process mining analysis.

The objective of the second essay is to build a framework on how auditors can utilize both variant and transaction value information when using process mining as a new form of audit evidence. Specifically, this framework is based on the auditor's risk assessment. In line with prior studies (Jans et al. 2014; Chiu and Jans 2017), the first step of our framework is to identify variants from the data and then classify variants into standard and non-standard categories and sub-categories based on different paths of the process instances. The second step sends all the non-standard process instances to auditors for risk assessment. Prior studies on audit risk assessment indicated that prioritized exceptions could improve audit efficiency (Kim and Vasarhelyi 2012; Issa and Kogan 2014; Li et al. 2016). Therefore, in line with previous research, the proposed risk assessment framework prioritizes identified exceptions based on both risk scores and the materiality threshold determined by the firm's business rule. Specifically, auditors assign risk scores to the sub-categories of business processes based on their judgments. And then the sub-categories will be classified into the following four risk levels based on the assigned risk scores: (1) very low risk (risk score = 1), (2) low risk (risk score = 2), (3) moderate risk (risk score = 3), and (4) high risk (risk score = 4). After that, the last two steps prioritize process instances based on the sum of risk scores and the materiality threshold.

The results from the second essay provide four risk prioritization methods for auditors to analyze material and high-risk business processes. The first risk prioritization method is based on the process instance's risk score, the second method is based on the purchase order's value, the third method calculates a new risk score for each process

instance based on both the risk score and the transaction amount (risk score x transaction value), and the fourth risk prioritization method provides a new risk score for each process instance based on the risk score and the value class (risk score x value class). Auditors could choose among the four proposed risk prioritization methods based on their judgments. For example, if the auditors believe that it is very important to examine large transaction value purchase orders, then they can analyze the prioritized process instances using method 2 (risk prioritization based on the transaction value), and if the auditors decide to investigate process instances based on both the transaction value and risk score, with more weights given to the transaction value, then they can use method 3 (risk prioritization = risk score x transaction value). The first additional test in the second essay shows that auditors could examine employees that involved in process instances with higher risk scores, and the second additional test identifies 16 irregular process instances that their transaction amounts are above the not for profit organization's purchase order approval limit.

Process mining can be used to detect fraudulent transactions that traditional audit methods fail to discover (Yang and Hwang 2006; Jans et al. 2014). To detect and prevent corporate fraud is one of the major objectives of audit practice. Corporate fraud refers to an organization's management improperly uses accounting schemes to falsify and report misleading financial statement, it includes (1) intentional embezzlements of corporate resource, (2) corruption and bribery, and (3) intentional misstatement of financial statement to misguide the stakeholders (i.e., financial statement fraud). There are several common fraud schemes, such as "side agreements," "channel stuffing," "improper capitalization of

expenses," which will lead to an overstatement of revenue or understatement of expense. A large number of prior literature has applied financial information to predict potential financial statement fraud risks (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. Examining non-financial information such as facilities growth could add value to the prediction of financial statement fraud; however, the generality of the prediction models is often compromised due to the limited sample available for non-financial information (Brazel et al. 2009).

The purpose of the third essay is to provide a framework on how process mining can be applied as non-financial information to detect corporate fraud schemes (e.g., "channel stuffing" and "bill and hold"). Specifically, the proposed framework maps the identified non-standard business processes in procurement and sales cycles with three fraud categories (i.e., revenue recognition issues, accounts receivable issues and inventory issues). For example, in an order-to-cash cycle, if a sales order has a frequent occurrence of "order adjusted: order return" or "invoice adjusted: invoice credit note" immediately after a fiscal year end without an approval process, then this non-standard sales path could be an indicator of the fraud scheme – "channel stuffing." The framework proposed in this essay indicates that process mining can be a powerful fraud detection method when auditors include the potential fraudulent patterns in their fraud detection process.

CHAPTER 2: PROCESS MINING OF EVENT LOGS: A CASE STUDY EVALUATING INTERNAL CONTROL EFFECTIVENESS

2.1 INTRODUCTION

Process mining of event logs is a method that analyzes business processes using information in the event log (Van der Aalst 2011). An event log is a collection of digital traces that automatically and chronologically record the actions in the system (Jans, Alles and Vasarhelyi 2013, 2014). Process mining has been widely applied in various research domains including computer science and management (Schimm 2003; van der Aalst and Weijters 2004; Rozinat et al. 2008; Wen et al. 2009). However, the application of process mining in auditing fields is in its infancy. Process mining provides a new aspect for auditing in the way that it analyzes the routing of transactions in the entire dataset instead of using only a selected sample from the data. Moreover, using business process focused information in the internal control framework could help auditors better identify control issues and therefore improve the effectiveness of internal control evaluation (Kopp and O'Donnell 2005).

This study builds on Jans et al. (2014), which provides insights on how process mining can be applied to the analytical procedure. Jans et al. (2014) applied process mining to the event log data of a large European bank and identified several anomalous transactions that have not been detected by their internal auditors when examining the same transactions using traditional audit procedures. However, instead of examining the full population of the event log, their study only manually investigated the six most frequent

variants and conducted several additional tests, based on specific business rules.[1] One of the main advantages of process mining is that the event log enables auditors to access the whole data population (Jans et al. 2010). Therefore, to show how process mining could benefit audit when auditors use all the available information from the event log, this study aims at completing the process mining analysis on the full population of an event log, including the remaining 974 variants[2] that Jans et al. (2014) did not cover in their paper.

Specifically, this paper focuses on how process mining can assist auditors in evaluating internal control effectiveness. The evaluation contains the following four analyses: First, perform a variant analysis to identify categories and sub-categories for standard and non-standard variants by examining the full population of an event log. This analysis investigates the standard and non-standard paths in the organization's business process and further classifies these paths into three categories, "missing activity," "activity not in the right order" and "redundant activities." Second, conduct segregation of duty analysis to identify individuals violating segregation of duty controls. Third, perform a personnel analysis to examine individuals with multiple potential control violations. Fourth, conduct a timestamp analysis to discover process instances that have lengthy process duration.

[1] Specific business rules including segregation of duty controls, payment made without approval and company-specific internal control procedures.

[2] Jans, Alles and Vasarhelyi (2014) use the 'Performance Sequence Diagram Analysis' plugin in ProM 5 and choose the flexible equivalent option to count the total number of variants. In this paper, we use Disco (https://fluxicon.com/disco) to count the total number of variants and it gives us 980 variants in total. This number is confirmed by several other open source process mining tools including most recent plugins in ProM 6 and the process mining R package - edeaR.

The results of the four analyses indicate that by classifying variants into standard/non-standard categories, it is possible to detect potential risks, the ineffectiveness of controls and inefficient processes by using a process mining approach. In addition, process mining could be a new type of audit evidence as process mining results could be an important part of audit work. For example, auditors could focus more on the purchase orders that are classified as non-standard variants, violate segregation of duty controls or have longest process duration, and they could also examine personnel that is involved in multiple potential violations or process instances that have very long process duration. These results support the idea that applying process mining to audit is a revolution that could change the way of conducting an audit.

The contribution of this study is three-fold. First, this paper utilizes the entire population of an event log when demonstrating how process mining could assist auditors in evaluating the effectiveness of internal control. Compared with the prior literature examining only six selected variants, we found additional audit-relevant issues that need auditor's further investigation. Second, this case study extends prior literature's process mining test by incorporating four analyses in the demonstration of using process mining to evaluate internal control effectiveness. The four analyses are variant analysis, segregation of duty analysis, personnel analysis, and timestamp analysis. Each analysis provides auditors with different aspects on the evaluation of an organization's internal control effectiveness. Third, this study manually[3] identifies categories and sub-categories of

[3] The manual variant classification only includes variants that have at least two process instances. The detailed explanation of manual classification is in the methodology section.

standard/non-standard variants using a real-life event log data in the procure-to-pay cycle. The discovered standard/non-standard variants enable auditors to gain insights into real-world business processes that conform to or deviate from the standard procurement process. In addition, auditors could use these categories/sub-categories when evaluating event logs in procure-to-pay cycle.

The remainder of this paper is organized as follows. Section 2 summarizes background and related studies. Section 3 describes the methodology. Section 4 introduces the case study and presents the results of variant analysis and three additional tests. Section 5 concludes the paper and discusses future research directions.

2.2 BACKGROUND AND LITERATURE REVIEW

2.2.1 Process Mining of Event Logs

In order to analyze information from event logs, there are four variables that must be extracted from each event log in the system: (1) Activity, (2) Process Instance, (3) Resource, and (4) Timestamp (Jans et al. 2014). Table 1 shows the required content of an event log for process mining.

Table 1: Required Variable of An Event Log for Process Mining

Content	Description
Activity	• The ***activity*** that the recorded transaction represents. • Example: sign and release in the procurement-to-pay process.
Process Instance	• The ***unique case*** that is followed throughout the process of interest • Example: an invoice, or the purchase order number in the procurement-to-pay process.
Resource	• The ***resource*** or party responsible for the activity, also known as originator or action owner. • Example: the person who conducts the activity (e.g., Vicky signs the purchase order, then she is the originator of the activity "Sign").
Timestamp	• The ***timestamp*** of the event. • Example: year, month, date, and time of the event (2006-11-07 10:00:36)

When utilizing process mining to analyze information from event logs, at least five types of analyses can be performed, namely, (1) process discovery; (2) conformance check; (3) performance analysis; (4) social networks analysis; and (5) decision mining and verification (Jans et al. 2010, Alles et al. 2011).[4] To understand and discover how an organization carries out its business processes, process discovery could be performed to event logs as fundamental analysis. Process discovery captures the firm's business processes in a process model. The model is visualized by using business process map which shows the process flow of all the activities occurred in a firm.

[4] Alles, Jans And Vasarhelyi (2011) provided detail explanations of the five approaches that can be used in process mining.

A variant in process mining is a single path followed by one or more process instances with identical routings. For example, if process instance 1 and process instance 2 both have the same routing "Create PO-Sign-Release-GR-IR-Pay," then we group process instance 1 and process instance 2 into one variant. Table 2 shows a detailed example of a variant and three corresponding process instances. All process instances that have identical routing will be grouped into the same variant, while process instances having different routings will be classified into different variants. By examining variants, auditors are able to distinguish between standard and non-standard routings occurred in the business. A standard variant is a group of process instances that their paths conform to the firm's standard business processes while a non-standard variant includes process instances that their paths deviate from the standard business processes described in the organization's business rule. Based on the understanding of standard and non-standard variants, auditors could evaluate client's related internal control effectiveness. For example, a standard procure-to-pay routing is: 'Create PO-Sign-Release-GR-IR-Pay,' while a non-standard procure-to-pay path could be: 'Create PO-Release-GR-IR-Pay.' Between these two variants, auditors should focus more on the second variant that is missing activity 'Sign' since this routing could indicate potential risks and/or ineffectiveness of controls, and therefore requires further audit work.

Table 2: Example of A Variant that Represents Three Process Instances

Process Instance	Sequence Number	Variant	Activity	Resource	Timestamp
450039741940	1	Variant 1	Create PO	U35824	1/10/2007
450039741940	2	Variant 1	Sign	G19091	1/12/2007
450039741940	3	Variant 1	Release	U42242	1/15/2007
450039741940	4	Variant 1	GR	G35730	1/16/2007
450039741940	5	Variant 1	IR	G10849	1/17/2007
450039741940	6	Variant 1	Pay	G10849	1/18/2007
4500397495780	1	Variant 1	Create PO	U21356	1/10/2007
4500397495780	2	Variant 1	Sign	U29598	1/11/2007
4500397495780	3	Variant 1	Release	G13307	1/12/2007
4500397495780	4	Variant 1	GR	U21356	1/29/2007
4500397495780	5	Variant 1	IR	G55584	2/8/2007
4500397495780	6	Variant 1	Pay	G55584	2/14/2007
45003965696410	1	Variant 1	Create PO	U45859	1/8/2007
45003965696410	2	Variant 1	Sign	G16977	1/9/2007
45003965696410	3	Variant 1	Release	U29598	1/9/2007
45003965696410	4	Variant 1	GR	U45859	1/12/2007
45003965696410	5	Variant 1	IR	G15330	1/18/2007
45003965696410	6	Variant 1	Pay	G15330	1/24/2007

2.2.2 The Application of Process Mining

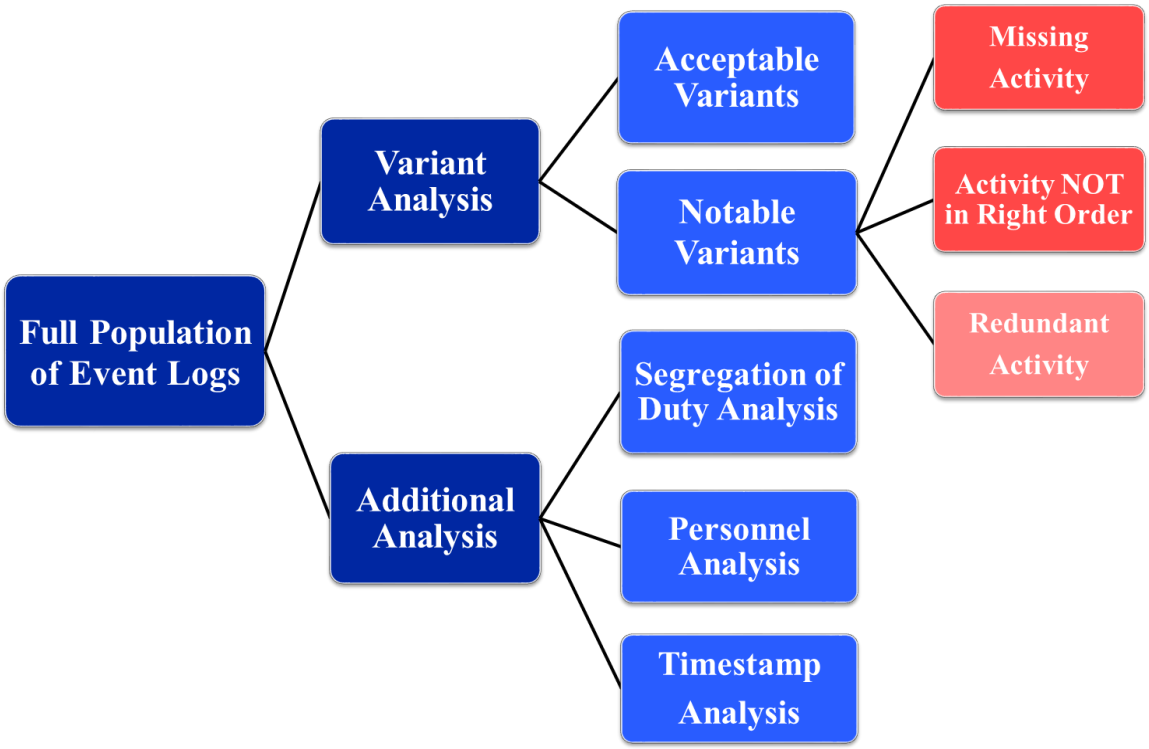
Process mining has been widely adopted in computer science, engineering and management research (Schimm 2003; van der Aalst and Weijters 2004; Rozinat et al. 2008, Wen et al. 2009). For example, it has been used to detect bottlenecks, examine conformance of processes, predict execution problems, and monitor deviations (van der Aalst et al. 2003; Rozinat and van der Aalst 2006; Rozinat and Van der Aalst 2008). Moreover, recently process mining of event logs has been applied to the auditing field. There are two main advantages of using process mining in auditing: (1) it provides the auditor with the entire population of event logs, (2) it provides a human-independent way of recording data (Jans et al. 2010; Jans et al. 2013).

Process mining enables new audit evidence that other methods cannot provide because it examines event logs based on business processes (Jans et al. 2014). Kopp and O'Donnell (2005) argued that the evaluation of internal control effectiveness could be improved if auditors use business process-focused information in the audit work. In addition, process mining can be used as non-financial information in fraud scheme detection (Chiu et al. 2017). Previous studies on examining fraudulent transactions using process mining showed that process mining could detect numerous anomalous transactions that traditional audit analytics techniques fail to discover, and the nature of event logs can assist auditors in preventing fraud in an early stage (Yang and Hwang 2006; Jans et al. 2011, 2013, 2014).

2.3 METHODOLOGY

A novel design in our paper is to evaluate internal control effectiveness using the full population of an event log, including the remaining 974 variants that Jans et al. (2014) did not cover in their analyses. In addition, we demonstrate four aspects on how auditors could apply process mining to evaluate the effectiveness of internal control, as shown in Figure 1.

Figure 1: Applying Process Mining to Evaluate the Effectiveness of Internal Control



The variant analysis focuses on examining the 980 variants from the full population of the event log and classifying these variants into standard and non-standard variants. In order to generate comprehensive categories and sub-categories that capture all the standard and non-standard business processes occurred in the procure-to-pay cycle of the bank, we manually classified 97.2 percent of the event log into categories and sub-categories of standard and non-standard variants. The manual classification only includes the variants that have at least two process instances, in other words, the categories and sub-categories are generated when there are at least two process instances with the same routing. The remaining 2.8 percent of process instances (i.e., 732 process instances) have been classified

into standard and non-standard variants based on the generated categories and sub-categories.[5]

Apart from analyzing variants, this study includes three additional aspects on how process mining could add value to auditors' evaluation of internal control effectiveness. First, segregation of duty analysis aims at finding out employees that violate segregation of duty controls by examining whether there is an employee responsible for two critical tasks in one process instance. For example, if employee B performs both sign and release on process instance 1, then both this process instance and employee B will be marked as non-standard and sent to auditors for further review. Second, the purpose of personnel analysis is to examine responsible personnel on multiple potential violations. This analysis combines the results from the variant analysis and the segregation of duty analysis by identifying the employees who are involved in both. For example, if employee C performs both process instance 1 and process instance 2, and process instance 1 is in one of the non-standard variants and process instance 2 violates segregation of duty control, then employee C will be marked as the personnel that is involved in multiple violations.[6] Third, the timestamp of each process instance has been examined to discover potential fraud or inefficient business process. The process duration test aims at finding out process instances that their starting date to the ending date is longer than the mean process duration.

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[5]The classification of the remaining 732 process instances is accomplished by using MySQL. For each category and sub-category in standard and non-standard variants, we generate corresponding SQL code and classify the 732 process instances into existing categories and sub-categories. For more information about MySQL, please visit the webpage: MySQL: https://www.mysql.com.

[6]In this example, employee C conducts multiple violations for two different process instances (i.e., process instance 1 and 2). It is also possible that employee C in the given example performs only one process instance (e.g., process instance 1) that is non-standard and violates segregation of duty control.

2.4 EVALUATING THE EFFECTIVENESS OF INTERNAL CONTROL USING PROCESS MINING: A CASE STUDY

2.4.1 Event Log Data from A Large European Bank

The data used in the case study is from a large multinational European bank that ranked top 25 in the world based on its total assets. The bank also operates in the United States, so it is mandated to comply with Sarbanes-Oxley Act (SOX) as other publicly traded companies in the United States. The procure-to-pay event log used in this study were extracted from the bank's SAP system, and the log has already been reviewed by the bank's internal auditors. The log represents the bank's procurement process of all purchases that led to an invoice in January 2007, represented by 26,185 process instances (a process instance in this event log is a single line of a purchase order). The event log contains 181,845 events and includes 7 activity types (Create Purchase Order, Sign, Release, GR, IR, Pay, and Change Line). All process instances are grouped into 980 variants. Table 3 and Table 4 shows the statistics and information of the event log data.

Table 3: Description of Event Log: Procure-to-Pay Process from A Large European Bank

Event	181,845
Process Instance	26,185
Activity	7
Activity Detail	(1) Create PO (2) Sign (3) Release (4) GR (5) IR (6) Pay (7) Change Line
Resources	272
Variant	980
Mean Process Duration	46.2 Day
Start	01/02/2007
End	01/25/2008

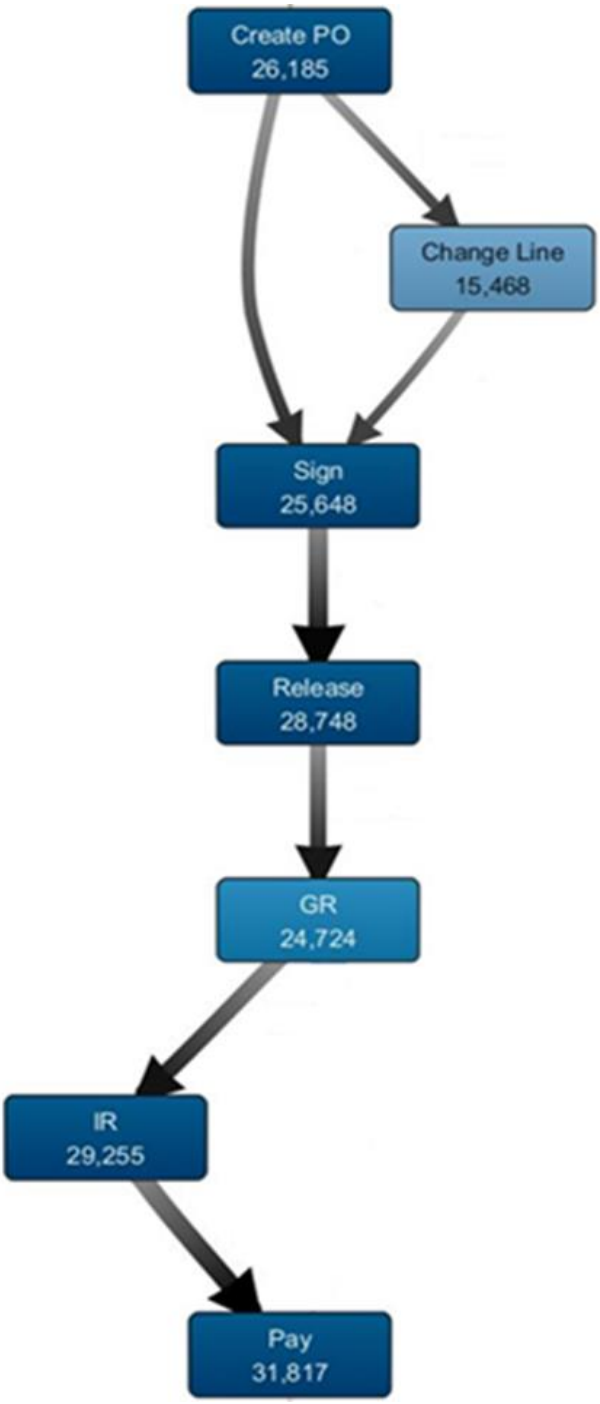
Table 4: Activity Frequency

Activity	Count	Percentage
Create PO	26,185	14.40%
Sign	25,648	14.10%
Release	28,748	15.81%
GR	24,724	13.60%
IR	29,255	16.09%
Pay	31,817	17.50%
Change Line	15,468	8.51%
Total	181,845	100%

Figure 2 shows the business process map of the procurement process in the bank. The arrows in Figure 2 stand for the frequency and direction of the process, the darker and thicker arrows represent more frequent business processes. The number in each box (the numbers beneath each activity) represents the overall occurrence of that activity, for example, 'Create PO' occurred 26,185 times and 'Change Line[7]' occurred 15,468 times in the dataset. The darker boxes represent higher occurrence activities, for example, the occurrence of 'Create PO' is higher than 'Change Line,' so the box for 'Create PO' is darker than the box for 'Change Line.'

[7] The activity 'change line' refers to changing line item of a purchase order. For example, if a purchase order originally has a line item '10 pencils,' changing it to '15 pencils' would result in a 'change line' activity for this purchase order.

Figure 2: Procure-to-Pay Process Map



2.4.2 Variant Analysis

By examining the full population of the event log, we discover four categories for standard variants and three main categories and 22 sub-categories for non-standard variants, as presented in Appendix A. The three main categories of non-standard variants include: (1) missing activity, (2) activity not in right order, (3) redundant activity. Specifically, (1) missing activity refers to a variant missing certain required activity (e.g., a purchase order missing sign in the process), (2) activity not in right order refers to the order of activities in a variant is different from that specified in standard procurement process (e.g., a purchase order having goods receipt occurs before signature), (3) redundant activity refers to a variant that has repeating activities (e.g., a purchase order has more than one sign occurred in the process). Based on the standard procurement process, the three main categories of non-standard variants can be further broken down into 22 sub-categories, as shown in Appendix A. It is worth to note that the three main categories of non-standard variants are generalized and can be applied not only in procure-to-pay cycle, but also in other business cycles (e.g., order-to-cash cycle). However, the four categories of standard variants and the 22 sub-categories in non-standard variants are specific to the procure-to-pay cycle; therefore, these categories and sub-categories need to be modified if being applied to other business cycles.

The classification results for standard and non-standard variants are displayed in Table 5. The results show that 95 percent of the variants have been classified into non-standard variants, indicating that these 6,987 process instances need auditors' further investigation to check whether it is standard. Non-standard variants could represent

inefficient of internal control process and potential fraud or errors in the business processes, depending on whether the organization's designed business rules allow these types of deviations from the standard variants. Therefore, these discovered non-standard variants can also be seen as exceptions, and they should be prioritized in the risk assessment procedure to improve audit efficiency (Kim and Vasarhelyi 2012; Issa and Kogan 2014; Li, Chan, and Kogan 2016).

Table 5: Variant Analysis – Overall Results

	Variant		Process Instance	
	Count	Percentage	Count	Percentage
Standard Variant	49	5%	19,198	73.32%
Non-standard Variant	931	95%	6,987	26.68%
Total	980	100%	26,185	100%

Table 6 shows the classification results for the three categories of non-standard variants. 'Missing activity' and 'activity not in right order' are the two categories that need more attention from auditors since their routings represent more severe problem such as missing approval process and having payments without authorization. On the other hand, 'redundant activity' is relatively less risky since the presence of this category could be just an inefficient business process. However, further investigation is still required since it is also possible that the process instances in redundant activity are fraudulent. For example, a duplicate 'pay' in a routing could be just a separate payment from one transaction, but it

could also be a duplicate/redundant payment for one transaction. The latter situation could be a fraudulent case if the employee who is responsible for the two 'pay' in the routing makes duplicate payment on purpose. In addition, the results from redundant activity could also be combined with traditional duplicate detection to identify potential fraud.

It is worth to note that a variant/process instance could be in multiple non-standard variant categories at the same time, for example, if the routing of process instance 1 is Create PO – GR – release – release – IR – Pay, then this process instance will be included in all three non-standard variant categories because it is (1) missing 'sign,' (2) having redundant 'release,' and (3) the 'goods receipt' in the process is not in right order (i.e., occurs before 'release'). Therefore, the sum of the variants (1,405) in the three categories is more than total variants (980) in our data. In addition, since Table 6 only represents non-standard variants and non-standard variants include fewer process instances compared with standard variants (as shown in Table 3), the sum of the process instances (7,783) is less than the total process instances in the data (26,185). The percentages shown in Table 6 are based on the total number of variants (980)/process instances (26,185) in the dataset. For example, in 'missing activity' category, the 551 variants represent 56.22 percent (551/980) of the variant in the data, indicating that over 50 percent of the variants in the entire dataset have certain required activity missing in the business process; and the 4,980 process instances represent 19.02 percent (4,980/26,185) of the process instances in the data.[8]

[8] In 'activities not in right order' category, the 23 variants represent 2.35 percent (23/980) of the variants in the data, and the 139 process instances represent 0.53 percent (139/26,185) of the process instances in the data. In 'redundant activities' category, the 831 variants represent 84.80 percent (831/980) of the variants in the data, and the 2,664 process instances represent 10.17 percent (2,664/26,185) of the process instances in the data.

Table 6: Non-standard Variant

	Variant		Process Instance	
	Count	Percentage	Count	Percentage
Missing Activity	551	56.22%	4,980	19.02%
Activity Not in Right Order	23	2.35%	139	0.53%
Redundant Activity	831	84.80%	2,664	10.17%
Total	980	100%	26,185	100%

As shown in Table 6, non-standard variants include three parts: (1) missing activity, (2) activity not in right order, and (3) redundant activity. The three categories can be further broken down into 22 sub-categories that each represent one type of non-standard variant in the procure-to-pay cycle.

Missing Activity

Table 7 presents the classification results for missing activity. The results show that activities 'sign', 'release' and 'goods receipt' are missing in several variants. Specifically, there are 40 variants (3,443 process instances) missing sign, three variants (three process instances) missing release, and two variants (three process instances) missing goods receipt.[9] The last two sub-categories capture the business processes that whenever a change line occurs in a variant, there should be an approval process follows. Dependent on

[9] When goods receipt indicator shows 'turn off' in the SAP system, it is standard for the process to skip the activity "goods receipt." Therefore, we have filtered out the variants that do not have goods receipt and the goods receipt indicator shows "turning off" in the original classification results. As a result, the results of goods receipt in Table 7 shows the variants and process instances that do not have goods receipt in the process and goods receipt indicator is 'on.'

different standards from different firms, the approval process could be either sign or release, or both sign and release. Accordingly, we have classified the variant into two sub-categories, change line without sign and change line without sign nor release.

The results in Table 7[10] indicate that 56.22 percent[11] of required activities are missing in the bank's procurement process, and 40 percent of the process instances do not have approval process after changing line.[12] These process instances need to be sent to auditors for further investigation since missing any required activity in the purchase order without appropriate reason could reflect the failure of controls or existence of unusual/anomalous transactions. For example, missing signature and release in a purchase order could result in payment without approval and missing goods receipt when goods receipt indicator is 'on' would affect three-way match process and could result in unreconciled differences in account reconciliation. It is worth to note that missing activity could also result from recurring business processes such as weekly/monthly payments on a lease or a rent.

[10] The total variant and process instance presented in Table 7 are the total distinct variant and process instance for this category, rather than the sum of the variant count and process instance count in Table 7. The numbers in this row are the same as the total variant and process instance for 'missing activity' in Table 6.

[11] The total variants (process instances) that missing required activities are 551 (4,980), which is not the sum of the variants (process instances) of each sub-category because some of the variants (process instances) missing more than one required activities.

[12] The percentage of process instances that do not have approval process (either sign or release) is calculated as follows: 4,293/10,864 = 40 percent. We did not use the sum of 4,293 and 1,574 because 1,574 of the process instances that do not have signature nor release followed by changing line are included in the 4,293 process instances that do not have signature followed by changing line.

Table 7: Missing Activity

Sub-category	Variant Frequency	Process Instance Frequency
Missing Purchase Order (PO)	0	0
Missing Signature (Sign)	40	3,443
Missing Release	3	3
Missing Goods Receipt (GR)	2	3
Missing Invoice Receipt (IR)	0	0
Missing Payment (Pay)	0	0
Change Line without signature	544	4,293
Change Line without signature nor release	494	1,547
Total	551	4,980

Activity Not in Right Order

Table 8 presents the classification results for the non-standard variant category "Activity Not in Right Order." The first and second sub-categories capture the business processes that goods receipt should occur after the approval process, and the approval process could be either sign or release, depends on the rules of specific firms. Our classification results for these two sub-categories show that all goods receipts occur after the approval process in the dataset. The second and third sub-categories capture the business processes that invoice receipt should occur after the approval process. The classification results indicate that there are five variants (nine process instances) do not have a signature before the occurrence of invoice receipt, and 15 variants (131 process instances) do not have a release before the occurrence of invoice receipt. The sub-

categories for payment capture three business processes: (1) payment should occur after the approval process (i.e., sign or release), (2) payment should occur after goods receipt, and (3) payment should occur after invoice receipt. The classification results show that there are (1) one variant (one process instance) pays without a signature, (2) two variants (three process instances) pay without approval,[13] and (3) eight variants (eight process instances) pay before receiving goods receipts.

The findings in Table 8[14] need to be sent to the responsible party for further analysis since these variants have large deviations from the standard procure-to-pay process and could indicate potential risks in the firm's internal control or represent anomalous transactions (e.g., unauthorized payments). For example, invoice receipt and payment occurred before sign and release could indicate payment made without an approval process, and completing the payment process before the occurrence of goods receipt and/or invoice receipt might result in incorrect payments or unreconciled difference in account reconciliation.

[13] The 3 process instances that have payment made before release do not have sign prior to the payment either.

[14] Please note that the total variant and process instance presented in Table 10 are the total distinct variant and process instance for this category, rather than sum of the variant frequency and process instance frequency. The numbers in this column are the same as the total variant and process instance for 'activity not in right order' in Table 6.

Table 8: Activity Not in Right Order

Sub-category	Variant Frequency	Process Instance Frequency
Goods Receipt (GR) occurs NOT after Signature (Sign)	0	0
Goods Receipt (GR) occurs NOT after Release	0	0
Invoice Receipt (IR) occurs NOT after Signature (Sign)	5	9
Invoice Receipt (IR) occurs NOT after Release	15	131
Payment (Pay) occurs NOT after Signature (Sign)	1	1
Payment (Pay) occurs NOT after Release (missing sign)	2	3
Payment (Pay) occurs NOT after Goods Receipt (GR)	8	8
Payment (Pay) occurs NOT after Invoice Receipt (IR)	0	0
Total	23	139

Redundant Activity

Table 9[15] shows the classification results for "redundant activity" category. The results indicate that six out of seven activities occur more than once in several variants. Specifically, "sign" occurs more than one time in 379 variants (1,094 process instances), "release" occurs more than one time in 209 variants (680 process instances), "goods receipt" occurs more than one time in 450 variants (548 process instances), "invoice receipt" occurs more than one time in 455 variants (527 process instances), and "payment" occurs more

[15] Please note that the total variant and process instance presented in Table 11 are the total distinct variant and process instance for this category, rather than sum of the variant frequency and process instance frequency. The numbers in this column are the same as the total variant and process instance for 'redundant activity' in Table 6.

than one time in 650 variants (1,830 process instances).

The redundant activity results in Table 9 are more likely representing lower risks in a firm's internal control compared with missing activity or having activity not in right order; the rationale is that activities that occur more than once could merely result from large amount purchase orders that required more than one signature, purchase with multiple shipments or inefficient process. For example, if a purchase order includes a $100 purchase of pens (each $10) and the buyer and vendor agreed that there would be 5 shipments with 2 pens per delivery, then the business process for this purchase order will include five goods receipts, five invoice receipts, and five payments. In this case, these activities are not redundant. Instead, they could be a standard business process for a purchase order with multiple shipments.

More than one signature or release occurred in a purchase order could result from inefficient business process, for example, if employee A signs a purchase order before taking a vacation without properly handover this work to employee B, then it is possible that employee B will sign the purchase order one more time and result in inefficient transition process. Although redundant activity generally represents lower risks, when activities occurred more than once in the procure-to-pay process without appropriate reason, it is also possible that these activities are indicators of fraudulent transactions. For example, if an employee intentionally pays a purchase order twice, then the second payment is redundant and could be fraudulent behavior.

Table 9: Redundant Activity

Sub-category	Variant Frequency	Process Instance Frequency
Redundant Purchase Order (PO)	0	0
Redundant Signature (Sign)	379	1,094
Redundant Release	209	680
Redundant Goods Receipt (GR)	450	548
Redundant Invoice Receipt (IR)	455	527
Redundant Payment (Pay)	650	1,830
Total	831	2,664

To further analyze each sub-category of redundant activities, we extract the top 10 process instances that have the highest frequency of occurrence for each activity, as presented in Table 10. For example, process instance ‘450040351510’ has the highest goods receipt occurrence (129 times) among all other process instances in the dataset. Table 10 is sorted by the top 10 occurrences of the signature, and all the top 10 process instances in each activity are highlighted in bold. As shown in Table 10, several process instances are included in more than one activity’s top 10 occurrence lists, indicating that these process instances have multiple redundant activities and the frequency of occurrence is high. For example, process instance ‘450040351810’ has 118 goods receipt, 112 invoice receipt, and 137 payment. The process instances that have more than one top 10 occurrence activity need to be flagged and sent to the auditors for further analysis because these process instances could indicate inefficient business processes or potential risks.

Table 10: Top 10 Redundant Activity

Process Instance	Variant	Create PO	Sign	Release	GR	IR	Pay
4500400507180	Variant 674	1	**21**	**20**	1	1	1
450040050710	Variant 281	1	**21**	**20**	2	2	3
450040050720	Variant 272	1	**21**	0	2	2	3
450040050740	Variant 270	1	**21**	0	2	1	1
450040050750	Variant 269	1	**21**	0	2	1	1
450040050770	Variant 276	1	**21**	0	2	1	1
450040050780	Variant 275	1	**21**	0	2	1	1
450040050760	Variant 277	1	**21**	0	1	1	1
450040050790	Variant 274	1	**21**	0	1	1	1
4500400507100	Variant 667	1	**21**	0	1	1	1
450040050730	Variant 271	1	**21**	0	4	2	2
450039573130	Variant 775	1	13	**13**	11	13	13
450039757010	Variant 914	1	10	**8**	12	7	8
450039757080	Variant 922	1	10	**8**	1	1	2
450039757090	Variant 124	1	10	**8**	1	1	1
4500397570100	Variant 124	1	10	**8**	1	1	1
450039896140	Variant 625	1	10	**8**	3	3	3
450039896160	Variant 195	1	10	**8**	2	2	2
450039896170	Variant 195	1	10	**8**	2	2	2
450040351810	Variant 548	1	5	0	**118**	**112**	**137**
450040350910	Variant 283	1	3	0	**76**	**70**	**86**
450040353610	Variant 426	1	3	3	**57**	**57**	**71**
450040351510	Variant 499	1	0	0	**129**	**105**	**117**
450040318310	Variant 423	1	0	0	**112**	**112**	**133**
450040320910	Variant 514	1	0	0	**59**	**60**	**86**
450040353910	Variant 541	1	0	0	**54**	**48**	**59**
450040353810	Variant 525	1	0	0	**33**	**33**	**45**
450040351610	Variant 517	1	0	0	**33**	**27**	28
450040351710	Variant 536	1	0	0	**27**	**27**	28
450039662310	Variant 804	1	0	0	1	1	**134**
450039662320	Variant 805	1	0	0	1	1	**77**

2.4.3 Additional Analysis

Segregation of Duty Analysis

In response to Sarbanes-Oxley Act (SOX) Section 404, most of the publicly-traded firms have controls related to segregation of duty in place to prevent one individual from responsible for multiple critical tasks in the business process. In our study, the bank has three controls related to segregation of duty: (1) in a purchase order, consecutive sign and release should be performed by two distinct employees;[16] (2) in a purchase order, consecutive release and goods receipt should be processed by two distinct employees;[17] (3) in a purchase order, consecutive goods receipt and invoice receipt should be performed by two distinct employees.[18] Table 11 presents the results of segregation of duty analysis, as conducted in the study of Jans et al. (2014): (1) 11 process instances (nine resources) have the same employee processes signature and release, and (2) 175 process instances (24 resources) have the same employee processes release and goods receipt. These results will

[16] If a purchase order has multiple sign and release occurred in the process, then the control only require consecutive sign and release to be performed by two distinct employees. For example, the sign and release in the following process should be performed by two different employees: 'PO—***sign—release***—GR—IR—Pay,' while the first sign and the second release in the following process instance could be performed by the same employee: 'PO—***sign***—release— sign—***release***—GR—IR—Pay.'

[17] If a purchase order has multiple release and GR occurred in the process, then the control only require consecutive release and GR to be performed by two distinct employees. For example, the release and GR in the following process should be performed by two different employees: 'PO—sign—***release—GR***—IR—Pay,' while the first release and the second GR in the following process instance could be performed by the same employee: 'PO—sign—***release***—GR—release—***GR*** —IR—Pay.'

[18] If a purchase order has multiple GR and IR occurred in the process, then the control only require consecutive GR and IR to be performed by two distinct employees. For example, the GR and IR in the following process should be performed by two different employees: 'PO—sign—release—***GR—IR***—Pay,' while the first GR and the second IR in the following process instance could be performed by the same employee: 'PO—sign—release—***GR*** —IR— GR —***IR***—Pay.'

be combined with the discovered non-standard variants from the variant analysis, and then the combined results will be used in the personnel analysis.

It is worth to note that although segregation of duty is a required control in most of the firms, it is possible that some of the firms could accept exceptions for extraordinary circumstances or smaller firms would not have the staff for this purpose. For example, many firms allow one employee to perform two critical tasks during the holiday season due to the lack of employees available in the firm on that season. Therefore, the results shown in Table 11 could indicate potential ineffectiveness of internal controls or exceptions under extraordinary circumstances. The process instances that potentially violate segregation of duty controls need to be further investigation based on the firm's specific business rules.[19]

Table 11: Segregation of Duty Analysis

	Process Instance Frequency	Resource Frequency
The same person performs 'Sign' and 'Release	11	9
The same person performs 'Release' and 'GR'	175	12
The same person performs 'GR' and 'IR'	0	0
Total	186	21

[19] The employees identified in Table 11 could potentially violate the segregation of duty control. However, every company has its own business process for the segregation of duty control; for example, a manager could have multiple roles in the accounting information systems and therefore would be able to sign and release a process instance without violating the control. As a result, the identified results in Table 11 should be combined with the employee's role in the company before determining whether the employees violate segregation of duty controls.

Personnel Analysis

The rationale of performing personnel analysis is that if an individual is involved in multiple violations, for example, employee A is involved in one of the non-standard variants and also violates one of the controls related to segregation of duty, then this individual has a higher potential of conducting fraudulent behavior compared with other individuals. The results are presented in Table 12, where row 1 to 6 show the count of individuals (resource) involved in non-standard variants and also violate segregation of duty controls,[20] and row 7 to 10 show the count of individuals involved in multiple categories of non-standard variants. For example, row 1 shows that eight individuals (eight process instances) involved in process instances that have the same person perform sign and release and also involved in the missing activity categories. Row 10 indicates that there are 30 resources (17 process instances) involved in all three categories of non-standard variants (i.e., missing activity, activity not in right order and redundant activity). These individuals who are involved in more than one potential violation provide audit-relevant information to auditors as auditors could examine all the process instances performed by these individuals and screen for potential fraudulent behavior.

[20] Please note that there is no individual involved in both 'activity not in right order' category and SOD controls, and there is no individual violates the two controls in SOD at the same time.

Table 12: Personnel Analysis

	Resource Frequency	Process Instance Frequency
SOD1 (Same person perform 'Sign' and 'Release') & Missing Activity	8	8
SOD1 (Same person perform 'Sign' and 'Release') & Redundant Activity	9	11
SOD1 (Same person perform 'Sign' and 'Release') & Missing Activity & Redundant Activity	8	8
SOD2 (Same person perform 'Release' and 'GR') & Missing Activity	19	58
SOD2 (Same person perform 'Release' and 'GR') & Redundant Activity	21	22
SOD2 (Same person perform 'Release' and 'GR') & Missing Activity & Redundant Activity	17	6
Missing Activity & Redundant Activity	205	663
Missing Activity & Activity Not in Right Order	33	129
Redundant Activity & Activity Not in Right Order	40	21
Missing Activity & Activity Not in Right Order & Redundant Activity	30	17

Timestamp Analysis

Process instances that have very long process duration could indicate inefficient business processes or could be a reflection of the potential anomalous transaction. For example, if a purchase order's starting date to ending date lasts for more than 100 days without appropriate reason, then it is possible that the process for this purchase order is inefficient or employees leave this purchase order open on purpose for fraudulent behaviors. In this study, we use the bank's mean process instance duration (i.e., 46.2 days)[21] as a

[21] The mean process instance duration is shown in Table 3

baseline and found that there are 5,968 process instances (22.79 percent) have process duration more than 46.2 days. Specifically, the top 10 process instances are long-running processes that last for more than 365 days, as presented in Table 13. The process instances with longer duration could indicate higher potential risks or inefficient controls, and they could also indicate that an employee is lazy, overburden, or incompetent. Therefore, process instances with long duration should be sent to auditors for further investigation.

Table 13: Top 10 Process Duration

Process Instances	Variant	Start Date	End Date	Duration (days)
450039593410	Variant 467	1/4/2007	1/25/2008	386
450039595410	Variant 354	1/4/2007	1/25/2008	386
450039593810	Variant 397	1/4/2007	1/14/2008	375
450039594310	Variant 660	1/4/2007	1/14/2008	375
450039597510	Variant 291	1/4/2007	1/14/2008	375
450039636610	Variant 656	1/5/2007	1/14/2008	374
450039757110	Variant 902	1/10/2007	1/18/2008	373
450039894250	Variant 583	1/16/2007	1/23/2008	372
450039673620	Variant 612	1/8/2007	1/14/2008	371
450040005720	Variant 379	1/19/2007	1/25/2008	371

2.5 CONCLUSIONS

The objective of this study is to demonstrate how process mining can be adopted in the evaluation of internal control effectiveness. The evaluation includes four perspectives: variant analysis, segregation of duty analysis, personnel analysis, and timestamp analysis. This paper extends prior studies in the same field by (1) examining the full population of event logs, (2) providing categories and sub-categories of standard and non-standard variants based on a real-life business process from a large European bank, and (3) conducting insofar most comprehensive analyses to demonstrate how auditors could use process mining in evaluating the effectiveness of internal control.

The event log data used in this study has already been examined by the bank's internal auditors who did not find any significant issue. However, our results from variant analysis and three additional tests raise several audit-relevant issues that need internal auditor's further investigations. First, in the variant analysis, there is 95 percent of the variants (6,987 process instances) being classified as non-standard variants, indicating that these variants do not conform to the standard procurement process and therefore need to be further investigated. Second, in the segregation of duty analysis, 186 process instances are found violating segregation of duty controls. Third, in the personnel analysis, a large number of personnel are found involved in more than one potential violations. Finally, in the timestamp analysis, 5,968 process instances (22.79 percent) have process duration longer than the bank's mean process duration (46.2 days), and the top 10 process instances are long-running processes that last for more than one year.

There are limitations associated with this study. First, most of the categories and sub-categories of standard and non-standard variants are based on the standard procurement process. Therefore, these categories/sub-categories need to be modified when examining event logs from other companies and/or business cycles. Second, this study demonstrates how process mining can be applied to evaluate the effectiveness of internal control by using only one company's event log data. The results can be more generalized if the methodology being applied to more firms and different business cycles. Third, our analyses are based on variables extracted from the event log, however, incorporating other variables, such as the transaction value, might help auditors gain more profound insights.

Future research could compare the categories/sub-categories of standard and non-standard variants with the organization's business rules. This could help auditors to identify whether the non-standard variants conform to business rules and further determine the riskiness of each sub-category in the non-standard variants. Another possible research direction is to examine the possibility for process mining techniques to timely discover unauthorized procedures through real-time monitoring systems and subsequently reduce the occurrences of potential fraud. For example, process mining could be integrated into the "audit by exception" concept, proposed by Vasarhelyi and Halper (1991). In this case, an alarm of exception will arise when the purchase order is *released* without a proper *sign*.

CHAPTER 3: VALIDATING PROCESS MINING: A FRAMEWORK INTEGRATING AUDITOR'S RISK ASSESSMENT

3.1 INTRODUCTION

Process mining is a technique that extracts the information from event logs in order to allow users to discover and improve business processes through the analysis of event logs (van der Aalst 2011; Alles et al. 2011). Previous studies on the application of process mining in auditing indicated that process mining could add value to auditing and could be applied to evaluate the effectiveness of internal control (Yang and Hwang 2006; Jans et al. 2009, 2010, 2011, 2013, 2014; Chiu and Jans 2017). When using process mining in auditing, the information that needs to be extracted from the accounting information system including process instance, activity, resource, and timestamp (Jans et al. 2014). For example, in a procure-to-pay process, a process instance is a purchase order number, the first activity in each process instance is "create purchase order," a resource is an employee who conducts an activity, and a timestamp is a date and time that an employee performs an activity.[1]

Most of the existing studies did not link event log information with the corresponding transaction amount when demonstrating why process mining can be new audit evidence. This is mainly due to the lack of available process mining log data and the nature of the information provided in the event logs (i.e., missing transaction value). The application of

[1] For instance, a purchase order has purchase order number "12345," and an employee - "Mary" performs the first activity "create purchase order" on March 18, 2018. In this example, "12345" is the process instance, "Mary" is the resource of the first activity - "create purchase order," and "March 18, 2018" is the timestamp for the first activity. A process instance could have multiple activities, resources, and timestamps.

process mining in auditing has just evolved, and therefore there is no or little real-life data available for related research, especially in accounting and auditing fields. Examining the information from event logs enables auditors to analyze their clients' data in terms of activities, variants, timestamps, and resources. Nonetheless, it is also critical for auditors to consider transaction values when making audit judgments on the exceptions found in process mining analysis.

The event log information utilized in process mining can be extracted from the client's accounting information system. Enterprise resource planning (ERP) systems, such as SAP, have become widely used in recent years (Scapens and Jazayeri 2003). Most of the firms no longer record transactions and business information on the paper-based accounting books or business records. Since all the transactions and business information are in the same accounting information system that stores the event logs, auditors can extract both event log information and corresponding transaction values when performing analysis using process mining.

The objective of this study is to build a framework on how auditors can utilize both routing and transaction value information when using process mining as new evidence in their audit work. Specifically, this framework is based on the auditor's risk assessment. In line with prior studies (Jans et al. 2014; Chiu and Jans 2017), the first step of our framework is to identify variants from the data and then classify variants into standard and non-standard variants categories and sub-categories based on different routings of the process instances. The second step sends all the non-standard variant sub-categories to auditors for risk assessment. Prior studies on audit risk assessment generally concluded that it is

necessary to prioritize the identified exceptions because this could improve audit efficiency (Kim and Vasarhelyi 2012; Issa and Kogan 2014; Li et al. 2016). Therefore, in line with previous research, the proposed risk assessment framework prioritizes identified exceptions based on both risk scores and the materiality threshold determined by the firm's business rule. Specifically, auditors assign risk scores to the sub-categories of business processes based on their judgments. And then the sub-categories will be classified into the following four risk levels based on the assigned risk scores: (1) very low risk (risk score = 1), (2) low risk (risk score = 2), (3) moderate risk (risk score = 3), and (4) high risk (risk score = 4). After that, the last two steps prioritize process instances based on the sum of risk scores and the materiality threshold.

The application of the proposed risk assessment framework on an event log from a not for profit organization shows that auditors could benefit from prioritized process mining results as they could focus on material and high-risk business processes. In addition, auditors could examine employees that involved in process instances with higher risk scores and material, and employees violate segregation of duty controls on process instances with material transaction value. Process instances above the threshold and have very long or very short process durations might indicate higher potential risks as lengthy process duration could indicate inefficient business processes and short process duration with material transaction value could be an indicator of potentially fraudulent behavior.

The contribution of this study is three-fold. First, this study proposes a framework for using process mining in auditors' risk assessment process. Specifically, the framework includes auditors' judgments on the risk level of procure-to-pay business processes. The

proposed framework can be applied to the procurement process in any firm with event log data. The identified process instances are prioritized to improve the efficiently of the audit. Auditors could choose among the four proposed risk prioritization methods when analyzing the identified process instances. Second, this paper utilizes the entire population of an event log data when demonstrating how process mining could be integrated into the auditor's risk assessment process. Third, by applying the proposed framework to the audit work, auditors could examine high-risk process instances with material transaction amount instead of investigating random sample with material transaction value.

The remainder of this paper is organized as follows. Section 2 summarizes background and related studies on process mining and audit risk assessment. Section 3 describes the proposed risk assessment framework using process mining. Section 4 introduces the case study and presents the results. Section 5 concludes the paper and discusses future research directions.

3.2 LITERATURE REVIEW

3.2.1 The Application of Process Mining in Auditing

Analyzing an organization's business process using existing event logs was first proposed by Agrawal et al. (1998). The idea of mining business processes has been widely adopted in various research domains including computer science and management. A large body of previous research proposed novel process mining models or compared the differences between exisiting process models and the oberved event logs in the accounting information systems (Agrawal et al. 1998; Cook and Wolf 1998; Schimm 2003; van der Aalst et al. 2003; van der Aalst and Weijters 2004; van der Aalst et al. 2004; Alves de Medeiros et al. 2006; Greco et al. 2006; Gunther and van der Aalst 2007; van der Aalst et al. 2007; Rozinat and van der Aalst 2008; Rozinat et al. 2008; Bozkaya et al. 2009; Folino et al. 2009; de Medeiros et al. 2007; Wen 2007; van der Werf et al. 2008; van Dongen et al. 2009; Goedertier 2009; Jans 2009; Wen et al. 2009; Adriansyah et al. 2011a; Adriansyah et al. 2011b, 2011c; van der Aalst et al. 2011; Weijters and Ribeiro 2011; Buijs 2012; de Leoni et al. 2012; van der Aalst et al. 2012; de Weerdt et al. 2013; Werner 2017).

Reliable information about the operation is essential for stakeholders to make decisions. The objective of auditing is to provide validation on information generated from a firm’s business processes. Traditionally, auditors select samples from the whole population to assess the operating effectiveness of process controls. With the development of technology in general and enterprise resource planning (ERPs) in particular, detailed information about processes in the form of event logs became increasingly abundant. With such development, current research such as van der Aalst (2010), van der Aalst et al. (2010)

and Jans et al. (2011, 2013, 2014) proposed the use of process mining in the auditing domain. Van der Aalst et al. (2010) introduced an auditing framework by the name of Auditing 2.0. The framework presented in their study showed that two types of data could be extracted from the information system, current and historical. Current data refers to process instances that are still running, while historical data represents the completed cases. There are also two types of models presented, De Jure and De facto. De jure models are considered as the required models, whereas de facto models describe what happens in reality. The auditors can then perform multiple tests to validate the company's process. The auditor can check if the historical data in the event log conforms to the desired model in order to detect deviations, locate and explain them, and measure their severity (Rozinat and van der Aalst 2008). The auditor can also compare de jure and de facto models in order to analyze the differences. Finally, auditors can diagnose de facto models by using model-based analysis techniques to check for deadlocks and other anomalies (van der Aalst et al. 2010).

Process mining enables auditors with new audit evidence as the examination of event logs focuses on business process transaction value (Jans et al. 2014). Adopting process mining in auditing has two main advantages (Jans et al. 2013): (1) It enables auditors to examine full population of event logs, rather than the current sampling method, and (2) The transaction entries are generated automatically from the ERP system, thus eliminating the dependency on potentially subjective data provided by the auditee. The aim of analyzing the event log is to determine how the process was undertaken, who was involved in the process, and what happened with a particular transaction. The process

perspective deals with how the process was undertaken by comparing the designed and actual models. The organizational perspective looks at the relationship between individuals associated with an activity in order to test for controls such as segregation of duties. The case perspective zeroes in on a single process instance by looking at its history and involved users to investigate anomalous transactions identified in other perspectives.

Yang and Hwang (2006) indicated that the process mining detection model could identify more healthcare fraudulent and abusive cases which the manually developed model did not capture. Process mining is not only capable of identifying potential fraud but also able to assist auditors in understating client's business process and evaluating internal control risks (Jans et al. 2013). 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). Applying process mining in auditing analytical procedure enables auditors to detect audit relevant issues such as anomalous transactions (Jans et al. 2014).

3.2.2 Audit Risk Assessment

Audit risk assessment refers to "*identify and appropriately assess the risks of material misstatement, thereby providing a basis for designing and implementing responses to the risks of material misstatement*" (PCAOB AS2110). Risk assessment is an important audit process which could ultimately affect audit fees, especially with the presence of serious internal control problems (Bell et al. 2001; Hogan and Wilkins 2008). As a result, prior research proposed various risk detection models to achieve the goal of accurately capturing potential risks within the client's business (Calderon and Cheh 2002; Carnaghan 2006; Chang et al., 2008). Specifically, Carnaghan (2006) used business process modeling to perform audit risk assessments at the business process level. The study identifies the commonly used business process modeling conventions include data flow diagrams, system flowcharts, REA models, event process chains, IDEF0 and IDEF3, UML diagrams, and business diagrams (BPMN). Calderon and Cheh (2002) applied neural networks in business risk auditing framework because these offer the capacity to simultaneously consider multiple types of evidence and assist auditors in risk assessment and decision making. Chang et al. (2008) implemented fuzzy theory and audit risk model on 43 critical risk factors identified by prior literature to improve the precision of audit risk assessment.

The process of audit risk assessment needs to be improved when there is a change of client's business environment. For example, Eilifsen et al. (2001) examined the fundamental changes in the audit process when accounting firms expand from basic financial statement audit to a new approach that includes external assurance and business

risk assessment. The new approach divides risk assessment into strategic risks and process risks. Moreover, Sutton and Hampton (2003) argued that complex contemporary business relationships such as e-business partnerships, outsourcing and co-sourcing, and co-dependence business partners have extended the business risk faced by a client. This purports that auditors need to better understand the implications of these relationships to reasonably assess business risk across the extended enterprise.

Auditors could benefit from prioritizing suspicious transactions identified in the risk assessment process (Kim and Vasarhelyi 2012; Issa and Kogan 2014; Li et al. 2016). Specifically, Kim and Vasarhelyi (2012) proposed to define risk indicators and to assign arbitrary scores based on their security. Issa and Kogan (2014) indicated that prioritizing outliers in the internal control risk assessment process could improve audit efficiency and Li et al. (2016) proposed that it is necessary to prioritize exceptions when conducting risk assessment because exceptions generated by a continuous auditing system could be overwhelming for internal auditors to deal with.

3.3. RISK ASSESSMENT FRAMEWORK

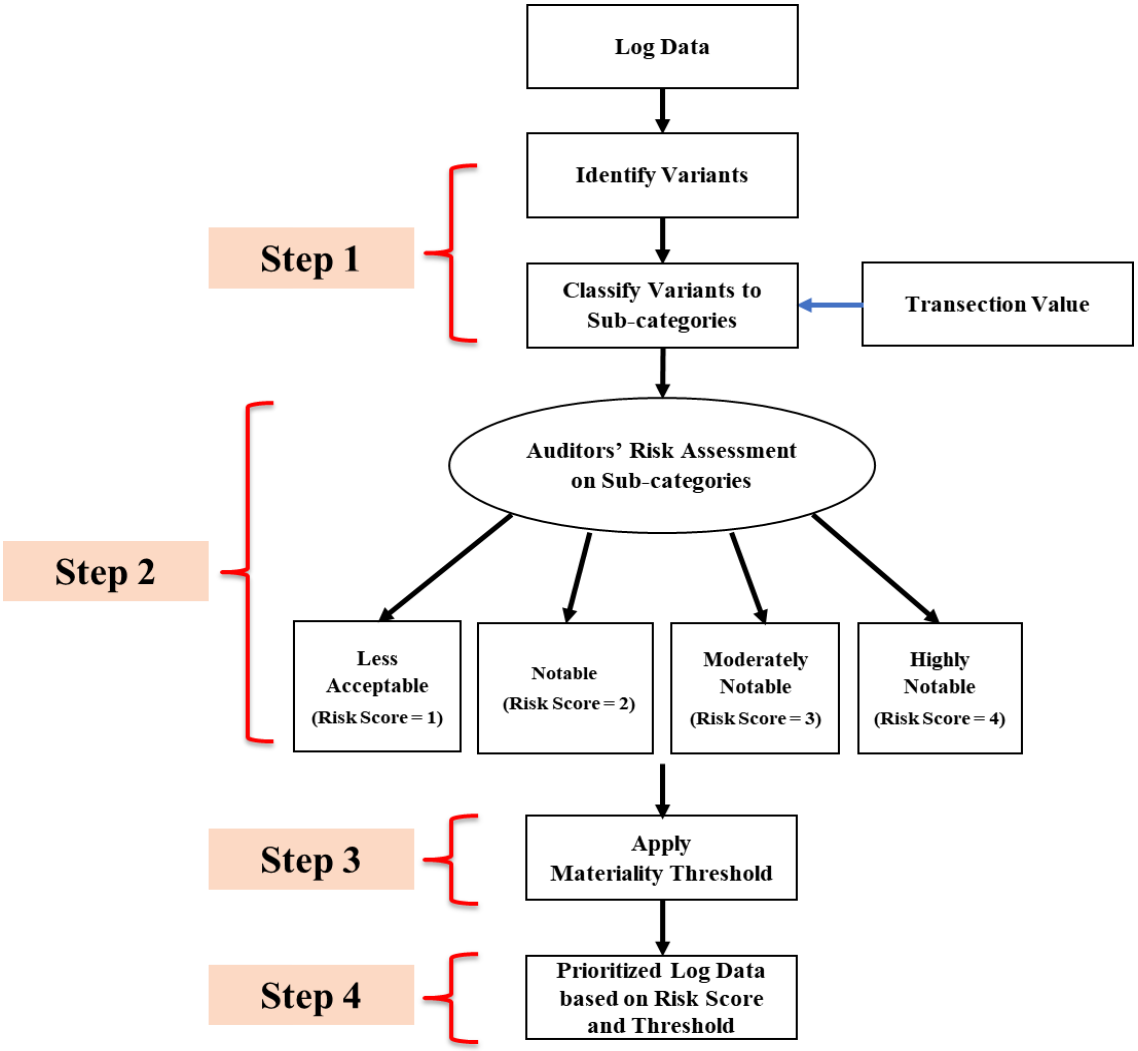
There are four steps included in the proposed risk assessment framework: (1) identify variants from the routings of process instances. (2) Classify the variants into standard and non-standard categories and sub-categories. Specifically, the classification of activity “signature” is based on the firm’s business rule for the purchase order approval process. Thus, transaction values are included in this step for classification. (3) The non-standard variant sub-categories will be sent to auditors for risk assessment. Auditors assign

risk scores based on their judgements on the potential risks of routings (sub-categories),[2] and then the sub-categories will be classified into the following four risk levels based on their assigned risk scores: “very low risk” (risk score = 1), “low risk” (risk score = 2), “moderate risk” (risk score = 3), and “high risk” (risk score = 4). (4) The materiality threshold is determined based on the company’s business rule. (5) Finally, auditors will receive prioritized process instances based on both risk scores and the materiality threshold.

Appendix B shows the standard and non-standard categories and sub-categories used in this study, which is built on a previous study in the same filed (Chiu and Jans 2017). The detailed steps of the risk assessment framework can be found in Figure 3.

[2] To generalize the proposed risk assessment framework, the auditors do not consider transaction value when assigning risk score for sub-categories. The rationale is that different firms will have different thresholds for purchase-to-pay process, and therefore the threshold will be applied later in step 3 based on different firms’ business rules.

Figure 3: A Framework of Risk Assessment using Process Mining



3.4 AUDIT RISK ASSESSMENT USING PROCESS MINING: A CASE STUDY

3.4.1 Event Log Data from A Not for Profit Organization

The data applied in this study is a real-life procure-to-pay event log data from a not for profit organization in the United States, as presented in Table 14. The event log contains 9,187 process instances, 66,808 events, and includes 5 activity types (Create Purchase Order, Signature, Goods Receipt, Invoice Receipt, Release[3]). In addition, there are 237 employees working on the 9,187 process instances. The event log data used in this study contains only the process instances that have all activities being labeled as "complete" in the system. For example, if a process instance's first activity "create purchase order" is being labeled as "incomplete," then we remove this process instance as the "incomplete" status indicates that this activity is still pending in the system for future actions. Figure 4 shows the business process map of the not for profit organization. The arrows in Figure 4 represents the frequency and direction of the process; the darker and thicker arrows represent more frequent business processes. The number beneath each activity represents the total occurrence of that activity, for example, 'Create PO' occurred 9,958 times and 'Sign' occurred 13,874 times. The darker boxes stand for higher occurrence activities, for example, the occurrence of 'GR' is higher than 'Create PO,' so the box for 'GR' is darker than the box for 'Create PO.' Table 15 shows the frequency of activity.

[3] The activity "release" in the not for profit organization's procure-to-pay process represents release the purchase order to the accounts payable department for payment. This is different from the activity "release" in the bank's procure-to-pay process, where the release represents release the purchase order to invoice receipt or goods receipt (Chiu and Jans 2017). Therefore, we revise the standard and non-standard variants categories accordingly when we classify variants into categories adopted from Chiu and Jans (2017).

Table 14: Description of Event Log: Procure-to-Pay Process from A Not for Profit Organization

Event	66,808
Process Instance	9,187
Activity	5
Activity Detail	(1) Create PO (2) Sign (3) GR (4) IR (5) Release
Resources	237
Mean Process Duration	13.1 Weeks
Start	08/16/2012
End	12/02/2016

Figure 4: A Procure-to-Pay Process Map from A Not for Profit Organization

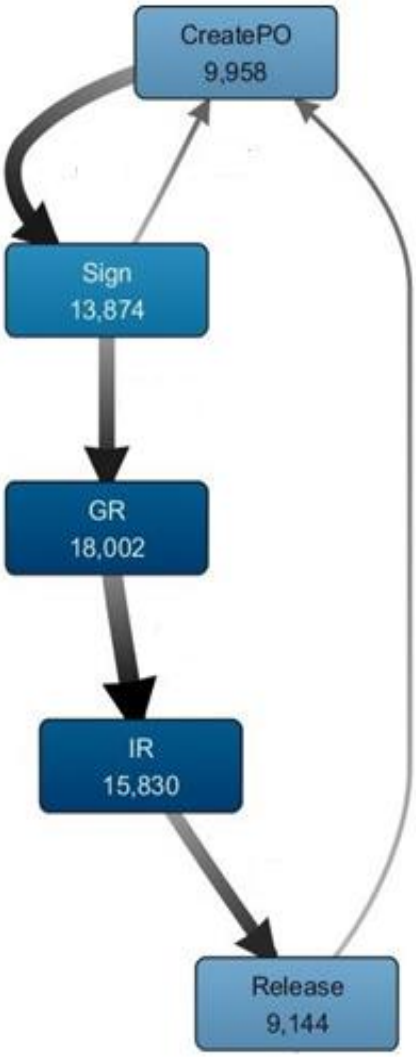


Table 15: Activity Frequency

Activity	Count	Percentage
Create PO	9,958	14.91%
Sign	13,874	20.77%
GR	18,002	26.95%
IR	15,830	23.69%
Release	9,144	13.69%
Total	66,808	100%

3.4.2 Step 1: Variant Identification and Classification

Process instances with the same number and order of activities will be grouped into the same variant. For example, if process instances A and B both have the following path: Create PO-Sign-GR-IR-Release, then they are grouped into the same variant. In other words, process instances have identical path within a variant and have different paths between variants. Therefore, the 9,187 process instances can be grouped into 876 variants, indicating that the 9,187 process instances have 876 different paths in terms of sequence and activity. The classification categories and sub-categories we applied in this paper are adapted from the discovered procure-to-pay standard and non-standard variants from Chiu and Jans (2017). The categories and sub-categories for standard and non-standard variants are revised based on the event log data used in this case study. Appendix B shows the revised categories and sub-categories for standard and non-standard variants. These categories and sub-categories have been used to classify variants in step 1 of the risk assessment framework. The changes we made from the original sub-categories including:

(1) the activity "release" in procure-to-pay process from not for profit organization represents release the purchase order to accounts payable department for payment, which is different from the release in Chiu and Jans (2017) where release stands for release purchase order to invoice receipt or goods receipt. Therefore, the sub-categories related to release in non-standard variants have been revised accordingly. (2) The payment information for all process instances is in the accounts payable department in this firm. Therefore, payment information is not available in this log. The sub-categories related to payment have been removed accordingly in the non-standard variants. (3) There is no "change line" activity in the procure-to-pay process from the not for profit organization. Therefore, the sub-categories related to "change line" in both standard and non-standard variants have been removed accordingly.

The full population of an event log has been classified into categories and sub-categories in standard and non-standard variants presented in Appendix B. The classification results are displayed in Table 16. The classification results show that 99.66%[4] percent of the variants have been classified into non-standard variants, indicating that these 3,918 process instances need to be further investigated. Moreover, there is 28.31% of the total variant missing required activity, 2.17% with activity not in the right order, and

[4] The variant count and percentage for standard and non-standard variants are more than 100% because we classify missing signature and redundant signature based on the company's business rules for signature. The business rule can be found in Table 19. For example, assume process instance A and process instance B have same routing and therefore are all in Variant A. If process instance A has two signatures and the value for PO is less than $50,000, then this process instance will be classified into "redundant signature" because it only needs 1 signature according to the firm's business rule. On the other hand, if process instance B has two signatures and the value for PO is more than $50,000, then this process instance will be classified into "standard variant" because any transaction over $50,000 requires two signatures. In this case, although process instances A and B are in the same variant (i.e., variant A), they have been classified into non-standard variant and standard variant, respectively, due to different amount for PO.

98.40% of the total variant have redundant activity. Table 17 shows the detailed classification results for non-standard variants. Non-standard variants can result from inefficient internal control processes and potential risks or errors in the firm's business processes (Chiu and Jans 2017). The 3,918 identified process instances in non-standard variant will be sent to step 2 for auditor's risk assessment. In step 3 and step 4 of the risk assessment framework, these identified process instances are further prioritized based on auditor's risk assessment and corresponding threshold determined by the firm. Auditors could benefit from prioritizing suspicious transactions identified in the risk assessment process (Kim and Vasarhelyi 2012; Issa and Kogan 2014; Li et al. 2016). It is worth to note that the 2 categories in standard variant[5] are developed based on the not for profit organization's standard business processes according to their business rules.

Table 16: Classification Results

	Variant		Process Instance	
	Count	Percentage	Count	Percentage
Standard Variant	8	0.91%	5,269	57.35%
Non-standard Variant	873	99.66%	3,918	42.65%
Total	876	100%	9,187	100%

[5] The 2 categories are: "standard procure-to-pay process" and "invoice receipt (IR) and goods receipt (GR) switch places", as presented in Appendix B, Panel A.

Table 17: Classification Results – Non-standard Variants

	Variant		Process Instance	
	Count	Percentage	Count	Percentage
Missing Activity	248	28.31%	1,395	15.18%
Activity Not in the Right Order	19	2.17%	33	0.36%
Redundant Activity	862	98.40%	2,994	32.59%

Missing Activity

The classification results for missing activity sub-categories are presented in Table 18. Specifically, there are 154 process instances missing signature, 1 process instance missing goods receipt, 1,089 process instances missing invoice receipt and 201 process instances missing release. We do not find any process instance missing purchase order. When identifying process instances that are missing signature, we include the not for profit organization's purchase order approval rules in the classification. For example, if process instance A has one signature but the value of purchase order is $10,000, then this process instance will be classified to missing signature sub-category as purchase orders with values over $5,000 are required to have two signatures. The business rules for purchase order approval are presented in Table 19. All the process instances that are identified in Table 18 as missing activity will be prioritized based on the riskiness of sub-category and corresponding threshold in the last step of the risk assessment framework.

Table 18: Missing Activity

Sub-category	Variant	Process Instance
Missing Purchase Order (PO)	0	0
Missing Signature (Sign)	61	154
Missing Goods Receipt (GR)	1	1
Missing Invoice Receipt (IR)	82	1,089
Missing Release	137	201
Total	248	1,395

Table 19: Purchase Order Approval Rules

Transaction Amount	Approval Rules
Up to $5,000	1 Signature
Up to $50,000	2 Signatures
Up to $100,000	3 Signatures
Up to $250,000	5 Signatures
Up to $500,000	7 Signatures

Activity Not in the Right Order

The classification results for activity not in the right order sub-categories are presented in Table 20. Specifically, there are 14 process instances with IR occurs before signature, 11 process instances have release occurs before GR, and 17 process instances with release occurs before IR. We do not find any process instance with GR occurs before sign or release occurs before signature. Process instances with activity not in the right order

could indicate potential risks or internal control problems within the firm (Chiu and Jans 2017). All the process instances that are identified in Table 20 as activity not in the right order are sent to risk prioritization in the last step of risk assessment framework.

Table 20: Activity Not in Right Order

Sub-category	Variant	Process Instance
Goods receipt (GR) occurs before Signature	0	0
Invoice receipt (IR) occurs before Signature	5	14
Release occurs before Signature	0	0
Release occurs before Goods receipt (GR)	8	11
Release occurs before invoice receipt (IR)	12	17
Total	19	33

Redundant Activity

The classification results for redundant activity sub-categories are presented in Table 21. Specifically, there are 576 process instances with more than one purchase orders, 1,755 process instances with more than one signature, 1,540 process instances with more than one GR, 1,580 process instances with more than one IR, and 135 process instances with more than one release. Redundant signatures are classified based on the purchase order approval rules presented in Table 19. For example, if process instance B has two signatures, but the value of purchase order is $1,000, then this process instance will be classified into redundant signature sub-category as purchase orders with values under $5,000 only require one signature. The occurrence of redundant activity could indicate

inefficient business process and potential internal control risks within the firm (Chiu and Jans 2017). For example, the occurrence of more than one ‘create purchase order’ activity in a process instance could possibly result from an employee accidentally enter duplicate purchase order information with same purchase order number (i.e., inefficient business process), but it could also happen because an employee try to modify purchase order value information on purpose (i.e., internal control risks). The process instances identified as redundant activity will be prioritized along with process instances with missing activity and activity not in the right order in step 4 of the risk assessment framework.

Table 21: Redundant Activity

Sub-category	Variant	Process Instance
Redundant Purchase Order (PO)	277	576
Redundant Signature (Sign)	410	1,755
Redundant Goods Receipt (GR)	747	1,540
Redundant Invoice Receipt (IR)	686	1,580
Redundant Release	101	135
Total	862	2,994

3.4.3 Step 2: Auditor’s Risk Assessment

The second step of the proposed risk assessment framework is to have auditors assign risk scores on non-standard variant sub-categories. The scoring of the 15 sub-categories in non-standard variant is developed with the assistance of 6 auditors from the major accounting firms in the United States. Panel B in Appendix B has been sent to the 6

auditors for risk assessment. They assign risk scores based on their judgments on the risk level of each non-standard sub-category. Specifically, risk score = 1 if the risk level is "very low risk," risk score = 2 if the risk level is "low risk," risk score = 3 if the risk level is "moderate risk," and risk score = 4 if the risk level is "high risk." Auditors' risk assessment on the 15 sub-categories is presented in Table 22. Table 22 shows that there are 6 sub-categories in "high risk," 3 sub-categories in "moderate risk," 2 sub-categories in "low risk" and 4 sub-categories in "very low risk."

Table 22: Risk Assessment on Sub-categories

Category	Sub-category	Risk Score	Risk Level
Missing Activity	Missing Purchase Order (PO)	4	High Risk
	Missing Sign	4	High Risk
	Missing Goods Receipt (GR)	4	High Risk
	Missing Invoice Receipt (IR)	4	High Risk
	Missing Release	4	High Risk
Activity Not in Right Order	Goods Receipt (GR) occurs before Sign	1	Very Low Risk
	Invoice Receipt (IR) occurs before Sign	2	Low Risk
	Release occurs before Sign	4	High Risk
	Release occurs before Goods Receipt (GR)	2	Low Risk
	Release occurs before Invoice Receipt (IR)	3	Moderate Risk
Redundant Activity	Redundant Purchase Order (PO)	3	Moderate Risk
	Redundant Sign	1	Very Low Risk
	Redundant Goods Receipt (GR)	1	Very Low Risk
	Redundant Invoice Receipt (IR)	3	Moderate Risk
	Redundant Release	1	Very Low Risk

The summary of risk assessment using classification results in step 1 are presented in Table 23, where 1,395 process instances being classified as “high risk”, 1,951 process instances being classified as “moderate risk”, 25 process instances being classified as “low risk”, and 2,819 process instances being classified as “very low risk”. The identified process instances have been sent back to the not for profit organization for further investigation. It is worth to note that the total process instance count (i.e., 6,190) in Table 23 is more than total process instances count for non-standard variants (i.e., 3,918) because a process instance could be classified in several sub-categories at the same time. For example, process instance A can be identified as missing signature (risk score = 4) and redundant release (risk score = 1) at the same time.[6] Therefore, the risk score calculation is the sum of all risk scores assigned to each process instance. Table 24 shows the Top 5 process instances that have the highest risk scores. For example, process instance 82329 (in the second column of Table 24) is missing signature (risk score = 4), has release occurs before signature (risk score = 3), has more than one purchase order (risk score = 3), has more than one invoice receipt (risk score = 3), has more than one goods receipt (risk score = 1), and more than one release (risk score = 1). Therefore, the risk score for process instance 82329 is 4 + 3 + 3 + 3 + 1 + 1 = 15, as shown in Table 24.

[6] For example, process instance A has the following routing: PO – GR – IR – Release – Release.

Table 23: Risk Assessment Summary

	Variant		Process Instance	
	Count	Percentage	Count	Percentage
High Risk	248	28.31%	1,395	15.18%
Moderate Risk	792	90.41%	1,951	21.24%
Low Risk	13	1.48%	25	0.27%
Very Low Risk	853	97.37%	2,819	30.68%
Total	873	100%	3,918	100%

Table 24: Risk Score Calculation

Sub-category	Process Instance 82329	Process Instance 88589	Process Instance 91133	Process Instance 78758	Process Instance 82835
Missing Sign (4)	1			1	1
Missing GR (4)					
Missing IR (4)		1	1		
Missing Release (4)		1	1		
Release occurs before IR (3)	1				
Redundant PO (3)	1	1	1	1	1
Redundant IR (3)	1			1	1
IR occurs before Sign (2)					
Release occurs before GR (2)					
Redundant Sign (1)		1	1		
Redundant GR (1)	1	1	1	1	1
Redundant Release (1)	1			1	1
Risk Score	**15**	**13**	**13**	**12**	**12**

3.4.4 Step 3 and Step 4: Apply Materiality Threshold and Risk Prioritization

The last two steps of the risk assessment framework are to prioritize process instances based on the risk scores and the firm's materiality threshold on the value of purchase order. Table 25 presents the purchase order approval rules along with value class and process instance count for each class. Different levels of value class have been developed to each approval rule based on the value of purchase order. As shown in Table 25, transaction amount less than or equal to $5,000 is in level 1, from $5,001 to $50,000 is in level 2, from $50,001 to $100,000 is in level 3, from $100,001 to $250,000 is in level 4, and from $250,001 to $500,000 is in level 5. The not for profit organization does not have any approval rule for transaction value larger than $500,000; however, there are 13 process instances in the non-standard variant that have an amount larger than $500,000. Accordingly, we add an additional value class for transaction value over $500,000 in the last column of Table 25. The six value classes are defined for the risk prioritization in step 4.

Table 25: Purchase Order Approval Rules and Value Class

Transaction Value	Value Class	Process Instance
Less than or equal to $5,000	Level 1	2,691
$5,001 - $50,000	Level 2	1,021
$50,001 - $100,000	Level 3	102
$100,001 - $250,000	Level 4	70
$250,001 - $500,000	Level 5	21
Over $500,000	Level 6	13

We use the first purchase order approval rule from the not for profit organization as the threshold for risk prioritization. In other words, the threshold for risk prioritization is $5,000. The rationale is that the firm request an additional signature for any process instance over $5,000, and therefore, process instances over $5,000 are considered important for the not for profit organization. Accordingly, we keep only the 1,227 process instances[7] that have transaction values over $5,000 when conducting risk prioritization in step 4. The Top 20 process instances that have transaction values larger than $5,000 are presented in Table 26. The process instance that has largest amount is 88702 (Value PO = $11,579,094), followed by process instances 84728 (Value PO = $10,740,859) and 80262 (Value PO = $3,228,000). The risk scores for these 3 process instances are 8, 4, and 4, respectively.

[7] Among the 3,918 process instances in non-standard variant, only 1,227 have transaction value over $5,000.

Table 26: Top 20 Process Instances (Value PO > $5,000)

Case ID	Missing Sign (4)	Missing GR (4)	Missing IR (4)	Missing Release (4)	Release occurs before IR (3)	Redundant PO (3)	Redundant IR (3)	IR occurs before Sign (2)	Release occurs before GR (2)	Redundant Sign (1)	Redundant GR (1)	Redundant Release (1)	Risk Score	Value PO
88702				1			1				1		8	$11,579,094.00
84728							1				1		4	$10,740,859.00
80262							1				1		4	$3,228,000.00
84850							1				1		4	$3,174,200.00
89106							1				1		4	$3,120,400.00
88749						1	1				1		7	$1,179,759.00
89503			1	1							1		9	$877,637.63
87830							1				1		4	$789,386.75
87334						1	1				1	1	8	$716,031.13
90055							1				1		4	$659,107.94
80015							1				1		4	$551,357.88
85421							1				1		4	$550,300.00
84988						1	1				1		7	$529,166.63
78758	1					1	1				1	1	12	$464,248.41
84507	1						1				1		8	$463,494.84
80071	1						1				1		8	$460,376.59
89855	1												4	$456,728.00
85376	1												4	$454,207.00
88854	1			1			1				1		12	$450,818.00
80559	1												4	$444,710.00

In step 4, four risk prioritization methods are provided, as displayed in Table 27, Panel A-D. Based on their judgments, auditors could select one of the proposed methods to determine the final risk prioritization results. Method 1 prioritizes the remaining 1,227 process instances based on their risk score. For example, Panel A in Table 27 shows that 17 process instances have a risk score more than 10, indicating that these process instances have higher risks compared to other process instances in the not for profit organization. Method 2 prioritizes the process instances based on their transaction values. Panel B in Table 27 shows that 13 process instances have transaction values larger than $500,000 (value class = level 6), indicating that these process instances have larger transaction amount compared to the all other process instances. Risk prioritization using method 3 is based on both risk scores and transaction values, with more weights given to the transaction

value.[8] The final risk score for each process instance is calculated by using the risk score times value PO. For example, Panel C in Table 27 shows that 11 process instances have a final risk score more than 5,000,000. Method 4 prioritizes process instances based on both risk scores and the value class, with equal weight given to the risk score and transaction value .[9] The final risk score for each process instance is calculated by using the risk score times value class (i.e., 1-6). Panel D in Table 27 shows that 14 process instances have a final risk score more than 40.

By providing four different risk prioritization methods, auditors could select the best approach for each organization based on their audit judgments. For example, if auditors believe that all the purchase orders with risk scores more than 10 need further investigation, regardless of the transaction amount, then they can use method 1. In addition, if the auditors would like to consider risk score and the transaction amount equally in the risk assessment, then they can use method 4 to calculate final risk scores and prioritize the results. The proposed risk assessment framework can add value to auditing in that auditors would receive process mining results based on analyzing the entire population of event logs, and the final outputs are prioritized to improve the audit efficiency.

[8] The risk prioritization in method 3 is giving more weights to transaction value because the amount of PO is significantly higher than the risk score. Therefore, the main component that is affecting the final risk score in method 3 is the value instead of the risk score. For example, a process instance that has a risk score = 15 and a transaction value = $6,000 will have much smaller final risk score (15*6,000 = 90,000) compared to the process instance that has risk score = 1 and transaction value = $500,000 (1*500,000 = 500,000).

[9] The risk prioritization in method 4 is giving equal weight to both the risk score and the transaction value because the numbers in value class (i.e., level 1- level 6) is similar to risk scores (i.e., 1-15). For example, a process instance that has a risk score = 15 and a value class = 2 will have similar final risk score (15*2 = 30) with the process instance that has a risk score = 2 and a value class = 6 (2*6 = 12).

Table 27: Risk Prioritization Methods

Panel A: Method 1 - Risk Prioritization based on Risk Score

Case ID	Missing Sign (4)	Missing GR (4)	Missing IR (4)	Missing Release (4)	Release occurs before IR (3)	Redundant PO (3)	Redundant IR (3)	IR occurs before Sign (2)	Release occurs before GR (2)	Redundant Sign (1)	Redundant GR (1)	Redundant Release (1)	Risk Score	Value PO
82329	1				1	1	1				1	1	15	$5,105.00
88589			1	1		1				1	1		13	$9,000.00
91133			1	1		1				1	1		13	$6,438.00
78758	1					1	1				1	1	12	$464,248.41
82835	1					1	1				1	1	12	$362,663.00
83762	1					1	1				1	1	12	$7,468.01
84014	1					1	1				1	1	12	$225,864.56
86159	1			1			1				1		12	$122,892.06
88854	1			1			1				1		12	$450,818.00
88858	1					1	1				1	1	12	$437,210.88
89078	1			1			1				1		12	$166,582.89
90296	1			1			1				1		12	$9,260.90
90297	1		1	1									12	$23,000.00
90822				1		1	1			1	1		12	$20,825.19
81280	1					1	1				1		11	$150,812.98
82301				1		1	1				1		11	$60,000.00
88664				1		1	1				1		11	$17,717.14

Panel B: Method 2 - Risk Prioritization based on Transaction Value

Case ID	Missing Sign (4)	Missing GR (4)	Missing IR (4)	Missing Release (4)	Release occurs before IR (3)	Redundant PO (3)	Redundant IR (3)	IR occurs before Sign (2)	Release occurs before GR (2)	Redundant Sign (1)	Redundant GR (1)	Redundant Release (1)	Risk Score	Value PO	Value Class
88702				1			1				1		8	$11,579,094.00	Level 6
84728							1				1		4	$10,740,859.00	Level 6
80262							1				1		4	$3,228,000.00	Level 6
84850							1				1		4	$3,174,200.00	Level 6
89106							1				1		4	$3,120,400.00	Level 6
88749						1	1				1		7	$1,179,759.00	Level 6
89503			1	1							1		9	$877,637.63	Level 6
87830							1				1		4	$789,386.75	Level 6
87334						1	1				1	1	8	$716,031.13	Level 6
90055							1				1		4	$659,107.94	Level 6
80015							1				1		4	$551,357.88	Level 6
85421							1				1		4	$550,300.00	Level 6
84988						1	1				1		7	$529,166.63	Level 6

Panel C: Method 3 - Risk Prioritization = Risk Score*Value PO

Case ID	Risk Score	Value PO	Value Class	Risk Prioritization = Risk Score*Value PO
88702	8	$11,579,094.00	Level 6	92,632,752.00
84728	4	$10,740,859.00	Level 6	42,963,436.00
80262	4	$3,228,000.00	Level 6	12,912,000.00
84850	4	$3,174,200.00	Level 6	12,696,800.00
89106	4	$3,120,400.00	Level 6	12,481,600.00
88749	7	$1,179,759.00	Level 6	8,258,313.00
89503	9	$877,637.63	Level 6	7,898,738.67
87334	8	$716,031.13	Level 6	5,728,249.04
78758	12	$464,248.41	Level 5	5,570,980.92
88854	12	$450,818.00	Level 5	5,409,816.00
88858	12	$437,210.88	Level 5	5,246,530.56

Panel D: Method 4 - Risk Prioritization = Risk Score*Value Class

Case ID	Risk Score	Value PO	Value Class	Risk Prioritization = Risk Score*Value Class
78758	12	$464,248.41	Level 5	60.00
88854	12	$450,818.00	Level 5	60.00
88858	12	$437,210.88	Level 5	60.00
82835	12	$362,663.00	Level 5	60.00
89503	9	$877,637.63	Level 6	54.00
88702	8	$11,579,094.00	Level 6	48.00
87334	8	$716,031.13	Level 6	48.00
84014	12	$225,864.56	Level 4	48.00
89078	12	$166,582.89	Level 4	48.00
86159	12	$122,892.06	Level 4	48.00
90727	9	$325,555.19	Level 5	45.00
81280	11	$150,812.98	Level 4	44.00
88749	7	$1,179,759.00	Level 6	42.00
84988	7	$529,166.63	Level 6	42.00

3.4.5 Additional Analysis

This study conducted two additional analyses, personnel analysis, and irregular process instance, on the event log data from a not for profit organization. Specifically, the additional analyses are performed based on the risk level and/or the threshold of transaction amount proposed in the risk assessment framework, as presented in Table 22 and Table 19.

Personnel Analysis

The personnel analysis aims at (1) analyzing employees involved in each risk level, either over or below the threshold, and (2) examining employees involved in all risk levels. The analysis results in Table 28 show that there are 150 employees involved in the process instances that are in the risk level "high risk", 215 employees involved in the process instances that are in the risk level "moderate risk", 31 employees involved in the process instances that are in the risk level "low risk", and 226 employees involved in the process instances that are in the risk level "very low risk". Specifically, for process instances that have more than $5,000 transaction values, there are 108 employees involved in high-risk process instances, 159 employees involved in moderate risk process instances, 15 employees involved in low risk, and 164 employees involved in process instances.

The last row of Table 28 shows that there are 8 employees involved in 3 process instances that are classified into sub-categories from all four levels of risk assessment, with 4 employees involved in 1 process instance over $5,000. The employees that are involved in process instances with multiple potential violations and above the firm's materiality threshold should be further investigated because these employees might be the reason for inefficient business process and have the potential of conducting fraudulent behavior.

Table 28: Personnel Analysis – Risk Level of Risk Assessment

	Resource		Process Instance	
	>5,000	Total	>5,000	Total
High Risk	108	150	426	1395
Moderate Risk	159	215	894	1951
Low Risk	15	31	8	25
Very Low Risk	164	226	1006	2819
Four Risk Levels	4	8	1	3

Irregular Process Instance

According to the not for profit organization's purchase order approval rule, as presented in Table 19, a process instance is required to have seven signatures for a transaction value up to $500,000. Moreover, there is no additional approval rule for any value beyond $500,000. In addition, the personnel responsible for the fifth, sixth and seventh signatures are already the top management in this firm (i.e., Chief Financial Officer, Senior Vice President, and Chief Operating Officer, respectively). Therefore, any purchase order created with transaction value above $500,000 should be considered as irregular process instance because it is over the limit of the purchase order approval rule for the not for profit organization. Our additional test shows that there are 16[10] process

[10] The number of process instances that have been identified as irregular transactions (16 process instances) is different from the count of process instances (13) in Table 25 because Table 25 only counts the process instances in non-standard variant and this additional analysis incorporates all process instances (9,187) in the event log. Recall that we classify "Missing signature" and "Redundant signature" based on the not for profit organization's purchase order approval rules (as shown in Table 19), which does not include any rules for process instances that have a value larger than $500,000. Therefore, the 16 process instances that have an amount more than $500,000 will be considered as standard variant under the firm's current business rule in

instances with a value over $500,000, and the largest purchase order value is $11,579,094. We also find that the signature count for all 16 process instances over $500,000 is less than seven signatures, indicating that these 16 process instances are missing required signatures and their values are above the limit for purchase order approval rule at the same time.

These process instances need to be sent back to management for examination as they could represent higher potential risks. For example, large amount purchase orders without proper approval processes could indicate potentially fraudulent behaviors of the personnel, and could also represent internal control problems as the system should capture purchase orders that have transaction values over the limit when they are created. However, it is also possible that the not for profit organization has a special business rule for purchase orders that have values larger than $500,000, and therefore these purchase orders do not need multiple signatures for the approval process. For example, the organization might have a business rule that any purchase order with a value more than $500,000 should be directly sent to the CEO for approval. In this case, this process instance would only have 1 signature in the process, and it conforms to the firm's business rule. Therefore, the identified 16 process instances could represent potential risks for the company, but further

terms of the activity "signature." The reason why there are 13 process instances that have an amount over $500,000 being classified as non-standard variant is due to the violations other than "Missing signature" or "Redundant signature" in their processes. For example, process instance 88702 is missing release, has redundant IR and has redundant GR (with no "signature" related issue). On the other hand, the 3 process instances that have been included in irregular process instance test but not in the non-standard variant are: 86565 (Create PO-Sign-Sign-Sign-Sign-Sign-GR-IR-Release), 91406 (Create PO-Sign-Sign-Sign-Sign-Sign-GR-IR-Release), and 81849 (Create PO-Sign-Sign-Sign-Sign-Sign-Sign-GR-IR-Release). These 3 process instances do not have any non-standard potential violations in terms of Create PO, GR, IR, and Release (i.e., these 4 activities occurred in all 3 process instances only once, and the orders are correct). In addition, their values are over $500,000 ($1,000,000, $1,000,000 and $780,000, respectively) and therefore cannot be classified as "Missing signature" or "Redundant signature" according to the not for profit organization's purchase order approval rules.

examination needs to be conducted based on the not for profit organization's business rules. The detailed purchase orders found in this test are presented in Table 29.

Table 29: Irregular Process Instance

Process Instance	Variant	Timestamp	Resource	Value PO
88702	Variant 711	2015-11-25 11:06:00	ABCD1	$11,579,094.00
84728	Variant 536	2015-01-13 12:30:00	ABCD56	$10,740,859.00
80262	Variant 157	2014-01-28 13:21:00	ABCD1	$3,228,000.00
84850	Variant 71	2015-01-26 12:01:00	ABCD1	$3,174,200.00
89106	Variant 157	2016-01-08 16:24:00	ABCD1	$3,120,400.00
88749	Variant 714	2015-12-02 14:58:00	ABCD1	$1,179,759.00
86565	Variant 32	2015-06-25 11:06:00	ABCD56	$1,000,000.00
91406	Variant 32	2016-07-26 13:50:00	ABCD56	$1,000,000.00
89503	Variant 772	2016-02-12 15:13:00	ABCD56	$877,637.63
87830	Variant 656	2015-09-28 09:02:00	ABCD1	$789,386.75
81849	Variant 409	2014-06-02 10:44:00	ABCD1	$780,000.00
87334	Variant 635	2015-08-18 15:05:00	ABCD1	$716,031.13
90055	Variant 808	2016-04-07 17:21:00	ABCD56	$659,107.94
80015	Variant 313	2014-01-08 14:37:00	ABCD1	$551,357.88
85421	Variant 158	2015-03-24 10:22:00	ABCD56	$550,300.00
84988	Variant 545	2015-02-09 09:00:00	ABCD56	$529,166.63

3.5 CONCLUSIONS

This study integrates process mining into the auditor's risk assessment process by combining process mining results (the riskiness of business processes) with a corresponding transaction value (total value on the specific purchase order). Specifically, auditors determine a risk score for each process mining sub-category based on their judgments of risk level on the routing, and then all the sub-categories will be further classified into four risk levels (i.e., high risk, moderate risk, low risk and very low risk). After that, all the process instances are prioritized based on the sum of risk scores and the materiality threshold. The final outputs from this process mining risk assessment are four proposed risk prioritization methods based on (1) risk score, (2) transaction value, (3) risk score x transaction value, and (4) risk score x value class. The auditors could choose among the four methods based on their judgments.

The application of process mining to the risk assessment process enables auditors to access to not only the transaction data but also the related business processes. The results of this study provide auditors with process instances that do not conform to the standard procure-to-pay processes. Moreover, the prioritized process mining results could improve the audit efficiency as the auditors would be able to focus on high-risk process instances with material transaction values based on their audit judgments. This study contributes to existing process mining and auditing research on how process mining can be incorporated into the audit process and the advantages of evaluating event logs when assessing risks. For example, auditors could focus on process instances that have the highest risk score

(risk score =15) when conducting the audit work or they could determine that process instances with the largest transaction value need to be examined further.

The two additional analyses also provide auditors with audit relevant information. First, auditors could focus more on the 108 employees that were involved in high-risk process instances over the threshold (> $5,000), or the 4 employees that were involved in process instances over the materiality threshold and being classified as high risk, moderate risk, low risk and very low risk at the same time. Second, the irregular process instance test shows that there are 16 process instances with purchase order value over the limit of the not for profit organization's purchase order approval rule; in addition, the signatures for each process instance found are less than seven signatures, indicating that these 16 process instances are missing required signatures and at the same time have transaction values more than the limit of the company's business rule. These process instances need to be sent back to the management for further investigation as missing required approval process in large amount process instances is highly risky. Results in this essay could shed light on how to apply process mining in the audit process and why process mining could be a new type of audit evidence.

There are limitations associated with this study. First, the sub-categories for classification used in the proposed risk assessment framework are based on procure-to-pay business process. Therefore, these sub-categories need to be modified when classifying event logs from different industries and business cycles. Second, this study demonstrates how process mining can be applied to auditor's risk assessment process using only one

firm's event log data. The results can be more generalized if the proposed risk assessment framework can be applied to multiple firms.

Future research could extend the proposed risk assessment framework by identifying sub-categories and assign risk scores based on different business cycles (e.g., order-to-cash cycle). In addition, the materiality threshold applied in this study is based on the business rule of the not for profit organization, future research could adopt the proposed risk assessment framework to firms in different industries or different business cycles, and then generalize commonly used materiality thresholds for auditor's risk assessment. Furthermore, future research could apply process mining to other audit processes to provide different aspects on how process mining can be used as new audit evidence, for example, applying process mining in fraud detection and prevention.

CHAPTER 4: A FRAMEWORK OF APPLYING PROCESS MINING FOR FRAUD SCHEME DETECTION

4.1 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 2017): (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: 2017-08-19 09:02:15).

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. 2007; Wen et al. 2009). Moreover, in recent years, process mining has also been applied to the auditing field, both in practice and in academia. 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 2017). 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; Chiu and Jans 2017).

To detect and prevent corporate fraud is one of the major objectives of audit practice. Corporate fraud refers to an entity's management improperly uses accounting schemes to falsify and report misleading financial statement in order to meet or beat the analysts' forecast; it includes: (1) intentional embezzlements of corporate resource, (2) corruption and bribery, and (3) intentional misstatement of financial statement to misguide the stakeholders (i.e., financial statement fraud). There are several common fraud schemes, such as "side agreements," "channel stuffing," "improper capitalization of expenses" etc., which will lead to an overstatement of revenue or understatement of expense. A large number of prior studies have applied financial information to predict potential financial statement fraud risks (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. Examining non-financial information such as facilities growth could add value to the prediction of financial statement fraud; however, the generality of the prediction models is often compromised due to the limited sample available for non-financial information (Brazel et al. 2009).

Process mining can be applied as non-financial information in the prediction of financial statement fraud because it enables the whole population of event logs and has the potential of adding value to auditing. The purpose of this paper is to provide a framework on how process mining can be applied to identify fraud schemes and assess the riskiness of business process. Specifically, the proposed framework captures how the suspicious patterns in process mining can be used to detect potential fraudulent transactions.

The contribution of this paper is two-fold. First, this paper proposes a framework that links non-standard variants/activities in process mining with corresponding fraud schemes to detect potentially fraudulent transactions. Second, the proposed framework can be applied to build a continuous fraud monitoring system that uses suspicious patterns and risk level 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 financial statement fraud, and section 4 concludes the paper and discusses future studies.

4.2 LITERATURE REVIEW

4.2.1 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 (Agrawal et al. 1998; Cook and Wolf 1998; Schimm 2003; van der Aalst et al. 2003; van der Aalst and Weijters 2004; van der Aalst et al. 2004; Alves de Medeiros et al. 2006; Greco et al. 2006; Gunther and van der Aalst 2007; van der Aalst et al. 2007; Rozinat and van der Aalst 2008; Rozinat et al. 2008; Bozkaya et al. 2009; Folino et al. 2009; de Medeiros et al. 2007; Wen 2007; van der Werf et al. 2008; van Dongen et al. 2009; Goedertier 2009; Jans 2009; Wen et al. 2009; Adriansyah et al. 2011a; Adriansyah et al. 2011b, 2011c; van der Aalst et al. 2011; Weijters and Ribeiro 2011; Buijs 2012; de Leoni et al. 2012; van der Aalst et al. 2012; de Weerdt et al. 2013; Werner 2017). For example, 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 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. 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.

Process mining techniques enable new forms of auditing (van der Aalst et al. 2010). For example, the alpha process mining algorithm can automatically extract a Petri net that concisely models behavior in the event log; in this case, the auditors can have an unbiased view of what has happened in the company (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 BAM (Business Activity Monitoring), BOM (Business Operations Management), BPI (Business Process Intelligence), and Data / Workflow Mining (van der Aalst 2011). Process mining techniques are able to deduce patterns and rules from facts. These facts are in the form of event logs, which have been derived from events performed at runtime (Bukhsh and Weigand 2012).

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. 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). 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 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 made without approval, violations of segregation of duty controls, and violations of company-specific internal procedures (Jans et al. 2014).

In addition, Chiu and Jans (2017) 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 2017). Process mining has been used by industry for real-time fraud detection. For example, ING bank (a European bank) applied process mining to analyze user's click path on a distributed stream computing platform (Bruin and Hendriksen 2016).

4.2.2 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.

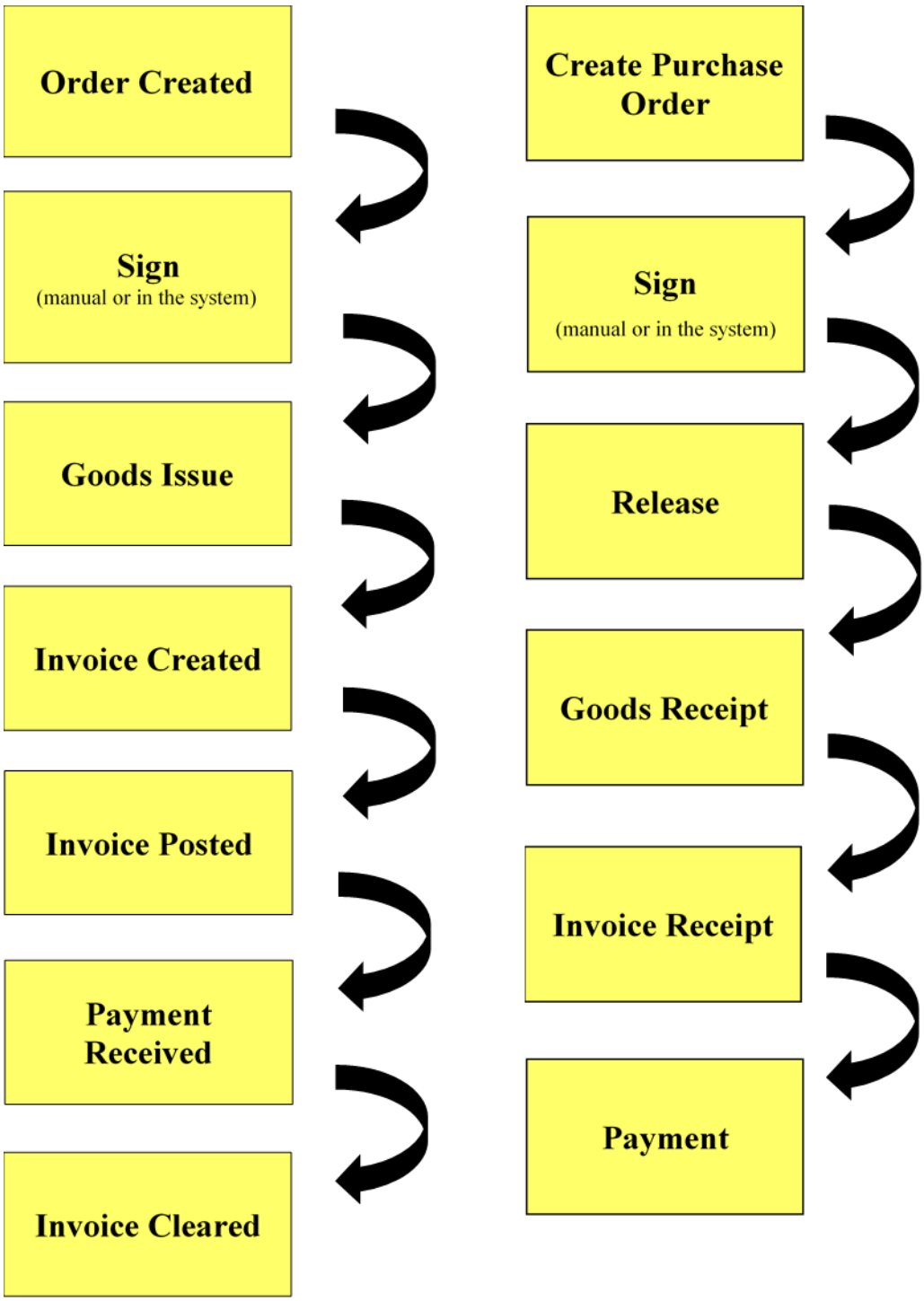
Therefore, numerous measures for earnings management are created to indicate the risk of financial misstatement and fraud, such as earnings persistence (e.g., Richardson et al. 2005), abnormal accruals and accruals models (e.g., Jones 1991; Dechow et al. 1995; Dechow and Dichev 2002; Kothari et al. 2005), 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. 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.

4.3 FRAMEWORK: APPLYING PROCESS MINING FOR CORPORATE FRAUD DETECTION[1]

To detect corporate 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 fraud detection are "order-to-cash" cycle and "procure-to-pay" cycle. The standard business process[2] for each cycle is: (1) order-to-cash cycle: "Order Created -> Goods Issue -> Invoice Created -> Invoice Posted -> Payment Received -> Invoice Cleared", and (2) procure-to-pay cycle: "Create Purchase Order -> Sign -> Release -> Goods Receipt -> Invoice Receipt -> Payment." It is worth 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 real-life order-to-cash event log data has a manual approval process and therefore there is no "signature" in the log, while the real-life 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 5.

[1] The proposed framework used full population of event logs to detect financial statement fraud.
[2] The standard business process is discovered from two real-world datasets (one Order-to-Cash cycle and one Procure-to-Pay cycle).

Figure 5: Standard Order-to-Cash and Procure-to-Pay Business Processes



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 the deviation from the standard business process will be considered as a non-standard variant or an exception (Issa 2013; Chiu and Jans 2017). Appendix C shows non-standard variant categories (i.e., variants that do not conform to standard business processes) for procure-to-pay and order-to-cash business cycles.[3] Panel A presented non-standard variant categories for procure-to-pay process extracted from Chiu and Jans (2017), and this paper extends their non-standard variant categories to order-to-cash process, as shown in Panel B. Following Chiu and Jans (2017), the categories and sub-categories of non-standard variant are defined and established by experts in the field based on the standard business processes of the two business cycles.

Based on the most common occurred corporate 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 and assigns the risk levels. The frequency and percentage of accounting fraud schemes from 1994-2016 are presented in Table 30. The fraud financial statement sample is collected from WRDS Restatement Database that contains 279

[3] The categories and sub-categories of non-standard variants presented in Appendix C are discovered from two real-life datasets (i.e., Order-to-Cash and Procure-to-Pay datasets), in addition, Appendix C has been reviewed by auditors from the major accounting firms in the United States.

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 30, 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. It is worth to note that one fraud-year observation could involve more than one fraud schemes, which result in the total frequency is 1,271 and the total percentage is 270.43%. After understanding the frequency and percentage of different fraud types and fraud categories, we link the non-standard variants to fraud categories.

Table 30: 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%

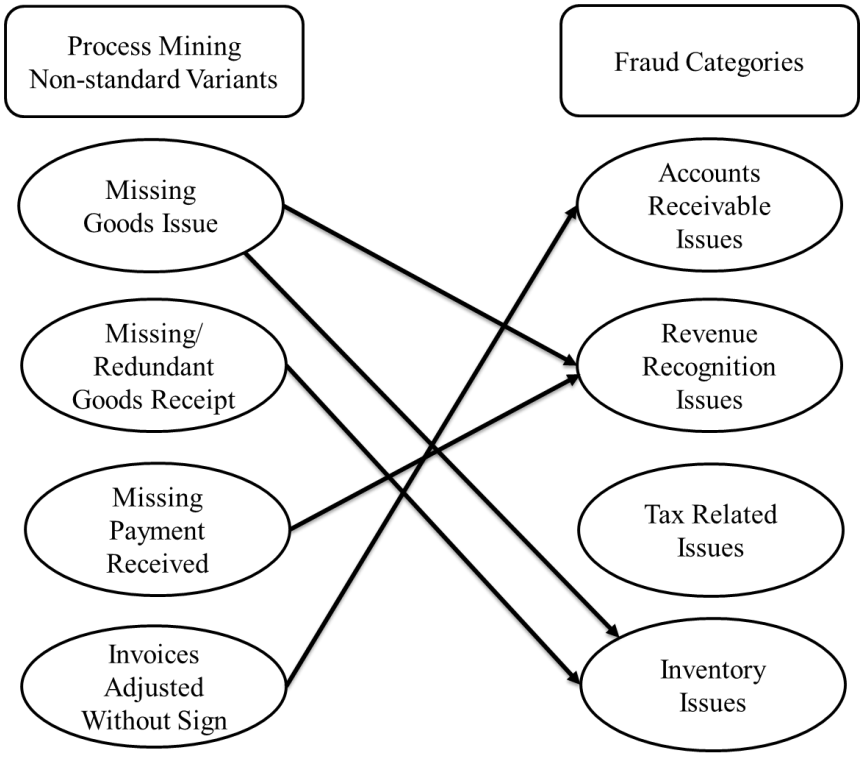
4.3.1 Mapping from Non-standard Variants to Fraud Categories

An overview of mapping from non-standard variants to fraud categories is presented in Figure 6. The items on the left are non-standard variants in process mining (e.g., Missing Goods Issue, Missing/Redundant Goods Receipt, Missing Payment Received and Invoices Adjusted without Sign) and items on the right are fraud categories (e.g., Accounts Receivable Issues, Revenue Recognition Issues, Tax-Related Issues and Inventory Issues). Based on the identified non-standard variants in process mining, Figure 6 shows how several fraud categories can be detected by examining the organization's non-standard variants.

For example, if one finds a sales order does not have "Goods Issue" and "Payment Received" 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 Issue" and "Missing Payment Received" bubbles are linked to the "Revenue Recognition Issues" bubble on the right. If a sales order does not have "Goods Issue" activity, then it is possible that this order has potential inventory issue such as "fictitious inventory" fraud scheme. Therefore, the "Missing Goods Issue" 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. For example, tax-related issues such as tax expense or deferral issues are not easy to be detected only by using process mining of event logs. Therefore, there is no non-standard variant linked to the "Tax-Related Issues" bubble.

Figure 6: Mapping Non-standard Variants into Financial Statement Fraud Categories



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. And 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 31 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 issue" or "payment received" activities could possibly 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 "payment received" occurs before "goods issue" 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. And “goods receipt” activity of “procure-to-pay” cycle should be examined in the prevention of fictitious inventory fraud. For example, if goods receipt occurs more than once or missing goods receipt document, it could be suspicious and needs to be sent to auditors for resolution. 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.

Table 31: Accounting Fraud Schemes and Suspicious Process Patterns

Accounting Cycle	Fraud Scheme	Non-standard Variant/Activity	Suspicion Pattern Example	Risk Level
Order-to-Cash	Altering Documentation	• Order Adjusted: Goods Issue Date • Invoice Adjusted	Frequent occurrence of order adjusted and/or invoice adjusted activities without approval process during the fiscal year-end period.	High
Order-to-Cash	Bill and Hold	• Goods Issue • Payment Received	Missing goods issue and/or payment received.	High
Order-to-Cash	Channel Stuffing	• Order Adjusted: Order Return • Invoice Adjusted: Invoice Credit Note	Frequent occurrence of order return or invoice credit note immediately after fiscal year end without an approval process.	High
Order-to-Cash	Up-Front Fees	• Payment Received • Goods Issue • Order Adjusted: Change Goods Issue Date	Payment received occurs before goods issue or invoice created.	Low
Order-to-Cash	Failure to Record Sales Allowances	• Payment Received	Missing payment received or incomplete payment	High
Order-to-Cash	Inflating the Value of Inventory	• Order Adjusted: Net Price	Order adjusted without an approval process Putting in improper price comparing to the market value	High
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	High
Others	Fraudulent Audit Confirmation	• All Activities	Matching trading partners corresponding event logs	High/ Medium/ Low
Others	Refresh Receivables	• Invoice Adjusted	Invoices adjusted occurs for many transactions without an approval process	High
Order-to-Cash	Promotional Allowance Manipulation	• Invoice Adjusted: Cash Discount	Many Invoice Adjusted: Cash Discount activities are entered.	Medium
Others	Bribery and Corruption	• All Activities	Using resource information in event logs to identify potential violation of segregation of duty controls	Medium

After identifying the standard business process and non-standard variants as benchmarks, the deviation of any variant from the benchmarks can be used to measure the risk level of each given process patterns, as presented in the last column of Table 31. For example, if a process pattern is more similar to a non-standard variant and less similar to a standard business process, it will be assigned a higher risk score than those variants that are more similar to a standard business process and less similar to a non-standard path. The distance or similarity of two variants is measured by (1) completeness (i.e., whether all

required activities in standard business process exist in the variant), (2) activities (i.e., whether there are frequent occurrences of a specific activity) and (3) orders (i.e., whether the order of each activity conforms to standard business process).[4] Any non-standard variant that is missing certain required activity or includes more than one potentially risky path (e.g., frequent occurrence of "goods receipt" and at the same time "missing signature") will be labeled as "high risk," and others would be labeled as either "medium risk" or "low risk." In the example of linking non-standard variant to the fraud scheme "channel stuffing," if order return or invoice credit note frequently occur right after fiscal year end without an approval process, this process will be considered as "high risk" because it is incomplete (i.e., missing approval activity) and contains too many abnormal activities (i.e., frequent order return). On the other hand, in the "up-front fees" fraud scheme presented in Table 31, if payment occurs before goods issued or invoice created, this process will be considered as "low risk" because it merely violates the order of a standard process.

Table 31 presents examples of the connection of non-standard variants and potential fraud schemes, and it also shows a method to measure the level of risk. With more and more fraud schemes are taken into account when conducting process mining, this framework will become increasingly accurate in predicting fraud risk level for each transaction, and the predicted transaction risk levels can be aggregated to indicate the risk level of a firm's financial statement.

[4] It is worth to note that the risk level assigned in Table 31 is only based on the riskiness of the non-standard variants. Future research could also assess risk based on the fraud schemes. For example, "bribery and corruption" fraud scheme is more likely to have a higher risk compared to the fraud scheme "altering documents."

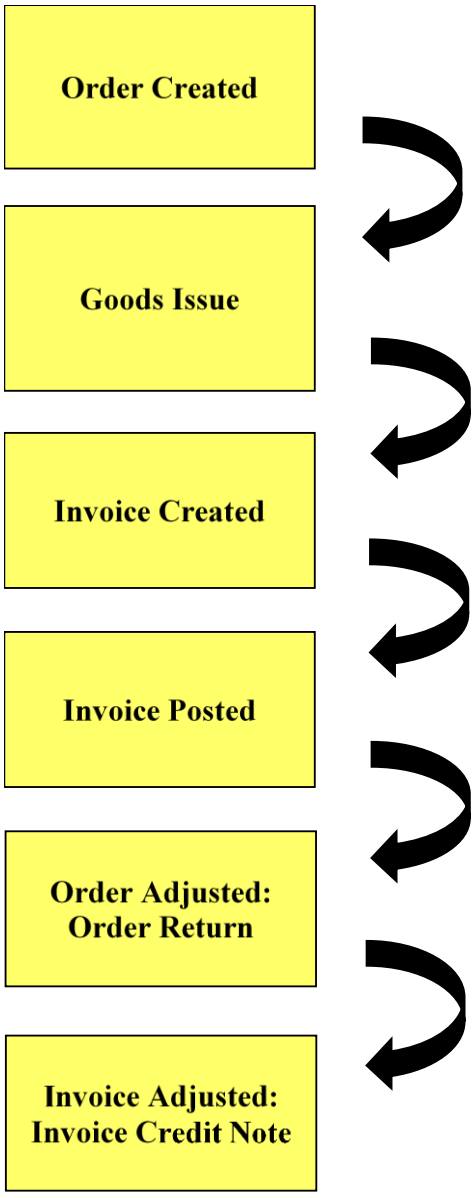
4.3.2 An Example of Detecting Fraud Scheme Using Process Mining

This section provides an example of detecting potential fraud scheme using a non-standard variant. As shown in Figure 7, 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.[5] 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 the January. This can be considered as 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 7.

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

Figure 7: Non-standard Variant for Channel Stuffing



4.4 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 a powerful fraud detection tool when auditors include the potential fraudulent patterns in their fraud detection process. The contribution of this paper is two-fold. First, this paper proposes 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. Second, the proposed framework incorporates risk assessment mechanism that indicates the risk level of each non-standard variant/activity. The risk level along with the proposed fraud schemes and non-standard paths can be used to build a continuous fraud monitoring system that applies suspicion patterns and risk level as filters to detect potential fraud.

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 worth to note that not all fraudulent transactions could be automatically detected by 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 and assigned risk levels.

Future research could extend the current framework by incorporating more fraud schemes and other accounting cycles when discussing how process mining can be used in

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

CHAPTER 5: CONCLUSION AND FUTURE RESEARCH

This dissertation contributes to auditing field by investigating how process mining can assist auditors in evaluating internal control effectiveness, assessing audit risk as well as identifying fraud schemes. The following summarizes the major findings and future works of the three essays.

The first essay demonstrates how process mining can be adopted in the evaluation of internal control effectiveness. The evaluation includes four perspectives: variant analysis, segregation of duty analysis, personnel analysis, and timestamp analysis. The contribution of this study is three-fold. First, this essay utilizes the whole population of an event log to show how process mining could assist auditors in evaluating the effectiveness of internal control. Compared with the prior literature examining only the six selected variants, we found additional audit-relevant issues from examining the entire population of an event log. Second, this study incorporates four different aspects (i.e., variant analysis, segregation of duty analysis, personnel analysis and timestamp analysis) in the demonstration of using process mining to evaluate internal control effectiveness. Third, this essay manually identifies categories and sub-categories of standard/non-standard variants using a large European bank's procurement event log data. The discovered standard/non-standard variants enable auditors to gain insights into real-world business processes that conform to or deviate from the standard procurement process. In addition, auditors could use these identified categories/sub-categories when evaluating event logs in the procure-to-pay cycle.

The results from variant analysis and three additional tests raise several audit-relevant issues that need internal auditor's further investigations. First, in the variant analysis, there is 95 percent of the variants being classified as non-standard variants, indicating that these variants do not conform to the standard procurement process and therefore need to be further examined. Second, in the segregation of duty analysis, 186 process instances are found violating segregation of duty controls. Third, in the personnel analysis, a large number of employees are found involved in more than one potential violations. Finally, in the timestamp analysis, 5,968 process instances (22.79 percent) have process duration longer than the bank's mean process duration (46.2 days), and the top 10 process instances are long-running processes that last for more than one year.

There are limitations associated with this study. First, most of the categories and sub-categories of standard/non-standard variants are based on the procurement process. Therefore, these categories/sub-categories need to be modified when examining event logs from other accounting cycles. Second, this essay demonstrates how process mining can be applied to evaluate the effectiveness of internal control by using only one company's event log data. The results can be more generalized if the method is applied to more firms and different business cycles. Third, the four proposed process mining analyses are based on variables extracted from the event log, however, incorporating other variables, such as the transaction values, might help auditors gain more profound insights.

Future research could compare the categories/sub-categories of standard and non-standard variants with the organization's business rules. This could help auditors to identify whether the non-standard variants conform to business rules and further determine the

riskiness of each sub-category in the non-standard variants. Another possible research area is to examine the possibility for process mining to timely discover unauthorized procedures through real-time monitoring systems and subsequently reduce the occurrences of potential fraud. For example, process mining could be integrated into the "audit by exception" concept, proposed by Vasarhelyi and Halper (1991). In this case, an alarm of exception will arise when the purchase order is *released* without a proper *sign*.

The second essay aims at integrating process mining into the auditor's risk assessment procedure by combining process mining results (the riskiness of business processes) with a corresponding transaction value (total value on the specific purchase order). Specifically, auditors determine a risk score for each process mining sub-category based on their judgments of risk level on the path. Next, all the process instances are prioritized based on the sum of risk scores and the materiality threshold. The final output from this process mining risk assessment is four risk prioritization methods for auditors to further investigate the identified process instances based on their judgment. The auditors could determine to further examine the non-standard process instances based on the prioritization using (1) risk score, (2) purchase order value, (3) risk score x purchase order value, or (4) risk score x purchase order value class.

The contribution of the second essay is three-fold. First, this study proposes a framework of using process mining in the risk assessment procedure. The proposed risk assessment framework includes auditors' judgments on the risk level of procure-to-pay business processes and therefore can be applied to the procurement process in any firm with an event log data. The identified process instances are prioritized using four methods

to improve the efficiently of the audit. The auditors could choose among the four proposed risk prioritization methods based on their judgments when analyzing the identified process instances. Second, this paper utilizes the entire population of an event log data when demonstrating how process mining could be integrated into the auditor's risk assessment process. Third, by applying the proposed framework to the audit work, auditors could examine high-risk process instances with material transaction amount instead of investigating random sample with material transaction value.

The application of process mining to the risk assessment process enables auditors to access to not only the transactional data but also the event log data which captures the business processes. The results of this essay provide auditors with process instances that do not conform to the standard procurement processes. Moreover, the prioritized results could improve the audit efficiency as the auditors would be able to focus on high-risk process instances with material transaction values using the four proposed risk prioritization methods. This study contributes to existing process mining and auditing research on how process mining can be incorporated into the audit process and the advantages of evaluating event logs when assessing risks. For example, auditors could focus on process instances that have the highest risk score (risk score =15) when conducting the audit work, or they could examine non-standard process instances that have very large transaction values.

The two additional analyses also provide auditors with audit relevant information. First, auditors could focus more on the 108 employees that were involved in high-risk process instances over the threshold (> $5,000), or the 4 employees that were involved in

process instances over the materiality threshold and being classified into all four risk levels at the same time. Second, there are 16 process instances with purchase order value over the limit of the not for profit organization's purchase order approval rule; in addition, the signatures for each process instance found are less than seven signatures, indicating that these 16 process instances are missing required signatures and at the same time have transaction values more than the limit of the company's business rule. These process instances need to be sent back to the management for further investigation as missing required approval process in large amount process instances is highly risky. Results in this essay could shed light on how to apply process mining in the audit process and why process mining could be a new type of audit evidence.

There are limitations associated with the second essay. First, the sub-categories for classification used in the proposed risk assessment framework are based on procure-to-pay business process. Therefore, these sub-categories need to be modified when classifying event logs from different industries and business cycles. Second, this study demonstrates how process mining can be applied to auditor's risk assessment procedure using only one firm's event log data. The results can be more generalized if the proposed risk assessment framework can be applied to multiple firms. Third, this study only shows how process mining can be applied to the risk assessment procedure; more analysis can be conducted to show how process mining can be included in other audit procedures, such as test of controls or test of details.

Future research could extend the proposed risk assessment framework by identifying sub-categories and assign risk scores based on different business cycles (e.g.,

order-to-cash cycle or payroll cycle). In addition, the materiality threshold applied in this study is based on the business rule of the not for profit organization, future research could adopt the proposed risk assessment framework to firms in different industries or different business cycles, and then generalize commonly used materiality thresholds for auditor's risk assessment. Furthermore, future research could apply process mining to other audit processes to provide different perspectives on how process mining can be used as new audit evidence.

The third essay provides a framework on applying process mining for fraud scheme detection. The framework proposed in this essay indicates that process mining can be a powerful fraud detection tool when auditors include the potential fraudulent patterns in their fraud detection process. The contribution of this essay is two-fold. First, this essay proposes a framework that links non-standard variants/activities in process mining with the corporate fraud schemes; therefore, auditors could use process mining as an analytical tool in fraud detection. Second, the proposed framework incorporates risk assessment mechanism that indicates the risk level of non-standard variants/activities. The risk level along with the proposed fraud schemes and non-standard variants can be used to build a continuous fraud monitoring system that applies non-standard variants and risk levels as filters to detect potential corporate fraud.

The limitation of this essay is that the proposed framework only includes non-standard variants/activities in two accounting cycles (i.e., procure-to-pay and order-to-cash) and several most commonly occurred fraud schemes. Not all fraudulent transactions could be detected by process mining analysis. 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 and assigned risk levels.

Future research could extend the current framework by incorporating more fraud categories/schemes and other accounting cycles when discussing how process mining can be applied to detect fraud. Furthermore, a validation can be conducted to simulate the application of the proposed framework to detect certain types of fraud schemes. Future research could also consider using clustering algorithm in assigning risk levels to the non-standard variants/activities. In addition, the risk levels should be assigned not only based on the path of the process instances, but also based on the riskiness of the fraud schemes.

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APPENDICES

Appendix A: Standard and Non-standard Variants - Discovered Variants

Panel A: Standard Variant

Category	Description
Standard Procure-to-Pay process	The variants "PO-Sign-Release-GR-IR-Pay" is the standard process in the procure-to-pay cycle.
Change line before sign and release	Change line occurs before sign, indicating that there is approval for changing line. • For example: "PO-Change Line-Sign-Release-GR-IR-Pay"
Change line with the approval process	Change line occurs after sign and release, but there is another set of sign and release followed by this change line. This indicates that there is approval for changing line. • For example: "PO-Sign-Release-Change Line-Sign-Release-GR-IR-Pay"
Invoice receipt (IR) and goods receipt (GR) switch places	The order of IR and GR is opposite from the standard procurement process. • For example: "PO-Sign-Release-IR-GR-Pay"

Panel B: Non-standard Variant

Category	Sub-category	Description
Missing Activity	Missing purchase order (PO)	Missing activity "PO" in the business process. • For example: Sign-Release-GR-IR-Pay
	Missing sign	Missing activity "Sign" in the business process. • For example: PO-Release-GR-IR-Pay
	Missing release	Missing activity "Release" in the business process. • For example: PO-Sign-GR-IR-Pay
	Missing goods receipt (GR)	Missing activity "GR" in the business process. • For example: PO-Sign-Release-IR-Pay
	Missing invoice receipt (IR)	Missing activity "IR" in the business process. • For example: PO-Sign-Release-GR-Pay
	Missing payment (Pay)	Missing activity "Pay" in the business process. • For example: PO-Sign-Release-GR-IR
	Change line without sign	In the business process, there is no sign after changing line. • 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 and release after changing line. • For example: PO-Sign-Release-Change Line-GR-IR-Pay
Activity Not in Right Order	Goods receipt (GR) occurs before Sign	"GR" occurs before "Sign" in the business process. • For example: PO-GR-Sign-Release-IR-Pay
	Goods receipt (GR) occurs before Release	"GR" occurs before "Release" in the business process. • For example: PO-Sign-GR-Release-IR-Pay
	Invoice receipt (IR) occurs before Sign	"IR" occurs before "Sign" in the business process.

		• For example: PO-IR-Sign-Release-GR-Pay
	Invoice receipt (IR) occurs before Release	"IR" occurs before "Release" in the business process. • For example: PO-IR-Release-GR-Pay
	Payment (Pay) occurs before Sign	"Pay" occurs before "Sign" in the business process. • For example: PO-Pay-Sign-Release-IR-Pay
	Payment (Pay) occurs before Release	"Pay" occurs before "Release" in the business process. • For example: PO-Pay-Release-GR-IR
	Payment (Pay) occurs before Goods receipt (GR)	"Pay" occurs before "GR" in the business process. • For example: PO-Sign-Release-IR-Pay-GR
	Payment (Pay) occurs before invoice receipt (IR)	"Pay" occurs before "IR" in the business process. • For example: PO-Sign-Release-GR-Pay-IR
Redundant Activity	Redundant Purchase Order (PO)	More than one "PO" occurs in the business process. • For example: PO-PO-Sign-Release-GR-IR-Pay
	Redundant Sign	More than one "Sign" occurs in the business process. • For example: PO-Sign-Sign-Release-GR-IR-Pay
	Redundant Release	More than one "Release" occurs in the business process. • For example: PO-Sign-Release-Release-GR-IR-Pay
	Redundant Goods Receipt (GR)	More than one "GR" occurs in the business process. • For example: PO-Sign-Release-GR-GR-Pay

	Redundant Invoice Receipt (IR)	More than one “IR” occurs in the business process. • For example: PO-Sign-Release-GR-IR-IR-Pay
	Redundant Payment (Pay)	More than one “Pay” occurs in the business process. • For example: PO-Sign-Release-GR-IR-Pay-Pay

Appendix B: Standard and Non-standard Variant – Not for Profit Organization

Panel A: Standard Variant

Category	Description
Standard Procure-to-Pay process[1]	The standard procure-to-pay process for not for profit organization is as follows: (1) PO value up to $5,000: *"PO-Sign-GR-IR-Release"* (2) PO value up to $50,000: *"PO-Sign-Sign-GR-IR-Release"* (3) PO value up to $100,000: *"PO-Sign-Sign-Sign-GR-IR-Release"* (4) PO value up to $250,000: *"PO-Sign-Sign-Sign-Sign-Sign-GR-IR-Release"* (5) PO value up to $500,000: *"PO-Sign-Sign-Sign-Sign-Sign-Sign-Sign-GR-IR-Release"*
Invoice receipt (IR) and goods receipt (GR) switch places	The order of IR and GR is opposite from the standard procurement process. • For example: "PO-Sign-IR-GR-Release"

[1] The standard procure-to-pay process for the not for profit organization need to take the purchase order approval rule into consideration, as presented in Table 19. That is, (1) 1 signature for PO value = $0 - $5,000, (2) 2 signatures for PO value = $5,001 - $50,000, (3) 3 signatures for PO value = $50,001 - $100,000, (4) 5 signatures for PO value = $100,001 - $250,000, (5) 7 signatures for PO value = $250,001 - $500,000.

Panel B: Non-standard Variant

Category	Sub-category	Description
Missing Activity	Missing purchase order (PO)	Missing activity "PO" in the business process. • For example: Sign-GR-IR-Release
	Missing signature	Missing activity "Sign" in the business process. • For example: PO-GR-IR-Release
	Missing goods receipt (GR)	Missing activity "GR" in the business process. • For example: PO-Sign-IR-Release
	Missing invoice receipt (IR)	Missing activity "IR" in the business process. • For example: PO-Sign-GR-Release
	Missing release	Missing activity "Release" in the business process. • For example: PO-Sign-GR-IR
Activity Not in Right Order	Goods receipt (GR) occurs before signature	"GR" occurs before "Sign" in the business process. • For example: PO-GR-Sign-IR-Release
	Invoice receipt (IR) occurs before signature	"IR" occurs before "Sign" in the business process. • For example: PO-IR-Sign-GR-Release
	Release occurs before signature	"Release" occurs before "Sign" in the business process. • For example: PO-Release-Sign-IR
	Release occurs before goods receipt (GR)	"Release" occurs before "GR" in the business process. • For example: PO-Release-Sign-IR-GR
	Release occurs before invoice receipt (IR)	"Release" occurs before "IR" in the business process. • For example: PO-Sign-GR-Release-IR
Redundant Activity	Redundant purchase order (PO)	More than one "PO" occurs in the business process. • For example: PO-PO-Sign-GR-IR-Release
	Redundant signature	More than one "Sign" occurs in the business process. • For example: PO-Sign-Sign-GR-IR-Release
	Redundant goods receipt (GR)	More than one "GR" occurs in the business process.

		• For example: PO-Sign-GR-GR-IR-Release
	Redundant invoice receipt (IR)	More than one “IR” occurs in the business process. • For example: PO-Sign-GR-IR-IR-Release
	Redundant release	More than one “Release” occurs in the business process. • For example: PO-Sign-GR-IR-Release-Release

Appendix C: Non-standard Variants in Process Mining

Panel A: Procure-to-Pay Cycle

Category	Sub-category	Description
Missing Activity	Missing purchase order (PO)	Missing activity "PO" in the business process. • For example: Sign-Release-GR-IR-Pay
	Missing sign	Missing activity "Sign" in the business process. • For example: PO-Release-GR-IR-Pay
	Missing release	Missing activity "Release" in the business process. • For example: PO-Sign-GR-IR-Pay
	Missing goods receipt (GR)	Missing activity "GR" in the business process. • For example: PO-Sign-Release-IR-Pay
	Missing invoice receipt (IR)	Missing activity "IR" in the business process. • For example: PO-Sign-Release-GR-Pay
	Missing payment (Pay)	Missing activity "Pay" in the business process. • For example: PO-Sign-Release-GR-IR
	Change line without sign	In the business process, there is no “Sign” after changing line. • 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. • For example: PO-Sign-Release-Change Line-GR-IR-Pay
Activity NOT in right order	Goods receipt (GR) occurs before sign	“GR” occurs before “Sign” in the business process. • For example: PO-GR-Sign-Release-IR-Pay
	Goods receipt (GR) occurs before release	“GR” occurs before “Release” in the business process. • For example: PO-Sign-GR-Release-IR-Pay
	Invoice receipt (IR) occurs before sign	“IR” occurs before “Sign” in the business process. • For example: PO-IR-Sign-Release-GR-Pay

	Invoice receipt (IR) occurs before release	"IR" occurs before "Release" in the business process. • For example: PO-IR-Release-GR-Pay
	Payment (Pay) occurs before sign	"Pay" occurs before "Sign" in the business process. • For example: PO-Pay-Sign-Release-GR-IR-Pay
	Payment (Pay) occurs before release	"Pay" occurs before "Release" in the business process. • For example: PO-Pay-Release-GR-IR
	Payment (Pay) occurs before goods receipt (GR)	"Pay" occurs before "GR" in the business process. • For example: PO-Sign-Release-IR-Pay-GR
	Payment (Pay) occurs before invoice receipt (IR)	"Pay" occurs before "IR" in the business process. • For example: PO-Sign-Release-GR-Pay-IR
Redundant Activity	Redundant purchase order (PO)	More than one "PO" occurs in the business process. • For example: PO-PO-Sign-Release-GR-IR-Pay
	Redundant sign	More than one "Sign" occurs in the business process. • For example: PO-Sign-Sign-Release-GR-IR-Pay
	Redundant release	More than one "Release" occurs in the business process. • For example: PO-Sign-Release-Release-GR-IR-Pay
	Redundant goods receipt (GR)	More than one "GR" occurs in the business process. • For example: PO-Sign-Release-GR-GR-IR-Pay
	Redundant invoice receipt (IR)	More than one "IR" occurs in the business process. • For example: PO-Sign-Release-GR-IR-IR-Pay
	Redundant payment (Pay)	More than one "Pay" occurs in the business process. • For example: PO-Sign-Release-GR-IR-Pay-Pay

Panel B: Order-to-Cash Cycle

Category	Sub-category	Description
Missing Activity	Missing order created	Missing activity "Order Created" in the business process. • For example: Sign-Goods Issue-Invoice Created-Invoice Posted-Payment Received-Invoice Cleared
	Missing sign	Missing activity "Sign" in the business process. • For example: Order Created-Goods Issue-Invoice Created-Invoice Posted-Payment Received-Invoice Cleared
	Missing goods issue	Missing activity "Goods Issue" in the business process. • For example: Order Created-Sign-Invoice Created-Invoice Posted- Payment Received-Invoice Cleared
	Missing invoice created	Missing activity "Invoice Created" in the business process. • For example: Order Created-Sign-Goods Issue-Invoice Posted- Payment Received-Invoice Cleared
	Missing invoice posted	Missing activity "Invoice Posted" in the business process. • For example: Order Created-Sign-Goods Issue-Invoice Created- Payment Received-Invoice Cleared
	Missing payment received	Missing activity "Payment Received" in the business process. • For example: Order Created-Sign-Goods Issue-Invoice Created-Invoice Posted-Invoice Cleared
	Missing invoice cleared	Missing activity "Invoice Cleared" in the business process. • For example: Order Created-Sign-Goods Issue-Invoice Created-Invoice Posted-Payment Received

	Order adjusted without sign	In the business process, there is no "Sign" after "Order Adjusted." • For example: Order Created-Sign-Order Adjusted-Goods Issue-Invoice Created-Invoice Posted-Payment Received-Invoice Cleared
	Invoice adjusted without sign	In the business process, there is no "Sign" after "Invoice Adjusted." • For example: Order Created-Sign-Invoice Adjusted-Goods Issue-Invoice Created-Invoice Posted- Payment Received-Invoice Cleared
Activity NOT in right order	Goods issue occurs before sign	"Goods Issue" occurs before "Sign" in the business process. • For example: Order Created-Goods Issue-Sign-Invoice Created-Invoice Posted-Payment Received-Invoice Cleared
	Invoice created occurs before sign	"Invoice Created" occurs before "Sign" in the business process. • For example: Order Created-Invoice Created-Sign-Invoice Posted- Payment Received-Invoice Cleared
	Invoice posted occurs before sign	"Invoice Posted" occurs before "Sign" in the business process. • For example: Order Created-Goods Issue-Invoice Created-Invoice Posted-Sign-Payment Received-Invoice Cleared
	Invoice posted occurs before invoice created	"Invoice Posted" occurs before "invoice Created" in the business process. • For example: Order Created-Sign-Goods Issue-Invoice Posted-Invoice Created-Payment Received-Invoice Cleared
	Payment received occurs before sign	"Payment Received" occurs before "Sign" in the business process. • For example: Order Created-Goods Issue-Invoice Created-Invoice Posted-Payment Received-Sign-Invoice Cleared

	Payment received occurs before goods issue	"Payment Received" occurs before "Goods Issue" in the business process. • For example: Order Created-Sign-Invoice Created-Invoice Posted-Payment Received-Goods Issue-Invoice Cleared
	Payment received occurs before invoice created	"Payment Received" occurs before "Invoice Created" in the business process. • For example: Order Created-Sign-Goods Issue-Payment Received-Invoice Created-Invoice Posted-Invoice Cleared
	Payment received occurs before invoice posted	"Payment Received" occurs before "Invoice Posted" in the business process. • For example: Order Created-Sign-Goods Issue-Invoice Created- Payment Received-Invoice Posted-Invoice Cleared
	Invoice cleared occurs before Sign	"Invoice Cleared" occurs before "Sign" in the business process. • For example: Order Created-Goods Issue-Invoice Created-Invoice Posted-Payment Received-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 Issue-Invoice Cleared-Invoice Created-Invoice Posted-Payment Received
	Invoice cleared occurs before invoice posted	"Invoice Cleared" occurs before "Invoice Posted" in the business process. • For example: Order Created-Sign-Goods Issue-Invoice Created-Invoice Cleared-Invoice Posted-Payment Received
	Invoice cleared occurs before payment received	"Invoice Cleared" occurs before "Payment Received" in the business process. • For example: Order Created-Sign-Goods Issue-Invoice Created-Invoice Posted-Invoice Cleared-Payment Received
Redundant Activity	Redundant order created	More than one "Order Created" occurs in the business process.

		• For example: Order Created-Order Created-Sign-Goods Issue-Invoice Created-Invoice Posted-Payment Received-Invoice Cleared
	Redundant sign	More than one “Sign” occurs in the business process. • For example: Order Created-Sign-Sign-Goods Issue-Invoice Created-Invoice Posted-Payment Received-Invoice Cleared
	Redundant goods issue	More than one “Goods Issue” occurs in the business process. • For example: Order Created-Sign-Goods Issue-Goods Issue-Invoice Created-Invoice Posted-Payment Received-Invoice Cleared
	Redundant invoice created	More than one “Invoice Created” occurs in the business process. • For example: Order Created-Sign-Goods Issue-Invoice Created-Invoice Created - Invoice Posted-Payment Received-Invoice Cleared
	Redundant invoice posted	More than one “Invoice Posted” occurs in the business process. • For example: Order Created-Sign-Goods Issue-Invoice Created-Invoice Posted -Invoice Posted-Payment Received-Invoice Cleared
	Redundant payment received	More than one “Pay” occurs in the business process. • For example: Order Created-Sign-Goods Issue-Invoice Created-Invoice Posted-Pay-Payment Received-Invoice Cleared
	Redundant invoice cleared	More than one “Invoice Cleared” occurs in the business process. • For example: Order Created-Sign-Goods Issue-Invoice Created-Invoice Posted-Payment Received-Invoice Cleared-Invoice Cleared