Transparency promoted by process mining: an exploratory study in a public health product management process

Thais Rodrigues Neubauer[1], **Renata Mendes de Araujo**[2,1,3], **Marcelo Fantinato**[1], **Sarajane Marques Peres**[1]

[1]University of São Paulo, São Paulo, SP, Brazil, 03828-000

[2]Mackenzie Presbyterian University, São Paulo, SP, Brazil, 01302-907

[3]Brazilian National School of Public Administration, Brasília, DF, Brazil, 70610-900

thais.neubauer@usp.br, renata.araujo@mackenzie.br,

m.fantinato@usp.br, sarajane@usp.br

Abstract. *Public transparency enables the exercise of democracy by the active participation of citizens in the public management. Even though promoting transparency is an essential conduct in a democratic context, its practice is still incipient. In this context, process mining emerges as an agent to promote public transparency as the data related to public processes event logs may have the potential to enable visual and analytical analysis of the process execution. In order to exemplify how process mining might promote public transparency, we present a study considering the health products' management process of a health surveillance agency. Our analysis reveals details about the process execution logic as well as the actions that impact the efficiency of its management.*

1. Introduction

Transparency is one of the essential aspects on which the open government concept relies [Lahtrop and Ruma, 2010]. The promotion of transparency enables the exercise of democracy as it enables active participation of citizens in public management. Even though open government and democracy rely on transparency, its definition is difficult and sometimes controversial [Erkkilä, 2020] and its practice is still incipient. Most of the time, governments do not provide enough and adequate tools for the citizens to be aware and comprehend the executions of processes under public administration at the same pace as they create laws and procedures to expand the access to information.

Process mining brings together data science and process science techniques. The aim of this area is to extract knowledge from event logs generated during the execution of the different phases of a business process to provide a better understanding of the process. Therefore, process mining plays a central and strategic role in organizations as its techniques provide ways for business processes to be automatically discovered, analyzed, and improved [van der Aalst, 2011, 2016]. Academics and practitioners in process mining recognize enhancing business process transparency as an opportunity for its use in organizations, since it provides the visualization of the actual business process flow based on real-life data [Martin et al., 2021].

This paper argues that, in the context of public management, the application of process mining techniques has the potential to enable both organization and citizens, to better understand how the processes have been executed. Thus, greater transparency is promoted since the citizens can access and understand how the processes are actually being carried on. Once the transparency increases, the active participation of citizens in public management tends to increase as well.

In this study[1], we apply process mining techniques to the context of processes under public administration. The data and information related to the registration request of health products to Anvisa (Brazilian National Health Surveillance Agency) were provided by the agency in the Open Data Brazilian Portal. The main goal is to evaluate how the application of process mining techniques supports transparency in processes under public administration. This paper is organized as follows: Section 2 summarizes concepts related to the conducted study; Section 3 provides the related work; Section 4 describes the study execution logic; Section 5 presents the results; and Section 6 concludes the paper.

2. Background

In this section, we present the concepts related to the discussions reported in this study.

2.1. Transparency in Public Administration

Open government relies on essential aspects comprising information access, citizen participation, transparency, collaboration among governmental bodies and civil society, and innovation in public policy management [Lahtrop and Ruma, 2010]. Behind this concept lies the very basic idea that governments should be susceptible to public opinion presuming the existence of three major pillars [OGP, 2011]: i) public information transparency promotes social control; ii) citizen participation improves government efficiency and decision making quality; and iii) collaboration engages citizens into government actions.

Although frequently associated with contemporary governance and key to hold public administration accountable, transparency is still difficult to define and sometimes controversial [Erkkilä, 2020]. Transparency in public administration functions differs across countries and cultures. In Brazil, the concept of transparency is strongly connected to disclosing public administration data and information [BRASIL, 2012] and to the idea of providing interaction channels with citizens [BRASIL, 2017]. This is primarily to the fact that in the Brazilian Information Access Law [BRASIL, 2011] transparency is defined considering two dimensions: *active transparency* - public administration discloses information to society by own initiative, regardless of any request; and *passive transparency* - public administration publishes information upon citizens' and society's requests.

Transparency is also considered core to citizen participation and collaboration since it is only possible to take part into public decisions and innovation of public services when citizens are aware of how public administration works and performs. The lack of citizens' effective understanding of how governmental institutions provide their services may lead citizens to perceive these services as complicated, bureaucratic, and unnecessary. Understanding the operation, challenges, and limitations of a public service process, is crucial for citizens and public institutions to feel confident in dialogue, discussing and thinking about improvements and innovations in such services [Laitinen et al., 2018; Blomkamp, 2017], creating an opportunity for business process management

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to be a reasonable basis for service transparency, understanding, and interaction with citizens [Cappelli et al., 2007; Alfaro et al., 2015; Carvalho et al., 2022].

2.2. Process Mining

A *process* can be generically described as a set of *activities*, how they should be executed and in which order. According to Weske [2007], a *business process* consists of a set of activities coordinately executed in an organizational and technical environment to achieve a business goal. A process is a chain of events, activities and decisions [Dumas et al., 2018]. From the organizational perspective, good business process management ensures consistent results and allows to benefit from enhancement opportunities that may add value to the organization and its clients [Dumas et al., 2018]. Process model is one tool to proceed with process management. A *business process model* is a set of activity models and execution restrictions between these models [Weske, 2007]. The main reason for modeling processes is to facilitate their understanding and to share knowledge about them among involved actors [Dumas et al., 2018]. Business process models can be expressed by formalisms [van der Aalst, 2019], from Directly-Follows Graph (DFG) to Business Process Management Notation (BPMN) [Object Management Group (OMG), 2011].

Even though process models are essential tools to achieve success in business management since they bring to organizations awareness of how their processes are being executed [Dumas et al., 2018; Weske, 2007], organizations commonly do not formalize these models. Process mining plays a central and strategic role in organizations as its techniques provide ways for business processes to be automatically discovered, analyzed, and improved [van der Aalst, 2011]. The process mining implementation relies on some basic concepts. The *trace* concept is defined as a sequence of activities related to a process. Executions of a trace originate a *case* and a set of unique traces, i.e. traces describing the exact same activity sequence, is commonly named as *variant*. Each activity execution in a case is an *event*, which can be described in terms of the executed activity, execution timestamp, resources involved in the execution etc. A collection of cases compound an *event log* in which the executions of a process observed during a time period are registered. In process mining area, this concepts are applied to: i) automatically *discover* models; ii) replay and analyze data from or related to the process models (*conformance check)* [Rozinat and van der Aalst, 2008]; and iii) provide information to process *enhancement* [van der Aalst, 2016]. These activities characterize the three basic types of process mining: discovery, conformance check and process enhancement.

3. Related work

One research strand in business process management is the possibility of extending processes to the environment external to the organization, promoting transparency and allowing clients to take part in improvements and innovation processes [Schönthaler et al., 2012; Pflanzl and Vossen, 2013; Rangiha and Karakostas, 2013]. However, external actors need to understand how the process was defined and is performed to feel able to interact and contribute. Examples in literature discuss how process management techniques and approaches can increase citizen understanding and participation when it comes to public processes. In [Gomes and Araujo, 2012], the authors proposed the use of process animation to promote understanding of rules in public services. Engiel et al. [2014], Oliveira et al. [2020] and Carvalho et al. [2022] proposed distinct innovative ways of translating technical business process models into descriptions more suitable for citizen understanding. De Classe et al. [2021] suggests the use of business process-based digital games to help citizens understand and experience public processes. Pires and Araujo [2020] prescribes a method to analyze public process models to identify opportunities for citizen engagement, whilst Diirr et al. [2014] proposes tools to engage citizens and public administration into collaborative conversations about public processes.

On the other hand, works on the application of process mining techniques to promote transparency were not frequently reported in the literature, but some initiatives have been discussed in recent years. The work of Unger et al. [2021] proposed the application of process mining techniques as an innovative way of analyzing Brazilian judicial data from a process-oriented perspective. The results indicate process mining analysis allowing the identification of most frequent activities and process bottlenecks, providing insights about inefficiencies root causes. da Costa and Rodrigues [2020] followed a similar path in terms of demonstrating how to apply process mining tools to analyze the Brazilian Navy processes and indicating that it enables the identification of real process maps, bottlenecks and procedural deviations. González and Delgado [2021] focused on the process mining task of compliance checking. The authors proposed an approach to model compliance requirements using BPMN and evaluate these requirements fulfillment in Uruguay's e-government with process mining conformance checking techniques. They concluded the approach helps in modeling the requirements due to the fidelity to reality of process executions brought by the event log data as well as due to the help provided in reasoning and controlling the requirements related to regulations and applicable laws. Sangil [2020] also explored conformance checking, applying it to data about Philippines' public process aiming at uncovering how these processes have been executed and verifying their conformance with related laws. The authors explicitly indicated the approach provides greater transparency, efficiency and general accountability by enabling the identification of inappropriate behaviours no matter how small the deviations were.

The main issue in our study is to discuss opportunities for how information obtained through process mining can support transparency about public service processes. Furthermore, our work suggests an *ad hoc* method for combining strategies and tools in an analysis effort that can be reused or can inspire new initiatives.

4. Method

The study discussed in this paper has an applied and exploratory nature and aims at illustrating how process mining can promote transparency in public service processes. This is an empirical study with the possibility of analytical generalization regarding the promotion of transparency. The study execution logic is shown in Figure 1.

The event log used refers to the "Petitions for Registration of Health Products" process within Anvisa. Anvisa is a regulatory agency of the Brazilian Health Ministry responsible for sanitary control of all products and services (national or imported) subject to sanitary surveillance, such as medicines, food, cosmetics and many others. Datavisa is an information system which gathers country-wide data on health products and enterprises registration and controls the process workflow within the agency. Datavisa event log is available at the Brazilian Open Data portal[2].

[2]The event log data provided by Anvisa is published at `dados.gov.br/dataset/`

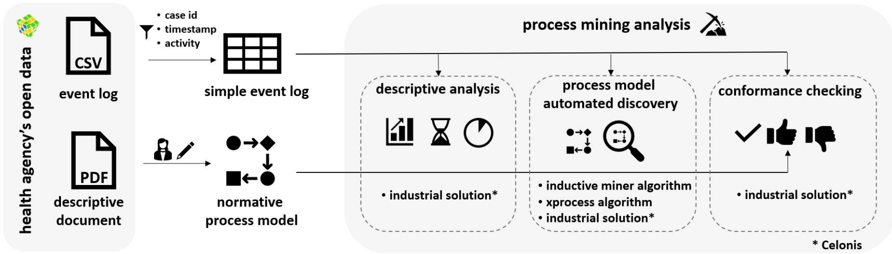

Figure 1. Method applied to promote transparency using process mining

The process underlying the event log spans the period from January, 2001 to October, 2021 and includes information about: (i) identification and classification of requests (petition or process); (ii) characterization of requests; (iii) type of product under analysis (for health or for diagnosis); (iv) current status of requests with the respective completion dates; (v) characterization of queues which the requests have been submitted to before; and (vi) description of the requests analysis steps. This last information was used as the process events' description for the analysis presented in this study by consulting a descriptive document on the requests analysis life cycle, provided together with the event log. The requests analysis steps cover queue organization activities - detailing the requests analysis, pauses for the execution of actions external to Anvisa's technical area, external to the agency or referring to other related processes - and appeals. The event log is composed by $150,758$ cases and $674,987$ events.

Based on our interpretation of the information available in the descriptive document about the life cycle of the analysis of requests, we inferred a normative process model, i.e., a possible logic the process owners would expect to be followed in the requests analysis. The inferred normative process model, in BPMN notation, is shown in Figure 2[3]. This model serves as *a priori* knowledge for inspiring analysis from the model representing the *de facto* process mined from the event log.

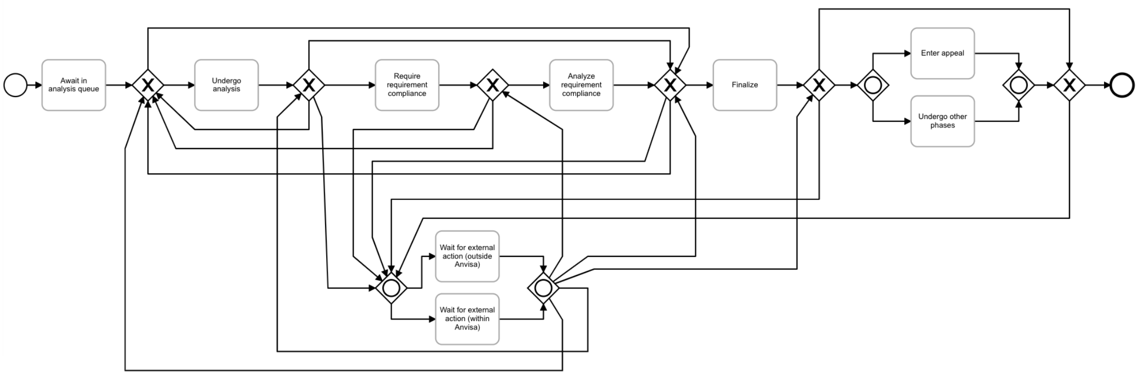

Figure 2. Normative process model inferred by the authors from reading the descriptive document on the life cycle of the analysis of requests

In this study, process mining was used in three senses: descriptive analysis, pro-

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peticoes-produto-para-saude-na-anvisa. The filtered event log used is available at github.com/pm-usp/public-transparency, as well as the figures presented herein.

[3]The inference on this normative model was made by the authors of this paper. It was not validated by the process owners and may reveal authors' textual and contextual interpretation bias.

viding primarily quantitative information about the process being executed; automatic discover of process models to explain the actual logic performed in the agency; and conformance check to assess whether logic performed has followed the normative model.

5. Results and analyses

In this section, we discuss the results obtained from executing the method, cf. Section 4.

5.1. Descriptive analysis

Descriptive information comprises quantitative data about process execution: number of cases, process variations, bottlenecks, throughput time, rework etc. The first item identified by the descriptive analysis is the characterization of the process execution by the occurrence of 135 events per day, the initiation of 30 new cases per day and the occurrence of 4.48 events per case, on average. Until December 2003, when an average of nine cases per day was registered, the average of new cases per day was under three. The peak of 111 new cases per day on average was observed in May 2010. In addition, 777 variants were identified, showing there is a great diversity in the order of process activities' execution. The most common variant, present in 47.64% of cases ($71,816$ cases), follows the sequence: "Await in analysis queue", "Undergo analysis" and "Finalize". This is a very simple variant in which there are no activities related to intercurrences. The average throughput time [4] of cases following this sequence is 49 days. Making a comparison between the throughput time of all cases, we concluded that the occurrence of intercurrences adds about a month for the request finalization.

The most frequent intercurrences are: "Require requirement compliance", recorded in $26,385$ cases (17%) of cases and "Analyze requirement compliance", recorded in $26,208$ (17%) of cases. The activity "Analyze requirement compliance" occurs $56,263$ times, meaning that it occurred, on average, 2.15 times per case it appears (with the maximum of 12 occurrences in a case). This statistic reveals a rework situation that involves both the agency and the requests seekers, and suggests the effectiveness and efficiency of the process could be improved by creating more precise and detailed guidelines and procedures to guide the submissions of requests of health product registrations.

Regarding the throughput time, the average is 96 days, that is, the analysis of a request lasts about three months, on average. $4,147$ atypical cases with throughput longer than 500 days[5] were identified, with an average throughput time of 875 days. Contrasting this subset of outliers with the complete event log, we noticed that the occurrence of the activity "Wait for external action (outside Anvisa)" is a major responsible for increasing the throughput time since it occurs in 22% among the outlier cases (in contrast to only 1% of the cases of the complete event log). If we filter the outlier cases in which such an activity occurs, the average throughput time goes even higher: $1,390$ days (515 longer than the before mentioned average of the outlier subset).

Finally, a bottleneck was revealed in the sequence of activities "Await in analysis queue" and "Undergo analysis", affecting 97% of cases. Waiting for requests to go under

[4]Throughput time is the time elapsed between the first and last events of a case, calculated comparing the timestamp of these events.

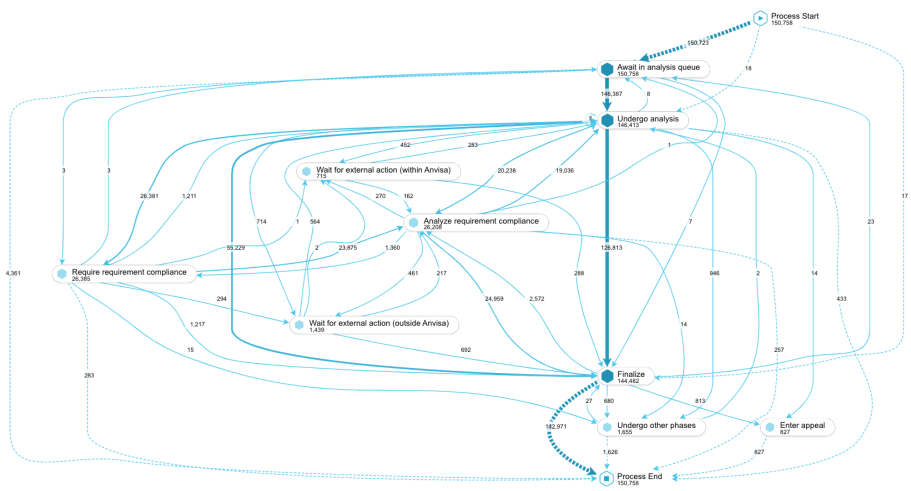
[5]The 500 days limit used to identify outliers regarding the throughput time was based on the upper limit of a boxplot analysis built upon the throughput time of all the cases present in the event log.

review consumes, on average, 62 days. For the cases following the most common variant, this waiting consumes 47 days on average. This bottleneck shows it can be worth investing in the workforce rearrangement (human resources) to bring process efficiency.

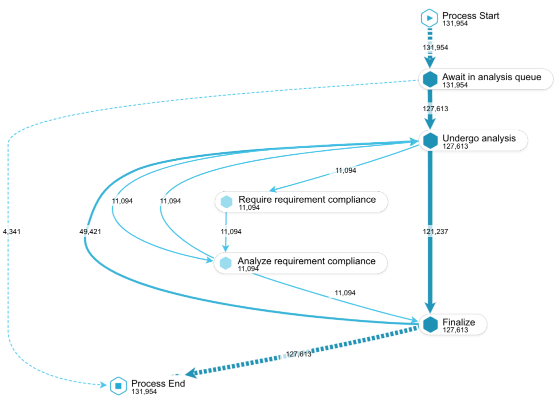
5.2. Process model discovery

The discovery of process models in process mining enables the AS-IS process view. However, automatically discovering this process logic is not an easy task. In this study, three strategies for discovering processes have been applied and two representations were used.

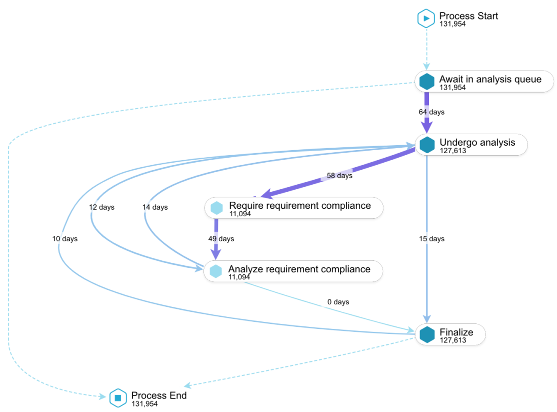
The models discovered using the EMS tool from Celonis expressed by DFG, are presented in Figure 3. Figure 3(a) presents the DFG for the model generated considering all the cases in the event log. Due to the quantity of process variants, the obtained model presents characteristics of a *spaghetti* model, exhibiting a complexity that compromises a visual analysis and, consequently, the comprehension of the process behaviour. Besides, the expressiveness of a DFG does not allow the representations of behaviours related to activities' parallelism and this can result in misrepresentation of certain behaviours.



(a) DFG obtained from full event log



(b) DFG obtained filtering the five most common variants



(c) DFG obtained filtering the five most common variants and with average time perspective

Figure 3. DFG representation of process model discovered by EMS tool

Despite the expressiveness limitation of a DFG, when it is used with a smaller diversity of variants, relevant information about the process can be revealed. In Figure 3(b), the presented model takes into consideration only the five most common variants (covering $131,954$ cases, 87.53%). This allows, for instance, the identification of the occurrence of “Undergo analysis” directly after “Finalize” being a common behaviour since it occurs in $49,421$ cases (32.77%). This second execution of “Undergo analysis” after the finalization of the case demonstrates either an inefficiency or a legit behaviour not properly described on the descriptive document. The former might arise a suggestion of investing in workforce training and the latter can arise the need for an update in the process documentation. Another example of analysis this model enables is the identification of $4,391$ cases finalized after entering in the analysis queue, without any analysis executed. This may indicate unnecessary resources’ overload during the initial phase in these cases.

Even though data sampling enables revealing relevant information, its analysis should consider other perspectives, such as the complete DFG in Figure 3(a) and in the descriptive analysis of Section 5.1. To exemplify, considering only the model presented in Figure 3(b) the low occurrence rate of 8.4% ($11,094$ cases) of the activities related to requirement compliance (“Require requirement compliance” and “Analyze requirement compliance”) may induce the misleading conclusion about process efficiency since the occurrence rate for these activities when analyzing the complete event log is 17% (cf. Section 5.1). The DFG in Figure 3(c) shows information on the average time elapsed between the execution of two sequential activities, or between two sequential executions of the same activity. This reveals the average time between “Undergo analysis” and “Require requirement compliance” is 3.9 times bigger than the average time between “Undergo analysis” and “Finalize”. It might indicate the complexity of cases in which an information supplementation is needed or a delay in the procedure of requiring supplementation.

BPMN notation provides greater expressiveness than DFG as it enables the indication of parallelism of activities (gateway AND) and exclusive choices (gateway XOR). Algorithms which generate this kind of model are faced with a complex problem and apply different techniques to deal with it. Therefore, different algorithms may discover different models from the same event log, revealing different knowledge about hidden behaviours in such event logs. In order to obtain models in which the process behaviours could be better represented, two algorithms for process model discovery were applied: the IMf variation of Inductive Miner [Leemans et al., 2014] and X-Processes [Fantinato et al., 2021]. Both algorithms aim at maximizing some process model quality measures. IMf[6] maximizes fitness (equivalent to seeking completeness) and X-Processes[7] maximizes fitness, precision, generalization (seeking to model behaviours not present in the log, but adhering to the logic of the process) and simplicity (seeking low-complexity notation models, for example, with few gateways or few sequence flows)[8].

The model resulting from the application of IMf is presented in Figure 4. It reveals structured logic which allows a better understanding of the process behaviour than that offered by the aforementioned DFGs. For instance, this model indicates that “Undergo

[6]The execution of IMf variant of Inductive Miner algorithm was conducted with parameters set to enable the search for a model with fitness measure close to 0.9.

[7]X-Process algorithm was executed to maximize the model quality measures based on the following weights: f-score$=0.7$ (combination of fitness and precision), generalization$=0.1$ and simplicity$=0.2$.

[8]These measures vary in the range $[0,1]$ and the implementation of the PM4Py library [Berti et al., 2019] was used to calculate them.

analysis" is an mandatory activity in a variant; it does not allow the activities "Wait for external action (within Anvisa)" and "Undergo other phases" occur in the same variant; it requires that both activities "Require requirement compliance" and "Analyze requirement compliance" occur in a variant; and it demands the occurrence of "Enter appeal" activity to necessarily happen after (although not necessarily directly following) "Finalize".

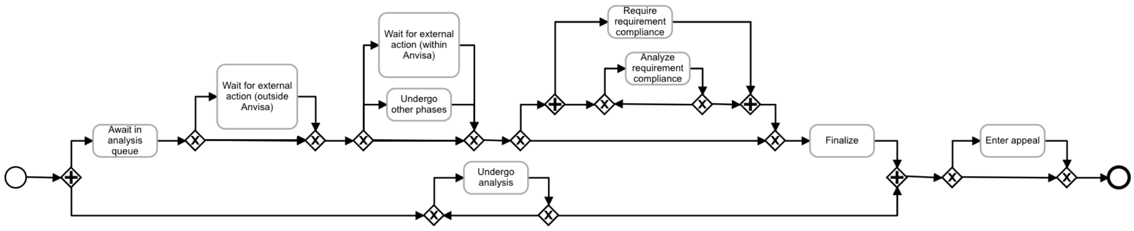


Figure 4. Process model in BPMN discovered by IMf-Inductive Miner. Model quality: fitness$=0.93$**; precision**$=0.62$**; generalization**$=0.99$**; simplicity**$=0.67$**.**

The resulting model obtained applying the X-Process algorithm is presented in Figure 5. A greater simplicity can be perceived by the easier comprehension that this model brings. In addition, this model differs from the others, for instance, on: demanding "Await in analysis queue" to be the first activity in a variant; defining the mandatory sequence of the activities "Require requirement compliance" and "Analyze requirement compliance"; positioning "Wait for external action" after the execution of a requirement; and allowing "Undergo other phases" to occur only after an occurrence of "Finalize".

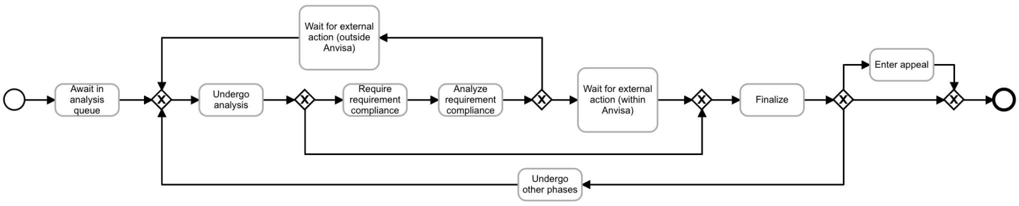


Figure 5. Process model in BPMN discovered by X-Processes. Model quality: fitness$=0.90$**; precision**$=0.99$**; generalization**$=0.98$**; simplicity**$=0.88$**.**

5.3. Conformance checking

Conformance checking is a process mining technique to compare the behaviours registered in event log data to the ones described by a normative process model [Rozinat and van der Aalst, 2008]. Considering that a normative model is built upon specific knowledge about the process execution, i.e. experience from people who work on this process, taking this model into consideration on the process analysis enables a greater alignment between the analysis and the real-world experience.

The process analyzed herein has 80% of the cases $(120, 685)$ in conformance with the normative process model of Figure 2. Table 1presents the most common violations identified when comparing the event log data and the normative process model. Such violations describe 19% of the cases. According to the normative model, the activity "Analyze requirement compliance" occurs either after a requirement request or after an action external to the process. Thus, violations involving this activity are related to unexpected decisions about analyzing compliance requirements. The analysis of the violation referring to the “Undergo other phases” also indicates the performance of procedures outside the expected context. The cases in which such violations occur should be analyzed in depth to verify whether they are justifiable workarounds, in which case the normative model could be updated, or there is a need to reinforce workforce training.

Table 1. Violations which occurred in at least 1% of the cases, ordered from the most common to the most rare. → refers to “directly followed by” relation between activities; “% Cases” informs the percentage of cases in which the violation occurred; “Effect” refers to how many days longer (+) or shorter (-) is the average throughput time for cases in which the violation occurred compared to cases in which the violation did not occur.

Violation description	% Cases	Effect
“Undergo Analysis” → “Analyze requirement compliance”	13%	+184
“Finalize” → “Analyze requirement compliance”	2%	+136
“Undergo analysis” → “Undergo other phases”	1%	-14

5.4. Possibilities for public transparency

Descriptive information (Section 5.1) about business process execution can be the first step in promoting transparency. Descriptive information elucidates and sheds more light on the details about process execution, promoting a more accountable process. Descriptive information could be provided by public agencies as open data or in process monitoring portals, as tools for active transparency. Additionally, it can be a way to demystify common assumptions about the process flow and a better understanding and/or critique about its execution, for example, details about the process and activities execution time.

How public service processes are performed by a public service provider is an opaque field. Process model discovery (Section 5.2) and conformance checking (Section 5.3) are opportunities for transparency. For example, public administration in Brazil is obliged to publicise service descriptions, known as “service letters to citizens”[9], explaining the expected process flow and how to use the service. However, this is not enough to truly understanding the process, specially on how it is actually performed.

It is interesting to think ahead on the possibilities that process model discovery and conformance checking might achieve regarding process understanding, auditability and debate if enough simplifications can be provided. Finally, it is worth thinking about the outreached possibilities of having process mining tools manageable by citizens, allowing them to perform analysis on their own.

6. Final remarks

In this study, we applied process mining techniques to the context of a process under Brazilian public administration to exemplify how process mining can promote public transparency. Besides descriptive analysis from the process execution data, the event logs, we also presented the results of applying process mining techniques to discover the process model and check conformance considering a normative process model. From the obtained results, we exemplified enhancement suggestions which could be made by

[9]Carta de Serviços ao Cidadão

anyone who accesses the revealed information. The usefulness of the revealed information is related to the capacity of the reader to interpret it. In this sense, the presented approach may benefit from techniques for translating revealed technical business process information into descriptions more suitable for citizen understanding.

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