

# Dissecting the Purchase-to-Pay Process: An exercise in Process Mining

## BPI Challenge 2019

C.J. van Dyk , Himalini Aklecha, Tom Kennes, and Elham Ramezani

KPMG Netherlands

{vanDyk.ChineadJustine, Aklecha.Himalini, Kennes.Tom,  
Ramezani.Elham}@kpmg.nl

[https://home.kpmg/nl/en/home/services/advisory/management-consulting/  
convert-your-data-into-insight/process-mining.html](https://home.kpmg/nl/en/home/services/advisory/management-consulting/convert-your-data-into-insight/process-mining.html)

**Abstract.** The 2019 Business Process Intelligence (BPI) Challenge requires participants to analyse and understand the Purchase to Pay (PTP) process of a large multinational company operating in the area of coatings and paints within the Netherlands. The process owner aims to gain business insights through addressing a variety of business questions. We analysed the data using a variety of process mining and analytical tools. This report summarises our understanding of the event log, as well as our analytical approach, and the different techniques and steps undertaken to successfully answer the business questions. Wherever applicable, we also provided additional analysis and discussed the limitations associated with working with such data in the absence of a more comprehensive understanding of the underlying business context.

**Keywords:** BPI Challenge · Process Mining · Purchase to Pay · Event Logs

## 1 Introduction

The BPI challenge is an annual process mining competition, which implores participants to utilise various tools, techniques and materials to analyse real life event logs in order to provide assorted business insights. This year, the event log [2] refers to the execution data of a Purchase to Pay (PTP) process, and contains purchase order items with one or more line items which. For each line item, there are roughly four types of flows in the data.

Purchase to pay is one of the back office processes that companies (especially large corporations such as the owner of this year’s data set), aim to standardise and streamline. This process is often handled and monitored in shared service centres for large corporations, and typically a large number of financial transactions take place within this process. Consequently, process efficiency and the corresponding compliance of this process is of great importance for the leadership of companies.

Small improvements in such a process can be materialised into millions of euros, given that the company is large enough. External stakeholders such as auditors also investigate this process in great detail as it has a direct impact on the financial statements of companies.

Within this report, we aim to leverage multiple techniques, including process mining, to visualise and reconstruct the corresponding PTP process as it has occurred within the system.

Although encouraged to report on a broader range of aspects, the process owners pose the following questions to be answered explicitly:

1. *Business Question 1*: Is there a collection of process models that can best describe process in the data?
2. *Business Question 2*: Which purchasing instances stand out? where are the deviations observed from the discovered process models? Are there any relation between contextual data of this process (such as invoice value) and detected deviations?
3. *Business Question 3*: What is the throughput time of the invoicing process as part of the overall PTP process?

In the remainder of this paper, we first give a *Management Summary* on the main findings of our analysis in Section 2. Section 3 gives an overview of the steps we took to reach our findings. The data overview is discussed in Section 4, with the assumptions made about the data stated in Section 5. Section 6 refers to *Business Question 1* and the utilisation of process mining to create a collection of descriptive process models which explain the process within the data.

In Section 7, we present descriptive statistics about different purchase orders, invoice values and reworks as well as leveraging process mining to discern any outliers or aberrations which may negatively impact business operations, thereby focusing on *Business Question 2*. Section 8 centralises around *Business Question 3* and the throughput time of the invoicing process. Additionally, the development of a technique used to match multiple invoices within an invoice line item will be presented. Lastly, we conclude the paper in Section 9 discussing the limitations of the data set, recommendations and possible follow up steps for the process owner.

## 2 Management Summary

In this section we provide an overview of the insights obtained for all the business questions previously mentioned in the Introduction (Section 1).

- For the given PTP event log, there are 251,734 purchase order items. This includes both complete (closed) and incomplete (open) cases. Complete cases are those which have the ending activity ‘Clear Invoice’ or ‘Delete Purchase Order Item’. Complete cases constitute 75% of all purchase order items (189,587 items), with a total net value of 12.6B euros.

- 63% of PO items are product related (PR) with a total net value of 3.49B euros, and 34% of PO items are non-product related (NPR) with a total net value of 8.92B euros.
- The average throughput time of the PTP process (189,587 completed order items) is 81 days.
- The only activities occurring prior to 2018 are ‘Create Purchase Requisition Item’, ‘Vendor Creates Debit Memo’ and ‘Vendor Created Invoice’.
- The main process deviation observed within PO items that belong to the item category ‘2-way match’, is that approximately 56% of the purchase order items begin with the activity ‘Vendor Creates Invoice’. Within a PTP processes, such a starting activity can indicate the occurrence of maverick buying, whereby purchase orders are made without the approval or formal ordering of the purchase order item. Maverick buying constitutes a total of 2.97 million euros for this item category.
- From a risk perspective, it is necessary that a payment block is placed before the payment is completed whenever there is a mismatch in the recorded net values in different events such as the creation of an order and goods and invoice receipt message. This occurs in 20% of order items (49,246 order items). For 17% of them it takes an average of 22 days between the recording of the invoice receipt and the removal of the payment block. Due to this, the average throughput time increases. Blocking is a process that should be minimised as much as possible. Blocking of the purchase order item only occurs in the ‘3-way match’ categories.
- Approximately 7.54% of complete order items (14,295 PO items) have rework activities such as the cancellation of goods and invoice receipts.
- In 77% of the cases, there is a 44 day delay between the payment of the invoice after the invoice receipt message is recorded. (For the invoicing process)
- We observed that the activities ‘Record Goods Receipt’ and ‘Record Invoice Receipt’ can occur in any order despite the specifications in the 3-way match item-category.
- In total, the complete cases have an automation rate of 8.47% and a change rate of 11.43%.
- After ‘Change’ activities occur, there is no ‘Change approval for purchase order’. This is peculiar as once creating changes, the purchase order should be reevaluated and approved once more.

### 3 Analysis Approach and Techniques

Given the overall objective of this report and the corresponding business questions, we applied several process mining techniques [1] in conjunction with various other analytical techniques (such as deploying SQL and python queries) to analyse the event log and derive discerning insights. Through applying such techniques, we aim to dissect the process owners purchase to pay process and provide them with unique results and insights which can be adopted to streamline business processes and potentially even reduce costs.

This was achieved through leveraging process mining solutions from Celonis [4] and open source tools such as ProM [3] and Python [5]. Our overall approach is illustrated in Figure 1. This figure will assist in visualising the different analysis steps taken. These steps are summarised below:

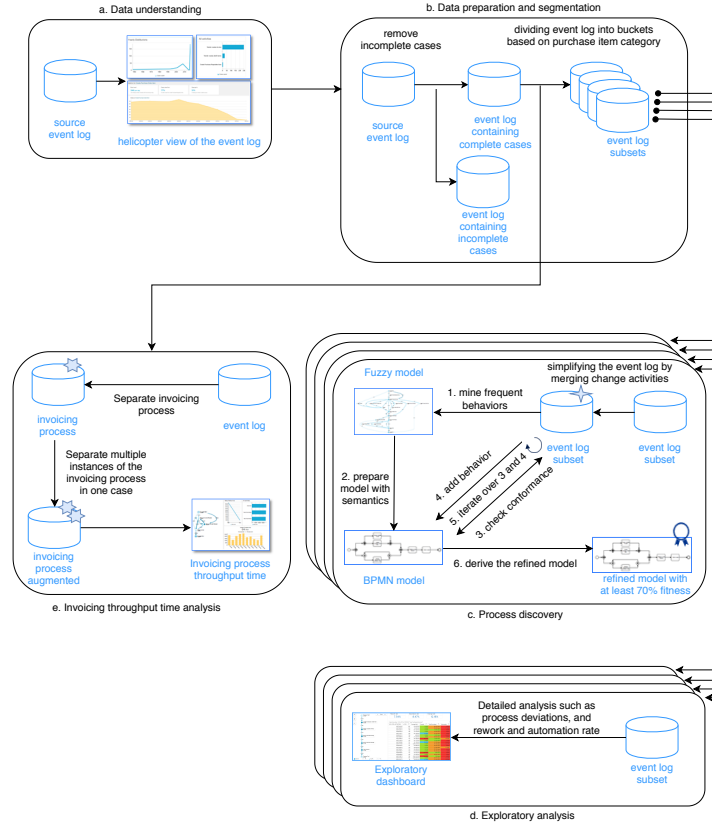


Fig. 1: Overview of the approach and steps taken to answer the business questions

- **Data understanding (Figure 1.a):** In this step we developed a helicopter view of the provided data set. The data and its corresponding characteristics will be discussed in detail in Section 4. Furthermore, we perform an exploratory analysis on the data and outline the assumptions that will be applied throughout the report.

- **Data preparation and segmentation (Figure 1.b):** First, we prepared the data by removing incomplete instances of the process (i.e. incomplete order items) to ensure our findings are derived from a stable state of the process. Furthermore, we segmented the event log into four subsets based on the purchasing item category (as suggested by process owners). This is done to derive a collection of models that each provide a comprehensive description of the respective subsets process behaviour. Details of this step will be discussed in Section 4.
- **Process discovery (Figure 1.c):** In order to learn a process model for each event log subset, we mine the most frequent behaviours in the data. From this we obtain four different process models that represent each event log subset. Additional behaviour is gradually added to each model in order to attain a well conforming model with respect to the event log. Furthermore, we analysed the differences between the collection of models discovered. The details of the steps taken are discussed in Section 6.
- **Exploratory Analysis (Figure 1.d):** Here, the different processes are further evaluated in order to determine whether there are any distinctive purchasing documents which stand out from the rest. In conjunction, different attributes and data sets will also be investigated with the objective of discovering any interesting or discerning features. This step will be discussed in detail in Section 7.
- **Invoicing Process throughput time analysis (Figure 1.e):** We separated the events related to the invoicing sub-process and further analysed the throughput times of this sub-process. Moreover, we also performed a detailed root-cause analysis to detect patterns in the process context that can explain long throughput times in certain cases. Details of this analysis step are found in Section 8.

## 4 Data Overview

Before delving into profound business insights, this section focuses on introducing the data and its various attributes. In addition, we perform an exploratory analysis and derive assumptions about the provided PTP data which will be applied throughout the rest of the report.

### 4.1 General Statistics about the Event Log

The event log provided for this challenge, in its entirety, is comprised of 76,349 purchase documents containing 251,734 line items (cases). A combination of the purchasing document number and corresponding line item number (PO item) is considered to be the case identifier. Furthermore, there are a total of 1,595,923 events and 42 unique activities in this event log. This averages to 6.3 events per PO item, with the largest number of activities in a case being 990, and the smallest being 2. The data elements of this PTP event log are shown in Table 1, along with various data attributes that characterise the different purchase order

items, hereby known as case level attributes, and their corresponding events, hereby known as event level attributes.

## 4.2 Data Understanding

From this, we can deduce key attributes that are vital when applying process mining. This includes Case ID, Activity and Timestamp which are all used as event log components. Among the listed attributes in Table 1, there are some attributes that are indicators. Firstly, *GR-Bases Inv. Verified* which is used to indicate if goods receipts based invoicing is required, and is either *true* or *false*. The same holds for *Goods receipt* which indicates whether a so called three-way match rule should be applied for the corresponding purchase order item or not.

In the given data there are important attributes such as *Item Category* that record control information about the purchase order items. They are described as follows:

- **Item Category: 3-way match, invoice before GR**  
For such PO items, the net value at the creation of the purchase order should match the net value at the time the goods are received (GR), furthermore, it should also match against the net value in the invoice (IR). Here, the GR-based IV flag is set to false and the Goods Receipt flag is set to true.
- **Item Category: 3-way match, invoice after GR**  
This follows a similar logic to the aforementioned case, however, the GR-based flag and Goods Receipt flag are both set to true.
- **Item Category: 2-way match**  
For this item category purchase orders do not require a GR in order to process an invoice. Additionally, the GR-based flag and the Goods Receipt flag are both set to false.
- **Item Category: Consignment**  
For these purchase orders, there are no invoices on a PO item level as this is handled entirely in a separate process. Here we see that the GR indicator is set to true, however the GR IV flag is set to false.

This attribute will be used further to divide the data to smaller subsets and subsequently, mine a model for each subset.

## 4.3 Exploratory Analysis of the Event Log

It is imperative to note the time span of data. Despite the data set pertaining to PO's submitted in 2018, from Figure 2 we observe that the time span of the entire process ranges from 1948 to 2020. When focusing on the specific activity 'Create Purchase Order Item' we see that PO items are only created in 2018 and 2019 (with 99.85% occurring in 2018), as seen in Figure 3. The activities occurring prior to 2018 are 'Create Purchase Requisition Item' and vendor side activities such as 'Vendor Creates Debit Memo' and 'Vendor Creates Invoice'. Albeit abnormal, it is assumed that this indicates that a purchasing process was

Table 1: Data Attributes Overview

Attributes	Case level (C) Event level (E)	Detailed Interpretation
case concept name	(C)	The Case ID for a given PTP process. It is the combination of the purchasing document number and the item number within each purchasing document. Hereafter known as the PO Item.
event concept name	(E)	It is the activity name and represents the events/steps that were executed in the PTP process.
timestamp	(E)	Timestamp of corresponding events. Represents when the activity of the specific PO Item was executed.
Company	(C)	Anonymised subsidiary from where the purchase request originated. There are 3 distinct anonymised company ID's.
Document type	(C)	High level type of a purchasing document. Categorises the type of document into either standard Purchase Order, framework order or EC purchase order.
Purchasing Document	(C)	Anonymized purchasing document identification. Anonymized due to privacy.
Purchasing document category name	(C)	Name of the category of the purchasing document.
Spend area text	(C)	High level description of the spending area for the purchase order item.
Sub-spend area text	(C)	Additional detailed description of the purchase item.
Vendor	(C)	Anonymised supplier
Item type	(C)	High level type of items purchased within purchase orders. Categorised as either consignment, limit, standard, service, subcontracting or third-party. Item types are defined according to the item templates supplied by SAP.
Item Category	(C)	Categorises the purchase orders into the different matching systems.
Spend classification text	(C)	Explanation of the class of the purchase item, either Non-product related (NPR), Product related (PR) or other.
GR-Based Inv.Verified	(C)	Indicator defining Item category. Flag indicating if GR-based (goods receipt) invoicing is required.
Goods receipt	(C)	Indicator defining Item category. A flag indicating if 3-way matching is required (true/false).
User	(E)	Indicates the type of user executing an activity (either 'batch', 'user' or 'none').
Cumulative net worth (EUR)	(E)	Cumulative net worth of the purchase order.

instigated many years ago (for example a contract being signed 10 years ago but still being used as the basis for purchases in 2018 and 2019). Further, the only activity pertaining to 2020 is ‘Vendor Creates Invoice’. This might relate to a contract that has already been set in motion, or it could simply be a data error.

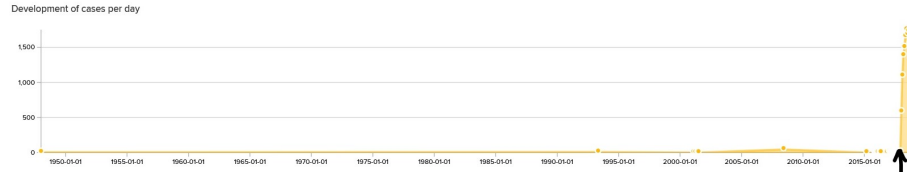


Fig. 2: Graph showing the time frame of events pertaining to the given PTP log. As observed, very few events occur prior to 2018 (marked with a pointer), and majority of the events occur in 2018 and 2019.

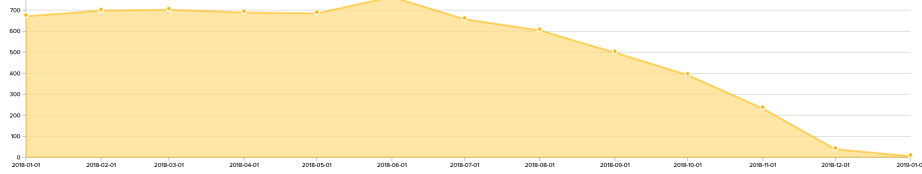


Fig. 3: Distribution of occurrences of activity ‘Create Purchase Order Item’ over time. All orders were created after 2018-01-01.

As previously mentioned, the data is further divided into four different categories where these categories correspond to the different matching systems, and hence, represent different process flows within the data. When visualising each process flow it is evident that they do not contain all activities, with some activities being unique to one event log subset (for example, ‘Block Purchase Order Item’ is unique to 3-way match, invoice before GR). An overall summary of the different event log subsets and their statistics can be found in Table 2. As can be seen in Table 2, 95% of the order items fall in the item category 3-way match, invoice before GR. However, the largest bucket with respect to monetary value (more than 8B euro) falls in the category 3-way match, invoice after GR.

#### 4.4 User Analysis

Additionally, despite the different user types, there is no distinct activity that one user (or user type) performs thus voiding the notion that a particular user corresponds to a certain position (such as a manager who would typically be in control of approval activities). This was discovered through applying the ‘Social



Table 2: Item-Category Overview (for complete order items)

Item Category	#PO Items	#Users	#Activities	Total Value (Eu-ros)	Net % of cases
2-way match	170	15	9	8.87M	<0.1%
3-way match, invoice before GR	179,429	557	39	3.96B	95%
3-way match, invoice after GR	9,578	245	36	8.63B	5%
Consignment	397	61	12	0	0.2%

Network Miner’ in ProM [3]. However, there were some interesting observations made, such as:

- ‘Change Approval for Purchase Order’ is executed only by manual users.
- Item category ‘Consignment’ has no ‘None’ users.
- ‘None’ users only execute the following activities: ‘Vendor creates invoice’, ‘Clear Invoice’, ‘Vendor creates debit memo’ and ‘Record service entry sheet’.
- ‘Create Purchase Order’ is executed by both Batch and Manual users.

## 5 Assumptions About the Data

In order to obtain a rough overview of possible subsets available in the data, we initially tried to apply several machine learning algorithms with respect to clustering and classification. However, the data did not seem to contain a combination of features that allowed for meaningful clustering. Therefore, there was no clear indication on how to sub-divide the event-log based on any other attribute besides from the item-category. The provided log file was then imported into ProM whereby the complete event-log was segmented into four smaller event-logs, based on the item category, namely ‘2-way match’, ‘3-way match, invoice before GR’, ‘3-way match, invoice after GR’, and ‘Consignment’. To gain an idea of each of their process flows, the event-logs were uploaded into Celonis. We used this tool to visualise individual process flows and identify (key) characteristics such that a well defined process model could be created.

As mentioned previously, we made certain assumptions about the data that will be adhered to throughout the report. The main assumptions and their reasons are stated as follows:

1. **SRM sub-process:** Activities relating to ‘SRM’ (Supplier Relationship Management) appeared to have their own distinct sub process as shown in Figure 6. In addition, SRM activities only occur in a total of 1,440 cases, given this, it was concluded that when constructing the relevant process models, any activity related to SRM would be excluded.

2. **Case status:** By analysing the process graph, we observe cases that do not end with typical PTP ending activities, and are therefore considered incomplete. To ensure for a full analysis, we make sure that the data is complete, i.e., have a **valid ending**. Thus by applying domain knowledge about PTP processes, we deemed that the activities ‘Delete Purchase Order Item’, and ‘Clear invoice’ were valid ending activities. Thereafter, we only considered PO items adhering to this as complete cases. This reduced the number of purchase order items from 251,734 to 189,587 (75% of the original data).

Before moving on to further analysis, we provide insights about the incomplete cases. We have that all incomplete cases (25%) are only instigated in the years 2001 (5 PO items), 2017 (32 PO items), 2018 (61,957 PO items), 2019 (15,384 PO items).

Figure 4 shows the last activities of all open PO Items. This allows the business to drill down to the most frequent open activities and make a decision of whether the item is waiting due to inefficiencies in the business or due to the vendor. Furthermore, Figure 5 shows the PO items open since past few months. This is the elapsed time and is calculated as the number of months (rounded values) between the execution date of the last event, for an open item, and today. For example, 9,947 PO items are still open past 4 months. A point to note here is that the data given contains events that have a timestamp of 2020. We assume that this is an outlier in our data and to avoid the graph showing a negative elapsed time, we have filtered out these items from the graph.

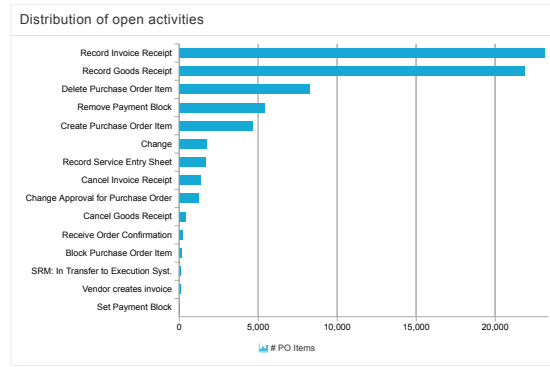


Fig. 4: Last executed activities for incomplete PO Items

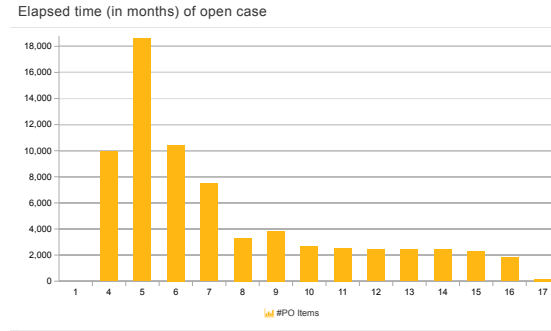


Fig. 5: Incomplete PO items and the elapsed time (in months) since they were last open

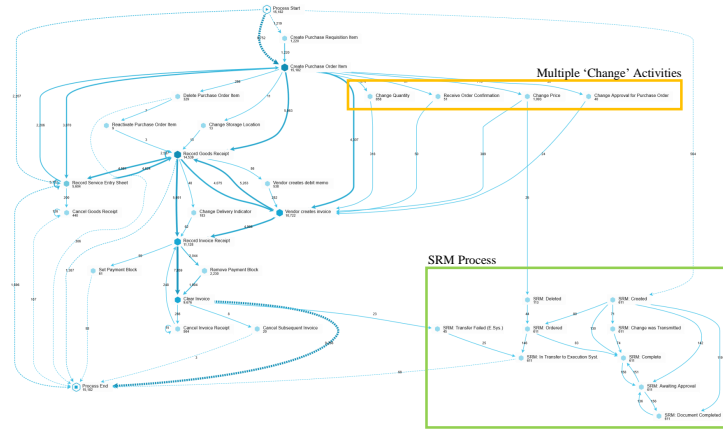


Fig. 6: Process discovery graph. Orange box shows the multiple ‘Change’ activities in parallel and the green box represents the SRM sub-process.

## 6 Creating Descriptive Process Models

The main aim of this section is to create a collection of process models that collectively describe the flow of purchase order items through the organisation’s PTP process (Figure 1c). Formally, these process models are graphically represented in Business Process Model and Notation (BPMN). In this section we will determine the different process models using the mining techniques of Celonis, and incrementally edit the model using a BPMN tool [6]. The creation of a BPMN model can be challenging, especially given the spaghetti-like nature of the PTP process. Hence, we performed a data pre-processing step when generating the different process models. We identified that there were a myriad of ‘Change’ activities relating to different changes in the purchase order item, as seen in Figure 7.

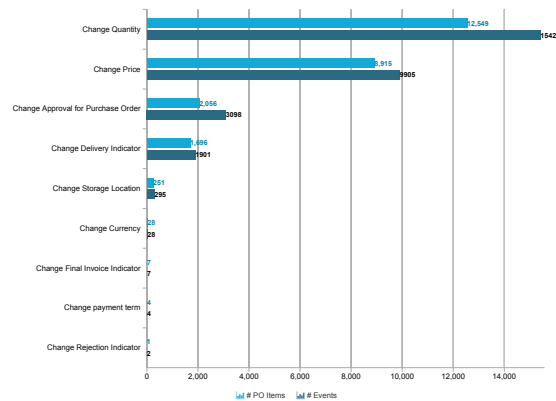


Fig. 7: Different 'Change' Activity with Case Frequency and Activities Frequency

Furthermore, as seen in the orange box in Figure 6, these activities often occurred parallel to each other, suggesting that they did not always have a well defined 'follows rule'. This results in a so called 'flower model' which does not help in understanding the actual flow of activities, as it implies that activities can occur in any order. Thus, in order to streamline the model a new activity called 'Change' was created which combined all the change activities except for 'Change Approval for Purchase Order', see Figure 8. This was due to the fact that this activity does not relate directly to changes in the PO, instead it appears to be a change within the process control.

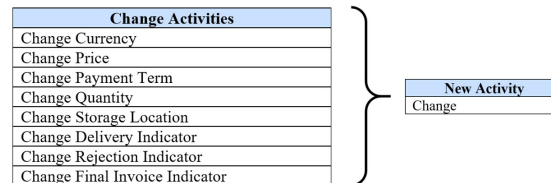


Fig. 8: Creating of new activity: 'Change'

A procedural approach was adopted in order to create each process model. The steps are as follows:

1. Divide the event log into subsets based on the four different item categories.
2. For each subset obtained from Step 1, select the most common variants from the as-is process and mine the same data set to obtain a BPMN model.
3. Based on the complexity of the previously obtained BPMN model, we further removed or incrementally added additional activities and edges to the model increasing its complexity. This ensured that we captured a higher number

of variants from the as-is process whilst still retaining the simplicity of the described model.

4. Perform conformance checking to ensure that the model from step 3 accurately represents and describes the population of data.

For each process model, the level of conformance with respect to their corresponding data population (percentage of cases which perfectly conform/align with the designed BPMN models) is stated below in Table 3.

Table 3: Process Model Conformance per Item Category

Data Model	Conformance Checking
2-way match	90 %
3-way match, invoice before GR	92 %
3-way match, invoice after GR	74 %
Consignment	92 %

#### Process Model: 2-way match

By following the steps stated above for all PO items within the ‘2-way match’ category, we obtained the process model depicted in Figure 9. This category constitutes less than 0.1% of the total data and has a total net value of 8.8 million euros (given the valid ending assumption). As depicted by the parallel gate in the model, the activities ‘Vendor creates invoice’, ‘Create Purchase Order Item’ and ‘Change Approval for Purchase Order’ can occur in any order as the first activity, with ‘Vendor creates invoice’ occurring first the most (40% of the time). This is corroborated by the most frequent process path (Figure 10). However, such behaviour, within the PTP process, is considered as a maverick buying. This is because the vendor has created an invoice due to a purchase order made, however, without this order being logged. We have that 8% of the PO items start with ‘Change Approval for Purchase Order’ and another 7% starting with ‘Create Purchase Order Item’. It is interesting to note the loop introduced for the activity ‘Change Approval for Purchase Order’. This is due to the fact that it is repeated approximately 32% of the time, average 2.1 times per case. This high frequency of change may be of concern which may have follow on effects such as higher throughput times and hence increased costs. Lastly, we see that 90% of the PO items end with the process fragment ‘Record Invoice Receipt’ and ‘Clear Invoice’. This model conforms with the selected population of data with a score of 90% (Table 3).

#### Process Model: 3-way match, invoice before GR

The process flow of PO items categorised as ‘3-way match, invoice before GR’ is displayed in the BPMN model in Figure 11. With a conformance of 92% against

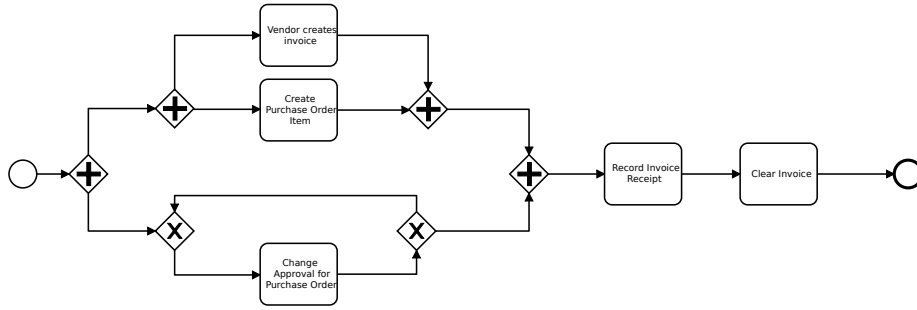


Fig. 9: BPMN model that describes the PO Items in the ‘2-way match’ item category.



Fig. 10: Most frequent process path for PO Items pertaining to ‘2-way match’ item category.

its data population, this bucket has a total net value of 3.96 billion euros and comprises the largest section of the of original data (95%). Here, 13% of the PO items begin with the activity ‘Create Purchase Requisition Item’ and in 99% of the cases are directly followed by the creation of the purchase order item. However, 85% of the PO items commence with the activity ‘Create Purchase Order Item’ hence the intuition behind allowing for both starting activities.

In contradiction to the namesake of this category, the recording of the invoice receipt occurs after the recording of the goods receipt, after which the corresponding payment is made (see most frequent process path, Figure 12). Moreover, there are multiple cases in which the two activities, corresponding to the GR and IR, are executed as a result of the activity ‘Vendor create invoice’. This behaviour is captured by the parallel gate. The model allows for both of the ‘valid’ ending activities to occur, that is, ‘Clear invoice’ (96% of cases) which indicated the payment of the invoice, and the deletion of the PO item ‘Delete Purchase Order Item’ (4% of cases). It is important to note that the deletion of the purchase order item occurring directly after its creation is highly inefficient and may lead to complexities and increased costs.

Other activities such as ‘Remove payment block’ are added to the model, and are executed when there is a violation in the 3-way-match, such that no incorrect payments are completed (occurs in 26% of the cases for this item category). Lastly, activity ‘Change’ is added to allow for multiple change events. Unlike the ‘2-way match’ process model, this model does not contain the activity ‘Change Approval for Purchase Order’ as it only occurs in 0.2% of the PO items. This means that there are a less changes within the process control allowing for a more streamline model. Additionally, ‘Change’ activities only occur in 2% of

the cases. In general, it appears that ‘3-way match, invoice before GR’ is most compliant with a PTP process compared to the other process models - that is it starts with ‘Create Purchase Order Item’ and ends with ‘Clear Invoice’.

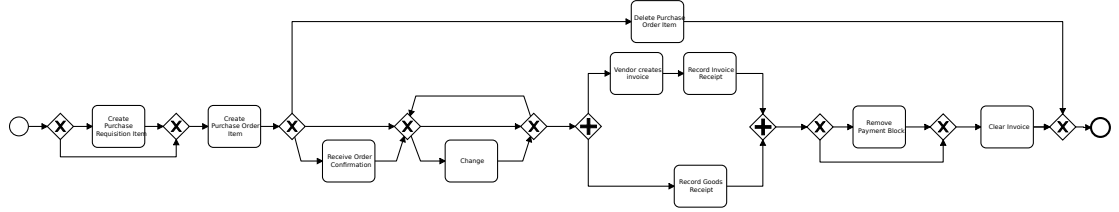


Fig. 11: BPMN model that describes the PO Items in the ‘3-way match, invoice before GR’ item category



Fig. 12: Most frequent process for PO Items pertaining to ‘3-way match, invoice before GR’ item category

### Process Model: 3-way match, invoice after GR

The process model describing the process flow of PO items categorised under ‘3-way match, invoice after GR’ is visualised in Figure 13, and has a conformance value of 74% (3). Representing 4% of the total data, it has a net value of 9.37 billion euros. Similar to the process model for ‘3-way match, invoice before GR’, this model allows for items to begin with the activity ‘Create Purchase Requisition Item’ or ‘Create Purchase Order Item’. In addition, given the multiple ‘Change’ activities, we introduced the a loop for the grouped ‘Changes’ activity (as explained in 3) This now allows for multiple changes in the PO item such as change in price, quantity and currency without restricting the different change activities to occur in a particular order.

Interestingly, this process model has the same frequently executed process path (Figure 14) as the ‘3-way match, invoice before GR’ (12). Again, we see that ‘Record Goods Receipt’ directly followed by ‘Record Invoice Receipt’, however, in this instance the ordering corresponds to the item category name. The process model does allow for multiple record goods receipts (on average 4.4 times per case) and record invoice receipts (on average 1.5 times per case) to be repeated several times, as expressed by the loop in the process model. For this category, an

interesting observation was made where activities corresponding to GR and IR are repeated in 1% of the cases. Although this is a small proportion of items, we introduce this behaviour into the model since it does not lead to complex loops and is considered to be a normal behaviour for a PTP process. Additionally, we see that the activities ‘Vendor creates invoice’ (in all PO items) and ‘Record Service Entry Sheet’ (in 24% of PO items) is also executed parallel to the GR and IR.

It is important to note the loop created for the activity ‘Record Service Entry Sheet’, which is unique to this item category and occurs on average 17.2 times per case. This is peculiar behaviour and may lead to additional costs, and therefore should be examined by the process owners. Further, the deletion of the purchase order item occurs both directly after the item creation, or after applying multiple changes. Once again this is inefficient and may lead to increased costs. Moreover, towards the end of the process model we observe that the invoice receipt is cancelled and then cleared, implying that it is paid. Although only occurring in 2% of the cases, this may pose a compliance issue. Once again, the process model ends with the ‘valid’ ending activities, ‘Clear invoice’ (97% of the PO items) and ‘Delete Purchase Order Item’ (3% of the PO items). Similar to the previous explanation, activity ‘Remove payment block’ is also added in the model.

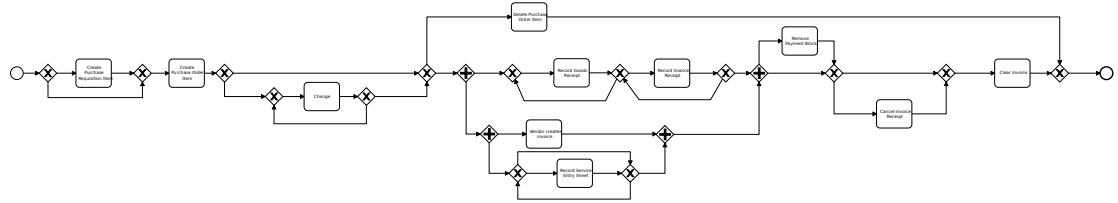


Fig. 13: BPMN model that describes PO Items in the ‘3-way match, invoice after GR’ item category



Fig. 14: Most frequent process for PO Items pertaining to ‘3-way match, invoice after GR’ category

### Process Model: Consignment

The item category ‘Consignment’ has a very interesting process flow. Firstly, it has a total net value of 0 euros and constitutes 0.2% of the total data (for valid



endings). Moreover, all of the PO items end with the activity ‘Delete Purchase Order Item’, meaning that they are deleted (as seen in Figure 16. In terms of cost savings and efficiency, this is highly ineffective. The process flow of this item category is displayed in Figure 15, and has a conformance rate of 92% (3). Within a consignment process, the vendor allows for goods to be stored in the organisation’s warehouse, and are then either consumed by the company (and hence deleted), or are given back to the vendor and as a result deleted from the item category.

In a similar fashion to both of the ‘3-way’ item categories, this process model also begins with either the creation of the purchase requisition item, or the purchase order item. Similarly, ‘Change’ activities are executed one or more number of times until the goods are received. Additional recording activities such as ‘Receive Order Confirmation’ and ‘Update Order Confirmation’ have been included in the model. For such a process, the purchasing company does not pay any amount to the vendor until the goods are used and a separate payment process is undertaken thereafter. Thus we do not see the activity ‘Record Invoice Receipt’ in the process model.

The model allows for additional activities such as ‘Cancel Goods Receipt’ (1.5% of PO items) and ‘Reactivate Purchase Order Item’, which occurs after the deletion of the purchase order item. This is rather interesting, as although it only occurs in 1% of the cases, why would a PO item be reactivated only to be immediately deleted again. Further, the activity ‘Update Order Confirmation’ is unique to this item category.

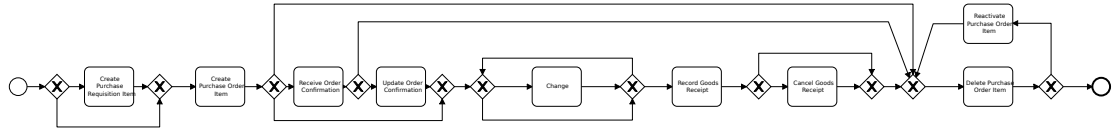


Fig. 15: BPMN model that describes the PO Items in the ‘Consignment’ item category



Fig. 16: Most frequent process for PO Items pertaining to ‘Consignment’ category

Collectively, these four separate process models provide an in depth analysis as to how the data is processed. Furthermore, process variants that deviated largely from the main process flow and cover a small proportion of cases were

not included in the final BPMN models. This is due to the fact that such cases are outliers and including them in the process model would only serve to over-fit the model. The accuracy of such models are corroborated by their high conformance results. It is imperative to employ multiple models in order to fully grasp the behaviour of the data.

## 7 Further Analysis, Deviations and Anomalies

Within this section, the PTP event log is further analysed in order to determine whether there are any purchasing documents which are highlighted against the rest. For this, different attributes and data sets (each of four data sets, segregated by item category, as well as the entire event log) will be investigated with the objective of discovering any interesting or discerning features. This section relates to Figure 1.d in the data approach overview.

In addition to throughput time bottlenecks, rework activities also contribute to the inefficiencies within a process. Consequentially, this can lead to costs increases, additional workloads, and delays in completion time. Such activities are executed when the previous activities were not completed correctly or when there is data missing prior to the rework. Thus, in the PTP process we consider the following activities as rework activities: ‘Cancel Goods Receipt’, ‘Cancel Invoice Receipt’, ‘Cancel Subsequent Invoice’, ‘Delete Purchase Order Item’, ‘Maintain GR/IR’, and ‘Update Order Confirmation’.

We analyse the rework rate of the process by drilling down on various attributes. Again, in order to simplify the analysis we perform rework analysis on each of the item categories separately. Here we define rework rate as the ration between the number of order items containing a rework activity compared to the total order items. Apart from rework, we also introduce the concept of automation. This is determined as the percentage of activities executed by digital agents such as batch users. Automating activities within processes helps to reduce costs by decreasing the amount of rework often caused by human error.

Table 4: Deeper analysis of the given PTP process per Item Category

Item Category	#PO Items	Average Throughput Time (days)	Rework Rate	Change Rate	Automation Rate
2-way match	170	76	4.12%	1.76%	0.29%
3-way match, invoice before GR	179,429	80	7.29%	6.64%	11.02%
3-way match, invoice after GR	9,578	90	8.73%	22.55%	19.44%
Consignment	397	18	100%	8.06%	2.27%

From Table 4, we conclude that item category ‘3-way match, invoice after GR’ has the largest bottleneck in terms of rework rate, change rate, and automation rate.

In order to achieve a general overview of the process flow, we observed the as-is discovered process graph and dive deeper into the analysis we drill down on various categories in combination with other process attributes to highlight the main inefficiencies:

- **Process deviations**
  - The most common variant is ‘Create Purchase Order Item’ which occurs as the starting activity for 84% of the cases, where as ‘Create Purchase Requisition Item’ is a starting activity for only 12% of the cases.
  - For PO items in the ‘3-way match, invoice before GR’ category, the goods receipt message is recorded prior to the invoice receipt message in approximately 88% of the items.
  - For item category ‘2-way match’ the most common variant starts with activity ‘Vendor creates invoice’ followed by the creation of the purchase order item. This covers 45% of the PO items pertaining to this category. Such a process flow signifies that a purchase was made before a formal approval or order was made - known as maverick buying. This deviation is also seen in other process variants of this category as well as in other item categories.
  - In both ‘3-way match’ categories, 3% of the purchase order items are created and the subsequently deleted.
- **Throughput times, rework rate and other inefficiencies**
  - When observing the PTP process in its entirety, we see that the rework and automation rates are rather low (7.53% and 8.47% respectively). item[–] ‘Workforce Services’ has the longest throughput time (275 days) whereby the sub spending area ‘HR Services’ and ‘Third Party Labour’ have significantly high average throughput times
  - For item category ‘2-way match’, the largest throughout time is taken from ‘Change Approval for Purchase Order’ to ‘Vendor Creates Invoice’, i.e., average of 71 days. This is effected in 35% of the cases. This means that there is a long waiting time for the company from the vendor’s side until the invoice has been created.
  - In item category ‘3-way match, invoice before GR’, ‘Record Invoice Receipt’ followed by ‘Clear Invoice’ has a throughput time of 45 days, affecting 69% of cases. This fragment is a part of the invoicing process which has been discussed in Section 8. However, we would like to point that long throughput time for an invoice payment cannot be considered without comparing it to the vendor’s/contract’s payment terms. For example, if the payment term for a vendor is 60 days, then all invoices corresponding to that vendor should be paid within 60 days of receiving the invoice. Paying the invoice in lesser number of days can cause the company to reduce the cash currently in the company. On the other hand, paying the invoice late is also detrimental to the company (eg. loosing cash discounts) and their relationship with the vendor.

- When drilling down on purchasing documents, the largest document (in terms of number of line items) ‘4507075965’ has a rework rate of 14.29%. Upon further analysis, we observe that these purchasing documents relates to the spend area ‘Real estate’ and ‘vendorID.1687’. Furthermore we observe that there is an automation rate of 0% for these line items. Through increasing the automation rate, rework could be reduced.
- Purchase Document 4507006057, has 84 purchase order items which consist only of the two activities ‘Create Purchase Order Item’ followed by ‘Delete Purchase Order Item’, where each purchase order item has the same timestamp for each activity. Therefore, it has a 100% rework rate.
- **Additional observations**
  - For item category ‘2-way match’ the activity ‘Change Approval of Purchase Order’ is executed 346 times in 166 PO items. This activity requires further investigation as it results in large throughput times. Furthermore, 32% of the cases start with this activity. Lastly, this activity is repeated multiple times (up to 12 times) in many PO items.
  - Spend area ‘Chemicals & Intermediates’ with only one sub spend area ‘Catalysts’ only has one purchase order item.
  - The Spending area of ‘Logistics’ can have multiple ‘Record goods receipts’
  - The only document type that supports the SRM process is ‘EC Purchase Order’.

## 8 Analysing Throughput Times of the Invoicing Process

A key area of interest for the process-owners is the invoicing process. This refers to the relationship between the *Goods Receipt*, *Invoice Receipt* and *Invoice Payment* (activity *Clear Invoice*). Thus in this section we provide a comprehensive analysis of the organisation’s invoicing process. Furthermore, we also drill down on different factors and attributes which may influence the throughput times such as vendors and document types. This section refers to Figure 1.e in the analysis approach overview.

Within the given event log, activities corresponding to the invoice process occur only in the years 2018 and 2019, thus pertaining exclusively to the years in which the PO items were created. In order to analyse the invoicing process directly, a truncated data set including only these activities was created. However, within the data it is apparent that each line item may have multiple events and consequentially multiple goods receipts and multiple invoices within the line item. In essence, there can be many goods receipt messages and corresponding invoices which are subsequently paid. Perhaps the simplest example to consider is paying rent, say yearly rent is \$1200. A purchasing document could have one item for paying the rent, but a total of 12 goods receipt messages with cleared invoices equalling 1/12<sup>th</sup> (\$100) of the total amount.

Overall, for each line item, the amounts of the line item, the goods receipt messages (if applicable) and the invoices have to match for the process to be

compliant. This is rather prevalent within logistical services where there may even be numerous goods receipts for one line item. Therefore, in order to combat this, a technique to match events within a line item (and determine how multiple goods receipts and invoices are related) is required.

### 8.1 Matching Events Within A Line Item

To match events within a line item, connections and correlations between event level attributes were first explored. However, within a line item, there were no distinctive features that allowed for a pattern or relationship to be identified. It was found that users executing the activity ‘Record Invoice Receipt’ and ‘Record Goods Receipt’ had no clear relationship, in terms of handover of work. Hence, given the nature of an invoicing process, irregardless as to ordering of the activities ‘Record Invoice Receipt’ or ‘Record Goods Receipt’, ‘Clear Invoice’ marks the end of the process. Therefore, through utilising this we can distinguish and group events with the line item, as depicted in Figure 17.

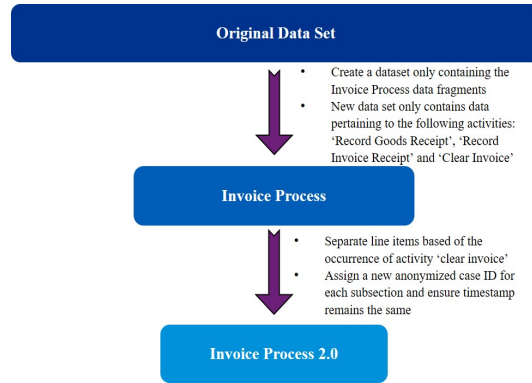


Fig. 17: Creation of new ‘Invoice Process’ data set

For each case, the invoicing process was considered complete if ‘Clear Invoice’ occurred after instances of both ‘Record Invoice Receipt’ and ‘Record Goods Receipt’ irrespective of their ordering. This would signal the start of a new sub-case, see Figure 18.

### 8.2 Insights

For the invoice process as a whole, the average throughput time from process start to process end is 64 days, with some being processed in less than 28 days and others taking up to one year. (Figure 19)

From the process graph (Figure 19, left), we observe that the majority of cases follow the path ‘Record Goods Receipt’, ‘Record Invoice Receipt’ then



Fig. 18: Matching Events Within A Line Item

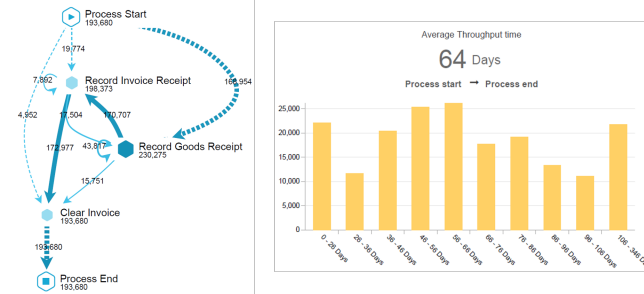


Fig. 19: Throughput Time of Invoicing Process

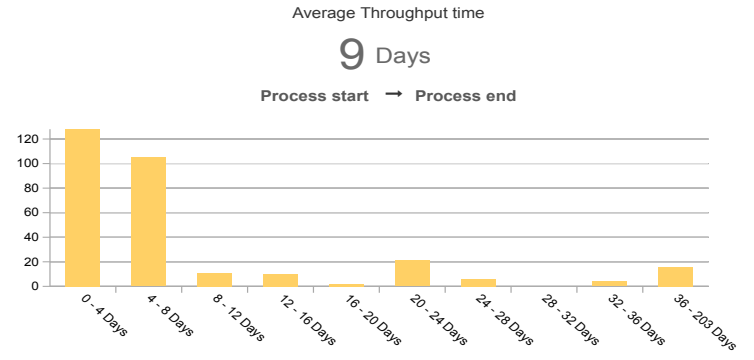
‘Clear Invoice’, however there are many repetitions for the activity ‘Record Goods Receipt’. This is most likely a result of the logistical services which, as previously stated, can have multiple GR messages for one line item. We analysed the invoicing process for different item categories separately (see Figure 20). Here we see that item-category ‘Consignment’ is not included. This is due to the fact that it does not include the activity ‘Record Goods Receipt’.

Both ‘3-way match’ categories have significantly higher total throughput time (TPT) than ‘2-way match’, which has the shortest average throughput time with majority of the invoices being completed within 8 days (Figure 20a) - this is because of the simplicity of the process model. The higher throughput times in ‘3-way match, invoice before GR’ (Figure 20b) may result from the fact that the invoice does not actually occur before the goods receipt as evident in the process model created in Section 6.

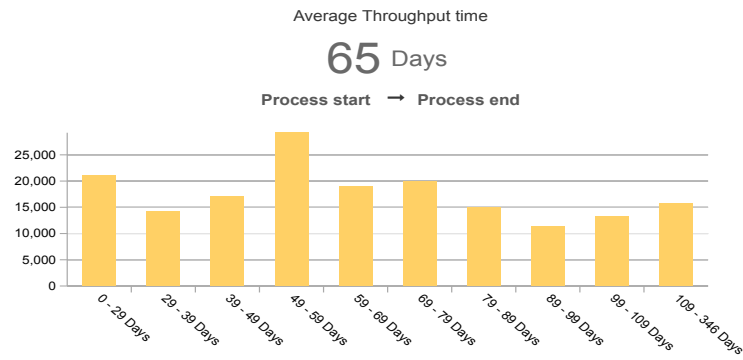
In order to gain a more comprehensive understanding of the total average throughput times (TPT), and what contributes to extended throughput times, we drill down on different attributes for complete cases.

- The document type ‘Standard PO’ has the longest average throughput time (60 days), and only occurs in both 3-way matching systems. This is due to a several reasons, firstly the 3-way matching systems contain all three invoicing process activities, therefore requiring additional time to process. Additionally, the vendors and spending areas associated with standard PO’s have the longest throughput times.

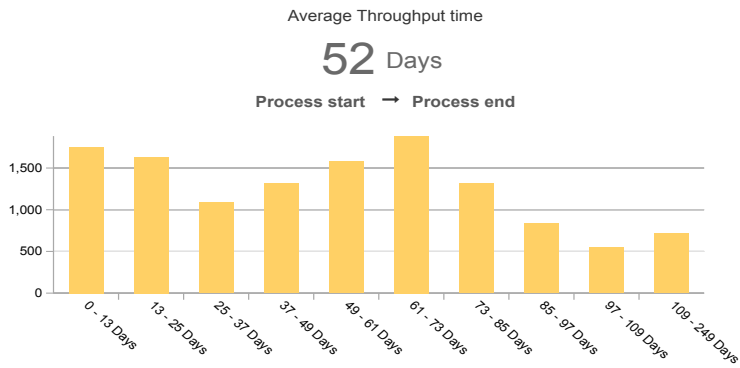
Fig. 20: Throughput Times of Item Categories



(a) Throughput Times 2-way match



(b) Throughput Times 3-way match, invoice before GR



(c) Throughput Times 3-way match, invoice after before GR

- The two vendors which have the longest throughput times (vendorID\_0402, TPT:332 days and vendor\_ID1413, TPT:210 days) relate each to only one case suggesting that perhaps the case is unique to the vendor, or one could change vendors to ensure a shorter TPT.
- companyID\_0001 has the longest TPT (100 days), and only one purchasing document with a net value of \$15,276. This raises concerns as to why this particular company is being used, and how come it only has one vendor.
- In contrast, companyID\_0003 has the shortest average throughput time whilst utilising vendors with the shortest TPT.
- Top six most commonly used vendors all have an average throughput time greater than 66 days.

## 9 Limitations and Conclusions

In this section we will outline the limitations we faced for the given dataset. We will conclude our findings and give some suggestions for further analyses.

### 9.1 Limitations of the Data set

Overall, the process flow of the data set was rather complex and chaotic with approximately 25% of the cases failing to meet the valid ending requirements, not to mention the extensive time span of the data. Given the amount of incomplete (open) cases, and purchase order items pertaining to 50 years ago, it is recommended that the data be refined. Additionally, there are a lot of cases which are created, undergo different activities and are then deleted. This in turn creates large amounts of rework and increases throughput times, negatively impacting process efficiency and possibly even increasing expenses.

It was rather difficult to turn such observations into business insights, given that no background information was provided. For example, within the invoicing process there are no invoicing numbers meaning that it was unable link the different invoice receipts to the clearing of the invoice to form clear invoicing activities. Moreover, the invoicing process did not include any information about the payment term meaning that there was no way to determine late or early payments. Since we do not know the origins of the data, or what the various attributes extensively mean and to what extent they correlate to one another, we are unable to quantify the impact of process deviations and provide direct business advice.

### 9.2 Conclusion

Within this report, we have leveraged process mining tools such as ProM and Celonis in order to create four succinct models that collectively provide an accurate description of the PTP process at hand. Each model had a conformance rating of at least 74% (with the highest being 92%) whilst still maintaining simplicity. These models were subsequently used as a basis to perform further in



depth analysis of the PTP process. We used the models to answer the subsequent business question, in particular relating to the throughput times of the invoicing process. In order to achieve this, an effective method used to match multiple events withing a line item was presented. These throughput times were thoroughly investigated, with additional insights provided in order to ensure a comprehensive analysis and understanding of different contributing factors was achieved. Finally, we highlighted any anomalies within the process, including bottlenecks, rework, automation rates and other general observations.

### 9.3 Future Work

Going forward, we would continue our work by conducting further predictive and prescriptive analysis and, through the combination of play-in, play-out and replay analysis attempt to construct an overarching process model which could explain the process in its entirety. Or conversely, determine alternative ways to segregate the event log to create more process models. In addition, given the high levels of rework in conjunction with relatively low automation rates, one area we would like to investigate the possibility, and business cases, of further automating the process. This can be achieved through identifying process fragments which are more suitable for automation and will lead to higher gain if they are automated.

## Acknowledgements

*We thank Ben Leijdekkers for his substantial contribution in preparing the business value of the insights found in this work.*

## Dashboard

Here you can view the dashboard (in Celnois [4]) created to derive insights and solve the business questions presented in this report:

[https://www.dropbox.com/s/lyihw98j8uf5vr/BPI2019\\_Dasboard%20%28password%20-%20KPMG\\_NL\\_bpi2019%29.CTP?dl=0](https://www.dropbox.com/s/lyihw98j8uf5vr/BPI2019_Dasboard%20%28password%20-%20KPMG_NL_bpi2019%29.CTP?dl=0)

## References

1. Wil M. P. van der Aalst: Process Mining: Discovery, Conformance, and Enhancement of Business Processes . 1st edn. Springer, Netherlands (2011)
2. DataSet Homepage, <https://data.4tu.nl/repository/uuid:d06aff4b-79f0-45e6-8ec8-e19730c248f1>.
3. ProM Homepage, <http://www.promtools.org/doku.php>.
4. Celonis Homepage, [https://www.celonis.com/?gclid=EAIaIQobChMIqPzitdS04gIVz-F3Ch1xyQtMEAAAYASAAEgLqs\\_D\\_BwE](https://www.celonis.com/?gclid=EAIaIQobChMIqPzitdS04gIVz-F3Ch1xyQtMEAAAYASAAEgLqs_D_BwE).
5. Python Homepage, <https://www.python.org/>.
6. BPMN model designing tool, <http://bpmn.io/>.