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Augmented Business Process Management: Adaptive SLT definition based on process variant analysis

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September, 2025

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TECHNOLOGY
AND ARCHITECTURE

Department of Information Science and Technology

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To my parents and my sister.

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Resumo

A rápida evolução tecnológica exige adaptações significativas nas empresas, especialmente no que diz respeito à crescente importância de respostas de suporte em tempo útil e à priorização de casos técnicos com base em diferentes requisitos dos clientes. Este trabalho investiga métodos inovadores para a definição de termos contratuais entre empresas e clientes, com o objetivo de gerir expectativas, fortalecer relações e facilitar o ajuste dinâmico de objectivos de nível de serviço. Através da análise de incidentes de uma empresa, e utilizando técnicas de mineração de processos, foi possível testar uma abordagem *naive* e uma outra utilizando análise de variantes para definir potenciais objetivos de níveis de serviço para os tempos de resolução dos incidentes. A primeira abordagem considera todos os incidentes como um único grupo, enquanto que a segunda utiliza mineração de processos e sugere valores para potencias níveis de serviço de acordo com as variantes do processo. Os resultados foram avaliados utilizando o Root Mean Square Error, e revelam diferenças entre as duas abordagens na definição dos tempos de resolução, com valores superiores a 1800 horas totais por processo, sendo que a abordagem orientada por variantes demonstra ter melhor desempenho e conformidade para ser utilizada numa potencial proposta de acordo de nível de serviço. Esta investigação destaca o papel crítico de contratos bem estruturados e níveis de serviço dinâmicos na gestão de expectativas dos clientes e na promoção de relações duradouras, oferecendo recomendações valiosas para otimizar níveis de serviço e melhorar a eficácia das respostas de suporte.

Keywords: Contratos de serviços, Gestão de Serviços, ITSM, Mineração de Processos, Acordos Adaptativos

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Abstract

Rapid technological evolution demands significant adaptations from companies, especially regarding the growing importance of timely support responses and the prioritization of technical cases based on varying customer requirements. This work investigates innovative methods for defining contractual terms between companies and customers, aiming to manage expectations, strengthen relationships, and facilitate the dynamic adjustment of service level targets. By analyzing a company's incidents and using process mining techniques, it was possible to test a *naive* approach and another using variant analysis to define potential service level objectives for incident resolution times. The first approach considers all incidents as a single group, while the second uses process mining and suggests values for potential service levels based on process variants. The results were evaluated using the Root Mean Square Error and reveal differences between the two approaches in defining resolution times, with values exceeding 1,800 total hours per process. The variant-driven approach demonstrates better performance and compliance, making it suitable for use in a potential service level agreement proposal. This research highlights the critical role of well-structured contracts and dynamic service levels in managing customer expectations and fostering lasting relationships, offering valuable recommendations for optimizing service levels and improving the effectiveness of support responses.

Palavras-chave: Service Level Agreements, Service Management, ITSM, Process Mining, Adaptive Agreements

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Acronyms

PICOC	Population, Intervention, Comparison, Outcome, and Context.
PM	Process Mining.
QoS	Quality of Service.
RMSE	Root Mean Square Error.
SLA	Service Level Agreement.
SLM	Service Level Management.
SLO	Service Level Objective.
SLR	Systematic Literature Review.
SLT	Service Level Target.
VM	Virtual Machine.

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Chapter 1

Introduction

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This chapter introduces the motivation of this work, describing how IT Service Contracts are processed, the role of Service Level Agreements, outlining some of the problems that organizations face nowadays and the main goals. Additionally, it includes the research questions and summarizes the main contributions.

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Chapter 1
Introduction

1.1 Background

Service management is evolving, and so is ITIL, the most widely adopted guidance on IT service management (ITSM) in the world [8]. ITIL4 provides the guidance organizations need to address new service management challenges and utilize the potential of modern technology, designed to ensure a flexible, coordinated and integrated system for the effective governance and management of IT-enabled services [8].

ITSM focuses on value for users and customers, emphasizing that what matters is not the technology itself, but the opportunities and outcomes it enables. As organizations adopt cloud-based service models, the service architecture and the distribution of responsibilities between consumers, providers, and internal IT teams change significantly [8].

ISO/IEC 20000 is a series of international standards and technical reports specifically focused on service management. The purpose of these standards is to help organizations gain greater control over their services, reduce costs, increase credibility, and comply with regulatory or contractual obligations. Sometimes, the ISO/IEC 20000 is referred to as the ITIL standard. The synergy between ISO/IEC 20000 and ITIL means that the growth in the use of ITIL is mirrored by the growth in the use of ISO/IEC 20000. ITIL and the 20000 series are owned by different organizations and are developed over different timescales, using different approaches [13].

Complementing this service management perspective, COBIT 2019 provides an overarching framework for the Enterprise Governance of Information and Technology (EGIT). It clearly distinguishes between Governance, which focuses on monitoring strategic objectives such as Service Level Agreement (SLA), and Management, which is responsible for planning and executing operational targets, including Service Level Target (SLT) and Service Level Objective (SLO) [18]. This distinction supports a data-driven approach that ensures service targets are realistic, transparent, and aligned with enterprise value creation.

One of the practices that is most frequently used in ITILv4 is Service Level Management (SLM). One of its key responsibilities is the establishment and negotiation of SLA. In the next section, we will examine how these concepts translate into IT Service Contracts taking into account the best practices of ITIL.

1.2 Motivation

1.2.1 IT Service Contracts

The base of all relations between companies are the contracts established between them. These contracts contain not only the business rules binding the entities, but they also usually define the potential rewards and penalties between parties in case of compliance or otherwise with

those rules. This approach enables both organizations to understand their responsibilities and expectations [25].

A contract is a legally enforceable agreement in which two or more parties commit to certain obligations in return for certain rights. It could be a simple one page until an extremely complex thousand page document [25].

Consequently, a contract is a bidirectional definition of responsibilities and repercussions. Not only does a contract define the commitments of the provider to the consumer, but it also defines the commitments of the customer to the provider. Each of these commitments is then backed by penalties in the event that one of the parties to the contract does not meet the commitment [21].

According to [25], in most scenarios, the agreement process will pass through the following steps until the formation of the contract:

- **Pre-contractual phase:** This phase will involve discussions between the parties involved to clarify goals, terms, and expectations. Usually, it's the draft of the agreements with the key elements for the contract itself, with pricing, timelines, responsibilities, rewards, and penalties.

- **Contractual phase:** After everything is well discussed between the parties, they proceed with the creation of a formal relationship between them, covering contract negotiation and validation operations with everything well stipulated - times, duration, and how the contract will be performed and monitored.

- **Ordering and Logistics phase:** This phase refers to where the service/product starts to be processed as an order and the delivery of the same.

- **Settlement phase:** This is when the invoicing and payments are going to be processed and settled.

- **Post-processing phase:** The last phase will be the focus on monitoring and managing the costs, what is being used and how it is being used. This will be helpful to assemble statistics about the entire contract elements.

The elements that are covered by the clauses on the business contract consist on: i) the description of parties involved (names, addresses, etc); ii) definition and interpretation of terms used, jurisdiction under validity, correctness and enforcement of the contract will operate; iii) duration and region of the contract; iv) services rendered, goods exchanged, rights granted, obligations associated each role, warranties, rejection, liability, termination and accounting provisions.

A business contract may contain penalties and rewards depending on the agreements defined under the contract. It may be defined that the buyer is eligible to charge a penalty to the seller for undelivered services/products or obliged to give a reward for better than on-time delivery of services or goods [4] .

Focusing on technology companies, undelivered services can be: i) applications down; ii) virtual machines unreachable; iii) backend issues coming from the provider, network issues,

etc; iv) incidents not resolved within a certain timeframe, and many more. These events will have a customer impact, thus not allowing to perform work as expected. These situations are typical candidates for the business rules that exist in service agreements. However, when a service is delivered exceeding expectation, that is to say, exceeding what's defined in a contract, a reward may be paid to the provider.

By using penalty-reward rules, one can improve the contact between the consumer and the service provider. This approach helps to build trust and maintain a relationship between both, avoiding uncertainty related to the delivery of services. In this case, both the customer and the provider are aware of their obligations and compensations [4].

1.2.2 The Role of Service Level Agreements(SLAs)

Nowadays, an organization is composed of various processes that can occur in multiple areas, such as: sales, finance, and production. Therefore, it is important to give full support to clients in these different areas in which a company operates.

IT processes are the number one source of issues, more than technology [9]. A process could have multiple activities, and, at any time, one of these activities could fail. To make things more complex, IT processes reside also on IT infrastructure components, and these are known to have failures [15].

Processes commonly refer to a collection of activities that are related with constraints that could named a goal or an outcome. Hence, when the process is executed within an organizational setting, it is referred to as a business process [2].

IT Processes, when properly delivered, ensure that the business applications' performance and availability are aligned with the IT Service Commitments. Organizations empower their employees by providing them with the essential tools and methods to perform their daily tasks effectively. Consider prominent companies like Amazon, Microsoft, and Meta - they have dedicated technical support teams that collaborate seamlessly to deliver comprehensive solutions. This unified approach extends beyond the tech industry and is also evident in automotive giants like Volkswagen, Peugeot, and Citroen, just to name a few.

What stands out is the orchestrated effort of multiple teams working together to provide top-tier customer support. To ensure clarity and alignment, contractual agreements between parties (the business and the IT) play a pivotal role in setting and managing customer expectations.

To excel in the response to the issues that happen on the infrastructure of a company, there is a need to have teams specialized in multiple technologies. Their goal is to give the best support possible to the customers, and at the same time, these teams will have an important role in the management and monitoring tasks, and check if every process is aligned with the expected goals. This methodology avoids certain problems from occurring. The definition of service goals, penalties, and rewards is usually projected in a contract between entities, one that is the customer and another one as the provider, which is called a SLA.

Service level agreements are the contractual component of Quality of Service (QoS) and are usually implemented as part of a larger SLM initiative [9]. SLM has been defined by Sturm, Morris, and Jander in Foundations of Service Level Management as "the disciplined, proactive

methodology and procedures used to ensure that adequate levels of service are delivered to all (IT) users in accordance with business priorities and at acceptable cost" [21].

Pursuant to other authors Blokdijk and Menken, *"The SLA is effectively a level of assurance or warranty concerning the level of service quality delivered by the service provider for each of the services delivered to the business."* [16].

To define or predict service targets to include in SLA is a challenging task. It requires the integration of information regarding individuals' interactions and their responsibilities, technical and/or process metrics, and future expectations concerning service deliveries.

For a service provider, it is desirable to prevent SLA violations during the SLA's validity in order to avoid financial consequences and a diminished reputation. In contrast, a service consumer wants to detect potential SLA violations under a ruling SLA. Providing many SLA aware services to many consumers implies that the consumers can invoke the service in parallel, requiring the monitoring of the performance-related to each service.[7]

As such, IT managers, need to navigate faster in the intricate relationships between the stakeholders in a fast-changing world. Therefore, the industry may need innovative ways to improve service management. As shown by [20], the importance of SLA is a fundamental component in ensuring that IT services work well within contemporary business contexts. How SLA should be specified does not seem to be among the top priorities for the IT services industry. While some lack interest, others claim that previous research related to the definition of SLAs specifications within IT services is short. This work partially addresses this perceived absence and introduces a method to mitigate the lack of scalability in defining and adjusting SLTs within SLA.

1.2.3 Understanding the Roles of SLOs and SLTs within SLAs

SLAs are formal contracts established between parties, which can refer to SLO and SLT. However, the primary role of an SLA is legal and commercial, as it defines responsibilities, guarantees, and possible penalties if the agreed service levels are not met. Therefore, SLAs serve as a contractual framework that formalizes commitments rather than as instruments for directly defining or managing service performance [8].

In contrast, SLOs and SLTs focus on the operational aspects of service delivery, as they specify how performance is measured, monitored, and optimized. Although SLAs can incorporate selected SLOs, they do not define performance themselves but rather formalize these objectives contractually. SLOs are essential for guiding service management practices and ensuring consistent delivery of high-quality services to customers.

In frameworks such as ITIL, particularly in *ITIL Foundation: ITIL 4 Edition*, concepts associated with service levels and targets are managed within the Service Level Management without directly mentioning terms such as SLO and SLT. ITIL will focus on value and user experience without focusing on isolated metrics. Although the framework does not explicitly reference terms such as SLO or SLT, it consistently maintains a clear conceptual distinction between them. This distinction is reflected in the way that expected service performance is defined, measured, and evaluated against agreed criteria.

In contrast, the ISO/IEC 20000 framework provides a more explicit differentiation between service level agreements and their associated measurable targets. According to ISO/IEC 20000, the value of a service lies in its utility and the achievement of expected outcomes. Improvement targets must be monitored and compared with actual performance to ensure compliance. This perspective underscores the importance of clearly defined and measurable targets to maintain alignment between agreed service levels and delivered service performance [13].

1.3 Research Drivers

1.3.1 Research Problems

- **RP1. Stiffness in defining service level targets** In most scenarios, service level targets, such as incident response time, severity, service request acknowledgement, are defined with very restricted/static values which sometimes can fail to align with support capabilities or customer expectations. This work is focused on breaking some of these static or inflexible targets.

- **RP2. Different needs of service level targets definitions between multiple organizations.** Each organization have their processes, which should be different from organization to organization. Different processes usually have different definitions. Because of that, it does not make sense to apply common targets to all of them, such as resolution time. One of the topics that will be covered in this work will be this limitation that we still face.

- **RP3. Permanent evolution in organizations' functioning dynamics.** Nowadays, technology is in constant evolution; however, most of the companies are not able to keep up with the increase in technology. Therefore, processes in companies tend to become older and outdated. On technical support processes, it is very easy to observe such disalignment, mainly in service level targets definitions, a situation that does not protect the company or even the customer.

Detailed information about these and other related research challenges are presented in Chapter 2 - State of the Art where a Literature Review (LR) is given.

1.3.2 Research Goals

In this work, the primary objective is to investigate the establishment of adaptive contract terms between companies and their customers to effectively manage their evolving expectations and cultivate strong relationships.

Specifically, our research aims to achieve the following objectives:

- **RG1. Assess dynamic SLT Adjustments:** We aim to explore in the literature the feasibility and effectiveness of dynamically adjusting SLT using process mining techniques. This involves investigating how agreement target perform and can adapt in response to changing business processes and customer demands.

- **RG2. Appraise Mitigation Strategies of Wrong Customer Expectations:** We seek to identify and define the key parameters for service targets and clauses that should be incorporated into contracts to minimize discrepancies between customer expectations and service delivery.

RG1 are related with **RP1 and RP2** and **RG2** with **RP3** located in section 1.3.1.

The rapid evolution of technology needs significant adjustments within companies. However, these transformations have also underscored the importance of timely support responses, especially when prioritizing cases based on urgency.

This work explores the vital role of SLTs within SLAs in addressing real and yet evolving support requirements and effectively managing customer expectations. Our research endeavors to provide valuable insights and practical recommendations for optimizing SLTs to align with the ever-evolving technological landscape and to prioritize the diverse needs of customers.

From the above goals, the following research questions emerge:

- **RQ1** - Which factors could influence the choice of implementing SLTs within SLAs in business relationships?

- **RQ2** - What could be dynamically adjusted enterprise service targets based on process and data mining methods?

Each **RQ** is related with a correspondent **RG** with the same index number located in section 1.3.2.

1.3.3 Expected contributions

The main contributions of this work are:

- **C1. Integration of Process Mining (PM) in the Service Level Management process:** This study presents a novel approach to leveraging process and data mining methodologies with the aid of Process Mining tools and Python code. By using Python libraries such as pm4py, the research demonstrates how to extract valuable insights from event logs and analyze process behavior systematically and efficiently. The developed Python code serves as a versatile tool for processing, visualizing, and interpreting process data, thereby facilitating the investigation of complex business processes and the definition of service targets.
- **C2. Practical Implications and Managerial Insights:** Beyond theoretical contributions, this research offers practical implications and managerial insights for organizations seeking to optimize the definition of their SLAs. By providing actionable recommendations, best practices, and real-world case studies, this work equips practitioners with the knowledge and tools necessary to implement effective process mining strategies and achieve tangible improvements in SLTs and consequently in SLAs performance.

1.4 Thesis Outline

The organization of this work consists of five chapters. The first chapter serves as an introduction, presenting the research problems and goals with a focus on SLTs. The second chapter delves into a systematic literature review, discussing the research methodology, planning the review, research questions, taxonomy, and reviewing relevant articles. The third chapter proposes a methodology for this work, describing the plan and the steps taken to achieve the desired outcomes. Chapter four focuses on presenting the results obtained when defining the dynamic service targets. Finally, chapter five draws the conclusions and carves guidelines for potential future work.

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Chapter 2.

State of the Art

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This chapter aims to explore the literature about the existing methods to define Service Level Agreements using a Systematic Literature Review (SLR) approach.

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Chapter 2
State of the Art

2.1 Introduction

According to [26], "A SLR is a research methodology to collect, identify, and critically analyze the available research studies (e.g., articles, conference proceedings, books, dissertations) through a systematic procedure."Defining the protocol is the first step of an SLR since it describes the procedures involved in the review and acts as a log of the activities to be performed. Obtaining opinions from peers while developing the protocol is encouraged to ensure the review's consistency and validity and helps identify when modifications are necessary. One final goal of the protocol is to ensure the replicability of the review. The Population, Intervention, Comparison, Outcome, and Context (PICOC) criteria break down the SLR objectives into searchable keywords and help formulate research questions. PICOC is widely used in the medical and social sciences fields to encourage researchers to consider the components of the research questions [11].

2.2 Research Methodology

The "Research Methodology" section of this SLR presents the systematic process and methodological framework employed to identify, select, and analyze relevant studies related to the research topic by detailing the search strategy, inclusion and exclusion criteria, data extraction methods and potential quality assessment procedures. This section aims to ensure the transparency and objectivity of the review process.

2.3 Planning the Review

Nowadays, there is an urgency in providing the right answer at the right time, since businesses are more demanding. Therefore, the support is increasing the way of giving prompt responses to customers and providing a solution for the issues that are being managed. Businesses should always be aligned also to IT Service Management, the key to maintaining those businesses is to ensure the operational, reactive, and proactive needs of the business have equal focus and importance [29]. The objective of this section is to identify factors that could be dynamically adjusted in the SLAs, recognize elements that should be added to those, and investigate the possibility of redefining a SLT for identical incidents through the mining of the processes. Notably, the review protocol will focus on searching specific library sources by specific search strings, filters, and criteria of inclusion/exclusion.

2.4 Research Questions

The research questions for this review are:

RQ1. *What literature exists using dynamically adjusted enterprise SLAs based on process mining methods?*

Justification. This question aims to explore how process mining can be used to adjust SLAs in real-time, ensuring that service commitments align with current performance metrics and customer expectations. With the advancements in technology, businesses are facing dynamic and ever-changing environments, making it crucial to optimize their Service Level Agreements (SLAs) continuously. There is an urgency to identify what could be dynamically adjusted in SLAs to bring more quality to businesses.

RQ2. *Which factors mentioned in the literature seem to influence the choice of implementing SLAs in business relationships?*

Justification. The research question highlights the increasing needs of businesses and the importance of considering certain factors that influence the decision to implement SLAs. Factors such as effective collaboration and communication, risk mitigation, and accountability in business relationships play a crucial role in shaping the adoption of SLAs. Additionally, the focus on customer satisfaction and quality assurance is vital in determining the suitability of SLAs for business partnerships. Furthermore, legal and regulatory compliance also emerges as a significant driver for implementing SLAs. By investigating these factors, the study aims to shed light on the considerations that impact the choice of SLA adoption, contributing to more informed and successful business relationships.

2.4.1 Search Strategy

Search Terms. This study has began by formulating research questions to guide our investigation. Subsequently, the relevant keywords were extract from these questions to design the search strategy for gathering necessary information. The search string consisted of main terms related to the research topics. Below is the search string used for this study:

("SLA"OR "service level agreements") AND ("ITSM"OR "service management") AND ("process mining")

Digital Libraries Searched.

In the pursuit of a thorough review, the search for relevant literature holds immense significance. To ensure comprehensive coverage, three primary digital libraries were extensively explored. Additionally, we manually added specific articles to supplement the search. The following digital libraries were queried to retrieve a diverse and comprehensive set of literature pertinent to our research questions:

- ACM Digital Library
- IEEE Xplore
- Scopus

Publications Time Frame. Regrettably, in recent years, there have been limited research reviews that explore the combination of SLAs and process mining. Given the urgent emergence and significance of process mining as a research area, this study focuses on the period between

2017 and 2023. To ensure comprehensive coverage, we considered SLRs, relevant publications, and journals as valuable sources for our research. By incorporating these diverse resources, we aim to bridge the gap in existing literature and offer valuable insights into the intersection of SLAs and process mining during this critical timeframe.

2.4.2 Selection Criteria

The selection of the libraries mentioned on above subsection was based on gathering the many articles and papers as possible. As baseline, it chooses three of the most well known libraries: ACM Digital Library, IEEE Xplore and Scopus.

Under the Search Stages Overview, it aggregates four sequential stages, which are described below:

Stage 1 - Retrieve automatically results from the digital libraries - The mentioned libraries were searched using the specific syntax of each database as mentioned on previous subsection. To restrict the search results, the query was configured in each repository to include only papers conducted within the prescribed period, between 2017 and 2023. Additionally, the automatic search was complement with a manual search to ensure a thorough and comprehensive review of the literature.

Stage 2 - Read titles and abstracts to identify potentially relevant studies - During the initial searching process, potentially relevant studies were identified based on the analysis of their title and abstract. Studies that were clearly irrelevant to the search or found to be duplicates were discarded from the search results across all digital libraries. In cases where there was uncertainty about whether a study should be included or not, it was retained for further consideration in a later stage of the review process.

Stage 3 - Apply inclusion and exclusion criteria on reading the introduction, methods and conclusion - In the next stages, the selected studies were thoroughly reviewed by examining their introduction, methodology section, and conclusion. Exclusion and inclusion criteria, as specified in Table 2.1, were applied to the studies. In case of existing doubts, the full study was read to ensure the study were not eliminate with important information.

Stage 4 - Obtain primary studies and assess them - By a thorough investigation, we wanted to establish whether the studies that have been grouped in are both credible and reliable as intended. It was through the use of this extensive list that only the best and most significant were picked for this review.

2.4.3 Data Extraction

In order to make easier the standardized information from the papers under analysis, it was designed a data collection form. The data collection allow to identify important details, for example publication date, publication type, authors. It also facilitates to address the relevant topics for the research questions of this work. Using the Data Collection form, it helps to maintain consistency and efficiency in extracting the relevant information from the selected studies.

Table 2.1: Exclusion and Inclusion Criteria applied at Stage 3.

Criterion	Description
Exclusion Criteria(EC)	
EC1	Studies published before 2017.
EC2	Studies not written in English.
EC3	Studies not related to the Service Level Agreement realm.
EC4	Studies not supported by data collected on any well designed experiment or did not use empirical data from a third party.
EC5	Studies merely theoretical or based on expert opinion without locating a specific experience, such as: editorials, prefaces, summaries of articles, interviews, news, analysis/reviews, readers' letters, summaries of tutorials, workshops, panels, round tables, keynotes and poster sessions.
Inclusion Criteria(IC)	
IC1	Publications should be "journal" or "conference" or "workshop" or "book".
IC2	Works that put process mining methods methods into practice with the goal of understanding and/or improving the definition of service level agreements.

2.4.3.1 Data Synthesis

The data synthesis process involved grouping findings from the selected studies to address the research questions presented earlier in subsection 2.3. The collected data was organized in a spreadsheet format, and the extraction process was manually conducted by the main author. The insights derived from data synthesis contribute to advancing knowledge in the field, identifying gaps for future research, and providing valuable guidance for practitioners and decision-makers. Obtained results, plots and findings are presented and discussed in section 2.4.4.

2.4.4 Conducting the Review

The review process involved formulating research questions and defining inclusion/exclusion criteria. The research papers were searched using the specific search string, consequently the studies were identified based on title and abstract analysis. Exceptional some studies needed to take a deep read into the article to identify if it makes sense to add. The Data Extraction was collected using a structured form and the findings were resumed to address the research questions and add outcomes. Then the actions defined in section 2.3 were followed.

2.4.4.1 Execute Search

The review process began by executing an automatic search followed by a manual search. According to the details outlined in section 2.4.1, the search was initially performed in early 2017 and updated until the end of 2023. To accommodate different search engines, the search string syntax was adapted accordingly. Afterward, the inclusion/exclusion criteria were applied to select relevant studies for further examination.

A total of 15 articles were initially identified, which were subsequently filtered using the defined inclusion and exclusion criteria, resulting in 9 articles. The summary results and workflow for this research can be found in Table 2.3.

The results of the search string execution in the chosen databases with the respective criteria applied are shown in Table 2.2.

Table 2.2: Search string execution

	ACM	**Scopus**	**IEEE Xplore**
("SLA"OR "service level agreements") AND ("ITSM"OR "service management") AND ("process mining"))	12	3	0
Removed by date	2	2	0
Removed by language	0	0	0
Removed by title	1	0	0
Removed by abstract	0	0	0
Removed by duplication	0	0	0
Removed by full reading	8	1	0
Final	8	1	0

Table 2.3: Digital Library Initial Search and Stages.

Digital Library		**Stages**			
		1	**2**	**3**	**4**
Libraries (ACM, Scopus, IEEE)	15 |−−>	15	11	10	9
Total (Input for Stage 1)	15				

2.5 Document the Review

Table 2.5 presents all the selected studies along with the details supporting the statistics displayed in section 2.5.1. In section 2.5.3, we present the primary findings, comments, and answers to each of the research questions, providing a comprehensive analysis of the study's results.

2.5.1 Demographics

Figure 2.1 presents that the majority of the articles were published in journals with a total 6 articles between 2019 and 2023, the year 2019 shows the higher number of journal publications with 3 journal, after this year only 1 article was published per next year.

Additionally, follows the articles published under conference with a total of 4 articles, 1 article in 2017 and 2021, the year with most publications was in 2019 with 2 articles. Interestingly, there was a slight increase in the number of research articles in 2019 before the impact of Covid, which was not expected since almost of the works and researches were less active.

From this increased number, it is possible to reflect that the businesses could have a necessity to tackle the topic of having dynamic SLAs to adjust their processes on the Covid years in order to increase performance and response to the many topics. The scarcity of articles in recent years, as evident from the figure, suggests that the theme of SLA and process mining is relatively new and has received limited attention from researchers.

Consequently, there is an opportunity for further exploration and investigation into the evolution of dynamic agreement targets in the context of process mining, which can be transposed for a potential future research in this area.

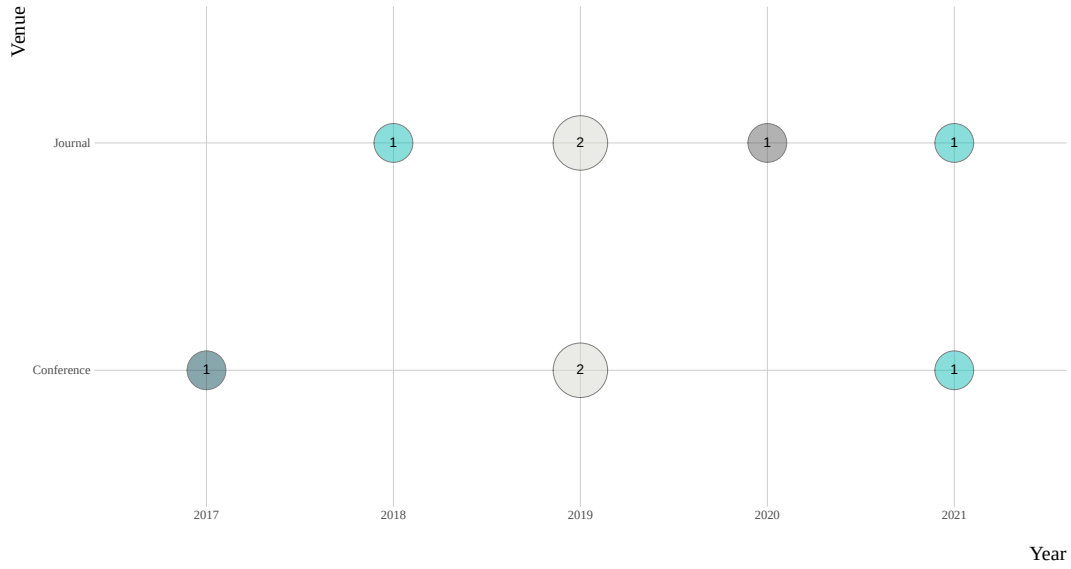


Figure 2.1: Number of studies per Venue Type per Year

Europe and Asia emerge as the most active regions in researching Service Level Agreements. The studies taken in these regions show that there are no evidence for collaborations in articles between Europe and Asia. It may show there is a necessity of increasing collaboration between regions, since researchers from different regions can give a different contributions to the articles, once they have different points of view fostering a global exchange of knowledge and expertise.

China is the most prominent country contributing to the research in this domain. Australia and United Kingdom follows China contributing to the investigation on this field. The collective efforts of researchers and institutions from China and Australia reflect a strong commitment to exploring and addressing key issues related to the domain, contributing to the global understanding of the dynamic agreement targets to be used in the field.

Regarding the number of studies published by each main author over the years, as shown in table 2.5 , it is notable that each author contributed to only one publication. This illustrates the difficulties in documenting and disseminating studies focused on adaptive agreement targets, which currently are relatively uncommon and representing some challenges as well.

2.5.2 A Taxonomy

A new taxonomy was created to better classify the articles reviewed in the related work section. This taxonomy helps to clearly identify the similarities and differences among the studies. The

criteria for this taxonomy were formulated as the articles were being reviewed. As a result, the taxonomy used in this review incorporates the criteria listed in Table 2.4.

Table 2.4: Taxonomy for related work classification

Domain	Acronym
Process Mining Focus	PMF
Service Level Agreement	SLA
Tickets/Incidents	TIN
Generic Study	G

2.5.2.1 Process Mining Focus (PMF)

This criterion helps the identification of the articles which are related to Process Mining. By using this criterion, it is possible to guarantee that the articles will involve process mining techniques, algorithms to be applied in this work and taking helpful conclusions related to that. The focus on Process Mining in some research articles and references helps to do more in-depth exploration of this particular field. At the same time, will be able to build a specialized knowledge based on this field and contribute to the advancements of Process Mining, by using it in different areas of application.

2.5.2.2 Service Level Agreement (SLA)

This criterion helps the identification of the articles which are related to SLA . By using this criterion, it is possible to guarantee that the articles will involve SLA procedures and having a specialized knowledge on this area. The focus on SLAs in some research articles and references helps to do more in-depth exploration of this particular field. Additionally, the SLAs classification of articles will often appear alongside with the Process Mining subtopic. This intersection is critical because it allows for a comprehensive analysis of how SLAs can be managed, monitored, and optimized through process mining techniques.

The integration of SLA-focused resources with process mining data involves several key steps:

- **Identification of SLA Components** - Identify service metrics, performance indicators, compliance requirements, and penalty clauses.
- **Correlation with Process Mining Data** - Gaining detailed insights into actual business process performance through process mining allows for the correlation of this data with SLA metrics. This approach helps in assessing compliance, identifying bottlenecks, and pinpointing areas for improvement.
- **Analytical Framework** - Create a suitable analytical architecture which could accommodate both qualitative and quantitative data. This structure would then be used to contrast anticipated service levels (SLAs) with the realized ones.
- **Best Practices and Recommendations** - Review best practices and recommendations for SLA management.

The provider must measure and monitor parameters such as response time, bandwidth, storage, reliability, deadline delay, throughput and cost during the service to avoid violations

that have been agreed in the SLA. Therefore, the SLA plays a role in adapting to dynamic environmental changes and heterogeneous resources [30].

2.5.2.3 Tickets/Incidents (TIN)

The criterion helps understanding and refining the processes associated with the handle of tickets within a company.

- **Defining Ticket and Incident Lifecycle:** Establishing clear definitions and stages for the lifecycle of a ticket or incident, from troubleshooting, waiting on master, resolution and closure.
- **Standardizing Procedures:** Creating standardized procedures for handling different types of tickets and incidents by categorizing for severity, type, and impact, and defining the appropriate response and escalation protocols for each category.
- **Integrating with Process Mining:** Using process mining techniques to analyze historical data on tickets and incidents by identifying patterns, penalties and bottlenecks on the ticket support which will need an improvement.
- **Best Practices and Recommendations:** Review best practices and recommendations for effective SLA management with the use of Process Mining.

2.5.2.4 Generic (G)

This criterion will be a generic topic associated with the other themes explained before, this will be more a generic one combined with SLAs, Process Mining, Procedures and Tickets.

2.5.3 Analysis and Findings

This section presents the selected studies which were carefully examined presenting valuable insights, key observations and notable trends within the domain of interest. It answers to research questions, identifying significant patterns and findings leading to conclusions and discussions in the succeeding parts.

RQ1. Which factors could influence the choice of implementing SLAs in business relationships?

According to Baskoro et al [9], factors such as the input values provided of data and what activities are carrying in behalf of a business process and violations of business boundaries are some of the factors that could influence the choice of implementing SLAs.

In the research study [27], researchers consider the SLA allocated is dependent on the way customers fill the questions sets and how the knowledge is collected by them. Factors such as potential latencies, any breeches under the service, incorrectly enters of information are some of the main factors that could influence a SLA over the business relationship.

The researchers Xu et al [32] consider some factors that may influence SLA in a perspective of business relationship, some of them are related to the ticket being vague and may not contain the actual root cause for the troubleshooting. Without having a proper statement some of them must bounce among multiple groups before being transferred to the group with the right

expertise. If a ticket is mistakenly transferred to an expert group that cannot solve the ticket, it might lead to a long maintenance time and violate the SLA impacting once more the SLA. Unfortunately, this kind of scenario can negatively influence business relationships.

Consequently, the researchers Mannhardt et al [23] consider that adverse incidents can also influence the SLAs, and also incidents not containing the precise information on the exact boundaries of an incident's influence on the process.

The article [27] proposes a way to redefine SLA with process mining. The researchers examine the extent to which effective service classifications can be made when customers give responses that do not reflect their current circumstance (perhaps through accident), adding in case of failure for all the questions. After receiving the customer requirement data, a system ticket is generated and then follows a query score and a SLA rank for the specific issue, in case of discrepancy in the SLA score calculation. A request is generated for recollection of the required data from the customer. The SLA calculator is based on process mining taking into account customer characteristics, household profiles, disposable income and online behavior by using an Acorn Guide.

Finally, the article [23] uses process mining to link identical incidents. This can also be used to redefine the SLAs having certain identical incidents and predict the service level targets in terms of response time, delays and violation of SLAs. The calculation of the effect of the incidents uses Markov chain Monte Carlo sampling (MCMC) methodology, and with it, is possible to estimate exact time boundaries of incidents like processing time in which the incident influenced the process performance. This is important when the delay estimation is to be used for a process-improvement scenario since problems need to be identified before a SLA is violated.

RQ2. What could be dynamically adjust enterprise SLAs based on process mining methods?

According to Baskoro et al [9], SLAs are hard to monitor and to predict due to a lot of operational issues, the researchers propose a new method to predict the fix time of an issue stating that some of the attributes which are normally ignored should be considered to dynamically adjust the SLA such as priority, criticality, status or recipient. However, they consider that some of them can be used in repairs at run-time and predictions of remaining repair time. Under the method proposed, the event attributes (priority, criticality, status, recipient, details) and the case can lead to a better performance in terms of predicting than using only the event attributes, since a case can be also interlinked to others.

Under the study [9], the authors referred a new approach to set dynamically the SLAs based on process mining, this study is more focused under the SLAs established for the use of IoT, however it can be identified under this scenario some adjustments that can be made to dynamically predict the SLAs such as classification of the customer of the household based on typical consumer behavior, such as: the customer priorization (cost, security or performance), the priorization impact in distinguishing each customer by the security factors (being impacted or not), the costs it brings and the performance in terms of response time as well.

Additionally, the researchers Jian Xu et al [32] consider important taken into account the

analisys of a ticket's problem type, problem description and resolution by denoting the problem category, problem symptom and solving steps. From these ones it may be possible to effectively predict the SLAs and create models.

Furthermore, the researchers from the [23] do not address directly what could be dynamically adjust SLAs, they identify variations, activity and process delays that can be optimized over the incidents. However, they do not point this directly.

The article [9] consider that case attributes such as issue type, priority, stars, and components as well, together with event attributes such as activities, time, costs and resources should be consider as elements to be included in the SLAs. Authors consider having all of these elements will help to build long-term relationships, since the SLAs are contemplating all of these factors and it will help software managers to understand and have their expectations correctly settled.

Additionally, the article [32] consider the elements problem category, symptom and solving steps, denoted by attributes like "problem type", "description" important and should be included in the SLAs. Problem descriptions have a greater contribution to routing recommendations, although, the combination of the ticket problem descriptions and the routing sequences can not only reduce the average steps to resolve tickets, but also increase the resolution rate of the routing algorithms. From this study, it is also possible to note that the continuous change of system runtime environments and system services can lead into the gradually decreasing recommendation accuracy and the resolution success rate of the algorithms using the built routing models based on the historical tickets. All of these, mentioned by Xu et al [32], will contribute to the long-term business relationships, since this increases the overall results and lead to customer trust over services, since it is possible to increase resolution success rate.

2.6 Summary

The findings from the research studies explain several key aspects related to **Service Level Agreements (SLA)** and **Process Mining**.

Adaptive SLTs continue to be relevant topic, even with the boost of technology. As described previously on this work, there is not much researchers investigating this topic. However, the studies can complement each other, since this is a known topic independently from SLAs and Process Mining. However, there is no specific study that mention dynamic SLAs generically.

From the investigation taken so far, it's important to note that SLTs have key aspects which need to take into account support hours, availability, response times and severity levels, and that each of these aspects may influence the adaptive SLA. Moreover, the implementation of SLAs is influenced by factors such as availability, prevention of SLAs violations and support hours. In a worst-scenario perspective, complex troubleshooting can lead to violations and prolonged maintenance times. Therefore, long-term and strong business relationships are important, since it is possible to avoid dissatisfaction related to the incidents. It becomes evident that long-term relationships can be established using a well-defined SLA with essential elements such as support hours, availability, response times, and repair times.

Additionally during the investigation was possible to understand some underlying and important predictive methods for mapping high-level requirements to low-level policy parameters

like clustering algorithms and neural processes. Using both methods was possible to provide an adjustment on SLA for different incidents. Similarly, optimizing SLAs can use as baseline the record of incidents because it can affect how it will behave on next times. Nevertheless, these algorithms are well known for their slow processing times and large need for computing resources.

Regrettably, there is not much information available about adaptive agreement targets with the use of process mining. This turns evident that agreement targets with process mining remain relatively unexplored in the research landscape. Despite that, the findings taken from the articles selected provide crucial insights into the potential benefits and challenges of integrating process mining into SLA management.

As such, there is an opportunity to contribute to technology and businesses with future investigations based on adaptive agreement targets, and as technology evolves and requirements demand efficiency, it is expected that there will be even more a necessity to adjust SLTs. A summary of the related work is presented in Table 2.5 and more details about each article can be found in Appendix A.1.

Table 2.5: Summary of related work

Reference	Article Title	PMF	SLA	TIN	G
[9]	Predicting Issue Handling Process using Case Attributes and Categorical Variable Encoding Techniques	yes	yes	yes	no
[27]	Using Process Mining to Formalise Service Level Agreement (SLA) Allocation	yes	yes	yes	no
[17]	Analysing Cloud QoS Prediction Approaches and Its Control Parameters: Considering Overall Accuracy and Freshness of a Dataset	yes	no	yes	no
[32]	Trouble Ticket Routing Models and Their Applications	yes	no	yes	yes
[6]	A Comparative Analysis of Data-Driven Consolidation Policies for Energy-Efficient Clouds	yes	yes	no	no
[23]	Estimating the impact of incidents on process delay	yes	yes	yes	no
[31]	Method towards reconstructing collaborative business processes with cloud services using evolutionary deep Q-learning	yes	no	no	yes
[19]	Modeling an optimized approach for load balancing in cloud	yes	yes	no	no
[28]	An approach for analyzing business process execution complexity based on textual data and event log	yes	yes	no	yes

Nowadays, businesses are always readapting to the operating practices. Because of that, the achievement of incident agreement targets is crucial for companies to ensure quality and provide a good customer experience service. Setting agreed goals correctly can help mitigate business risks and meet legal requirements. In order to mitigate certain risks under the businesses and certain unpredictable behaviors such as outages or incidents, there is a need in responding correctly to the needs of customers, setting right expectations, helping customers under those issues and resolve properly the problems behind an incident. As known when dealing with technology, we are dealing with many system events occurring every minute and sometimes at the same time, as a result, the management of tickets and cases need to identify if the events happening could be related to a particular case/ticket. Therefore, there is a constant necessity to have mining methods to respond to factors under the cases, the need of constant re-adapting the response to cases in order to enhance efficiency and set the right customer expectations. Under the review of the research, it clearly showed that there is a need to use process related methodologies to predict behaviors on cases that can be also related to the same well-known topics. To conclude, it was possible to note that there are not much studies and works under the topic of predicting the behavior of agreement targets and create adaptive agreement targets for different scenarios. This work will try to shed some light to this topic and contribute for the enhancement of the predicting methods for behaviors under the agreement targets management umbrella.

Chapter 3.

Methodology

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This chapter proposes a methodology to apply process mining in a context of achieving dynamic agreement targets.

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Chapter 3
Methodology

3.1 The PM2 Methodology

According to van der Aalst [1], process mining techniques can be used to discover process models by checking conformance of process models to reality and improving process models using data of actual process executions.

Consequently, process mining can be used to improve the performance of processes inside an organization's compliance to rules and regulations, providing a connection between data mining or machine learning techniques and the actual business processes [5].

Thus, a new methodology emerged, the PM2 Methodology rises from a need to guide companies executing their process mining projects with the goal to process performance or compliance to rules and regulations with ensuring to follow determined rules.

By using the PM2, process mining tasks can be conducted over concrete research questions in an interactive way and answered one by one [5].

Furthermore, the PM2 approach is broken down into six main stages: Planning, Extraction, Data Processing, Mining & Analysis, Evaluation, and Process Improvement & Support. Aligned with these six stages, there are other four related goals:

1. Research Questions derived from project goals
2. Performance Findings
3. Compliance Findings
4. Improvement Ideas to Achieve the Goals

In the **Planning** stage, the project's goals are turned into research questions, then, in the **Extraction** stage, data is collected from information systems. During the **Data Processing** stage, the data will be organized into event logs. The **Mining & Analysis** stage is responsible for developing process models and finding useful information. Consequently, in the **Evaluation** stage, the results are checked to see if they answer the research questions. Finally, in the **Process Improvement** stage, any ideas for improving the process are put into action.

To take decisions, it will be based on the available data, resources and the process context. Some different outcomes could be executed infrequently because the corresponding conditions are rarely fulfilled [24].

The PM2 methodology uses a cycle of analysis, where research questions and findings can be adjusted and improved as the project goes on.

This chapter will mainly focus in evaluating the project according to PM2 Methodology.

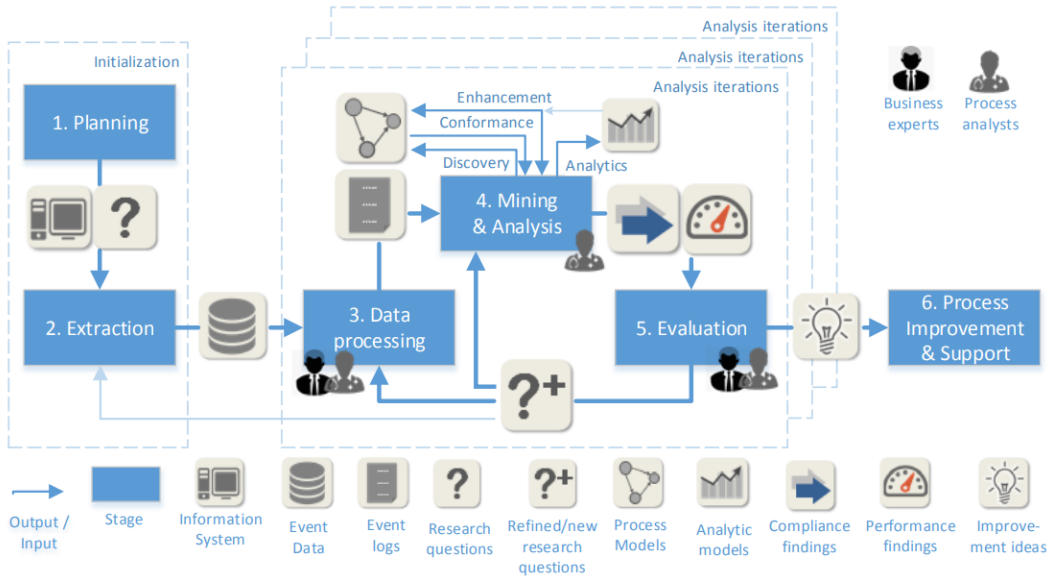


Figure 3.1: Process Mining Process Methodology. Adapted from [22]

3.2 Planning

In the 20th century, archbishop Richard Cushing used to tell under catholic masses that ***"Always plan ahead, it wasn't raining when Noah built the ark"****. This reinforces the importance of planning and this actually applies for life and nowadays in IT related projects as well. If we want to predict undelivered factors that can happen, we need to plan.*

The planning stage is the most crucial part in each project. Without a good structure of planning, it is not possible to deliver a good project with aligned goals and outcomes.

The main goals for starting process mining projects are aligned with the improvement performance of a business process or checking the compliance with respect to certain rules and regulations.

Under the planning part, it is needed to consider as inputs the organizations business processes, while as an output can be considered the research questions and the set of information systems supporting the execution of these business processes.

Splitting the planning part under three main topics, such as:

1. **Selecting business processes.** A project should always start by understanding the business process that needs to be analyzed and improved. Furthermore, to achieve the desired outcomes, one should understand the data that will be taken in hands such as the quality of event data, if the data is clear and have a good dataset with every specification or if there is missing or incorrect data.
   Additionally, considering how a business process may change over time and how to predict those behaviors, it is important to understand what data will be needed to work with.
   In this work, the entity involved is an Automobile Production European Car, however, due to privacy concerns, the name of the company can be disclosed. The dataset contains IT incident event data taken from their IT Service Management production system.

2. **Identifying research questions.** Research questions can be related to different aspects of business processes, e.g. quality, time, resource, cost [5]. As research questions, we needed to consider the following:
   RQ1. Which factors could influence the choice of implementing SLTs within SLAs in business relationships?
   RQ2. What could be dynamically adjusted enterprise service targets based on process and data mining methods?

3. **Composing Project Team.** The last activity involves the people that are working under the project. This work will involve two people analyzing the data: the student and the supervisor.

3.3 Extraction

According to Ronald Coase, a British Economist, "*If you torture the data long enough, it will confess*", aligned with this quote there is an explicit way of proverbing that if the data is correctly extracted with a clear understanding of the necessary attributes, we can produce relevant outcomes.

The **extraction** stage focus on extracting event data, and in certain cases, processes models. According to the authors Maikel L. et al, the focus should be on the research questions and information systems that support the execution of selected business processes. Below, it is identified three activities for this stage:

1. **Determining scope.** This activity defines the scope and level of detail of the event data, specifying which events to include, the relevant time frame, and the attributes and correlations to extract. For this work, the data is based on the incidents occurring in the period of 2021 until 2022 [5].

2. **Extracting event data.** Involves selection of the process and the methods to extract the data. Accordingly, we extracted the full dataset in a structured, Excel-like format, detailing the incident, severity level, assigned team, and the time allocated to each activity within the incident process.

3. **Transferring process knowledge.** It is aligned with the previous activity and involves understanding each attribute under the dataset, clearly identifying what is needed and how each attribute was achieved by discussing with the stakeholders within the company.

The next chapter will consolidate the methods used for data computation.

3.4 Data Processing

Carly Forina, ex-CEO of HP company, used to say "*The goal is to turn data into information, and information into insight.*".

This stage focuses on creating event logs with different views of the data obtained during the extraction stage. Subsequently, the data will be processed with process mining tools.

In fact, this next step will be specifically focused on that, that is, turning the data extracted into information that could be used to take action. Data processing was structured into the following four primary steps:

1. **Creating Views.** Event logs are specific views on global event data, created by defining case notions and event classes [5]. The use of views can allow to focus on specific data on certain teams, severities of incidents, countries and from there take those conclusions.

2. **Aggregating Events.** Aggregation of events can lead to reduce complexity and improve structure mining results. There are two types of aggregation: is-a and part-of [5]. Under this activity, the aggregation of the event data was applied by aggregating the whole dataset from different years, the 2021 and 2022 data.

3. **Enriching Logs.** Event logs, as any other data, can be enriched with various additional attributes. There are two ways of enriching the logs by deriving or computing additional events and data attributes or adding external data [5]. Applied to this work, the event data has been enriched with time to respond and how much time was spent under each process.

4. **Filtering Logs.** The filtering process is a process that normally is performed multiple times, since by filter the data from different variants, attributes can led to different conclusions. There are multiple ways of filtering it: can be using a slice and dice, variant based filtering groups and compliance based filtering. Under this activity, it was mainly applied the filter by variant and attributes to conduct the research.

3.5 Mining and Analysis

In the mining and analysis stage, we applied process mining techniques on the event log with the aim to answer the research questions by gaining insights into process performance. We followed the same approach as [5].

The input for this stage is the event log generated under the previous stages and the outputs will be the findings determined by each research questions. There will be an attempt to answer all the questions with the available data.

By using process mining, we expect to improve the efficiency in the processes behind the decision making process. When a standardized process is followed, process mining techniques can be used to evaluate how customer input affects the final output and their satisfaction [27].

In this stage, four important activities have been identified:

1. **Process Discovery.** By using an event log as input, the process will begin with processing discovery techniques. In this work, the process discovery techniques will focus on the use of the Disco Tool, and then from the results taken, a deeper analysis will be performed using the Python libraries related to the mining concept. The tools used for process discovery are completed by applying traditional algorithms, such as the fuzzy miner and

heuristic miner [24].

2. **Conformance Checking.** Usually, in this activity, the quality of the data is checked and if a process model already exists, the data is validated against the model and compliance checking is also conducted. However, in this scenario we do not deal with this type of analysis.
3. **Enhancement.**The enhancement activity will extend the process model information to the actual processes to understand how it can be enhanced. Data Inspection and manipulation of data can be declarative and procedural of process modeling formalisms [14].

4. **Process Analytics.** The process analytics activity will apply the techniques associated with the event logs and process models such as, data mining techniques or visual activities [5]. The analysis of this nature was a key focus throughout the course of this study.

3.6 Evaluation

The evaluation stage is a fundamental part of the process. It is relevant to evaluate the findings taken under the previous stages and check if it achieves the project's goals. In this stage, the inputs are usually the process models, performance and compliance while the outputs are mainly improvement of the research questions or the analysis environment conditions.

The two activities are staged below:

1. **Diagnose.** Under this activity, it checks the findings taken while using the mining and checking if the results are correctly set with the identification and redefinition of the research questions [5].

2. **Verify & Validate.** This activity is one of the most important since it verifies the error between the original data and proposed implementation. The Root Mean Square Error (RMSE) in this work will be used to evaluate the average difference between a statistical model with predicted value and the original values. It analyses how much deviates from the original values. The bigger the value in the RMSE, the bigger the deviation from reality and therefore less realistic and/or accurate the proposed service target is.

3.7 Process Improvement and Support

The objective of the process improvement & support stage is to use the gained insights to modify the actual process execution. The inputs of this stage are the improvement ideas while the outputs are process modifications. The activities are: implementing improvements and supporting operations [5].

1. **Implementing improvements.** The main goal of this stage is process improvement. This work will focus on time to respond, SLA metrics under the incidents, since the primary

focus is to have realistic service level targets and consequently dynamic agreement targets.

2. **Supporting operations.** After implementing the improvements, it is important to have a good support to make things effectively implemented. Certain IT companies may offer with specialized teams like data analytics or support teams to make this effectively.

Chapter 4

Dynamic Service Level Target Definition

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This chapter describes the implementation to achieve optimized service level targets based on total incident statistics and process variant statistics.

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Chapter 4
Dynamic Service Level Target Definition

4.1 Introduction

An SLA is a level of assurance or warranty concerning the level of service quality delivered by the service provider for each of the services delivered to the business. SLAs consist of formal agreements documented between service providers and clients. However, it must be noted that SLAs do affect the behaviour and help generate an appropriate service culture, which can then have an immediate beneficial effect and make longer-term improvements possible. If targets are appropriate and accurately reflect the requirements of the business, the service delivered will align with business requirements and meet the expectations of the customers and users in terms of quality service. When targets are not aligned with business needs, the service provider's activities and service levels will not be aligned with business expectations, and therefore problems will develop [16].

4.2 Extraction and Data Processing

This research develops methods and functions through Python programming. The development part and application section was applied with the use of the libraries pandas and pm4py.

Pandas library [1] is one of the most powerful and open-source libraries, built over NumPy library. It is used to manipulate data structures and functions that need to be used under structured data.

This type of library is primarily used for data cleaning, handling missing values, removing duplicates, and performing data manipulation operations like joins and merges.

Additionally, it is possible to conduct a data visualization by plotting data using functions or external libraries like Matplotlib.

The pm4py library[2] is a Python library open-source that supports process mining algorithms in Python.

Although the incident data was already available in an Excel-like format, analysis revealed inconsistencies and unclear attributes, reinforcing the need for additional preprocessing and validation within the Excel file.

An event log captures the execution of a process and its associated data. In process mining, a central concept is the case, which refers to a sequence of events representing a single end-to-end execution of the process [3].

Cases contain activities. In this scenario, our cases contained activity names that we had to rename. Troubleshooting is converted to "Ongoing Work", in case of waiting for the user to test is called "User Validation". An incident being work by a third-party tool is called "Third-Party Investigation". Beneath, in the activities related to an update incident, it was possible to identify

[1] https://pandas.pydata.org/
[2] https://pypi.org/project/pm4py/

many different ways to represent the same tasks. In such cases, the activity name was renamed to be the same.

For the data preparation, part of the event properties were mapped when converting to XES format using the Disco tool. XES does not prescribe a fixed set of mandatory attributes for each element (log, trace, and event); an event can have various numbers of attributes. However, to provide semantics for such attributes, the log refers to so-called extensions. An extension gives semantics to particular attributes. For example, the Time extension defines a timestamp attribute of type xs:dateTime [1].

Part of this work is also in the following methodology used under the article, properties such as CaseID, timestamp_begin and timestamp_end were important to use as a baseline to achieve the goal [10].

4.2.1 Control-Flow Perspective

As a first step, the Excel files containing all relevant data, column headers, and timestamps were imported into the Disco tool for analysis. The use of the Disco provides the functionality for the understanding of the variants, to extract the control-flow perspective, and the whole process statistics. At this stage, it is important to understand how the data was manipulated and used as inputs for the next steps.

Once the data load was completed, it became possible to interpret incident behavior through process maps. These visualizations provided insights into the sequence of steps each incident could follow, allowing for a deeper understanding of how incidents are managed and resolved across different workflows as presented in Figure 4.1. As shown, the process map generated by Disco reveals a total of 7,085 cases.

The Register incident event appears 7608 times in total, with up to 2 repetitions per case, suggesting that some incidents are reopened and re-registered.

Additionally, the activity presenting the highest absolute frequency is the Ongoing Work, with a total of 65 046. From the observation of the flow, it is possible to understand that some of those repetitions are going from the third-party investigation. This likely indicates that the third party adds notes and evidence to the incident, after which troubleshooting must be continued by the internal teams.

4.2.2 Case Analysis

By proceeding with an analysis under the statistics feature of the Disco tool, it is possible to observe which incident is taking the most time and has the most events, taking into consideration the number of variants.

From the dataset, it is possible to observe that one incident has the highest number of events, about 267 (as shown in 4.2) that occurred during the entire incident. This is not a good sign since the incident has many loops between statuses. Aligned with this, we observe a total duration of 103 days and 22 hours. It is predictable that if an incident contains many changing events, that will be reflected in the duration since it will take time for the teams to effectively analyze and troubleshoot.

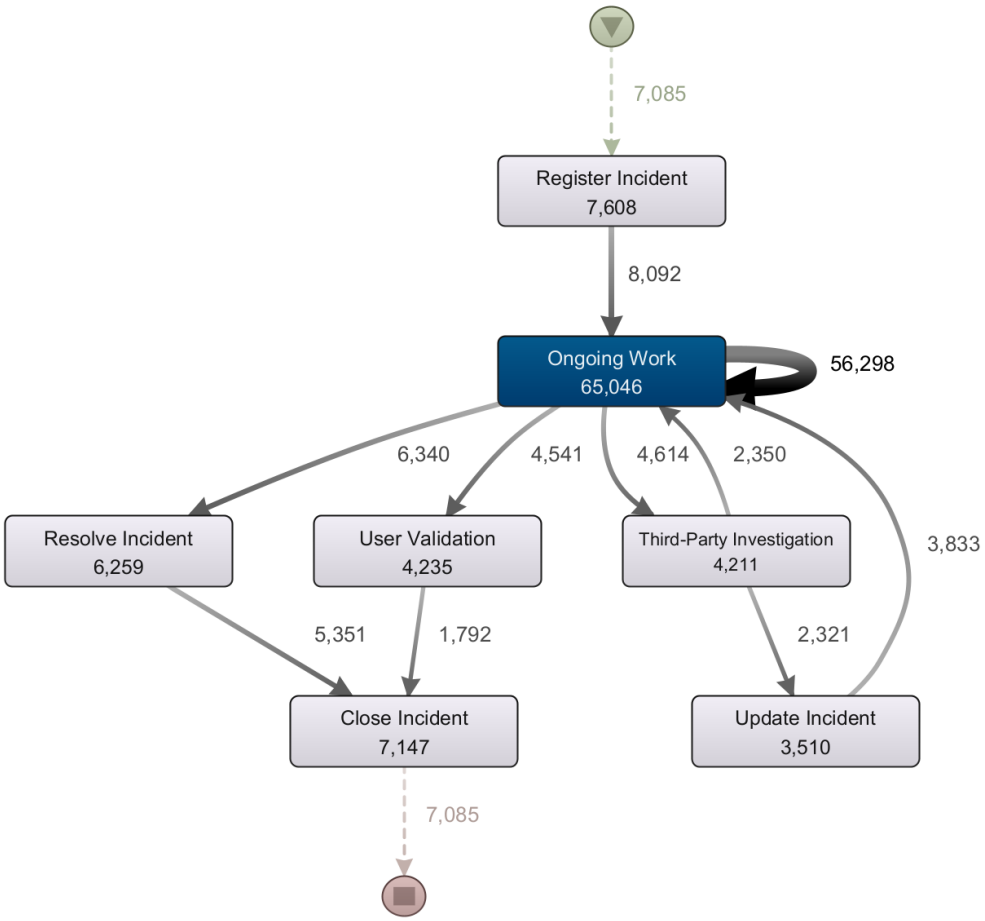
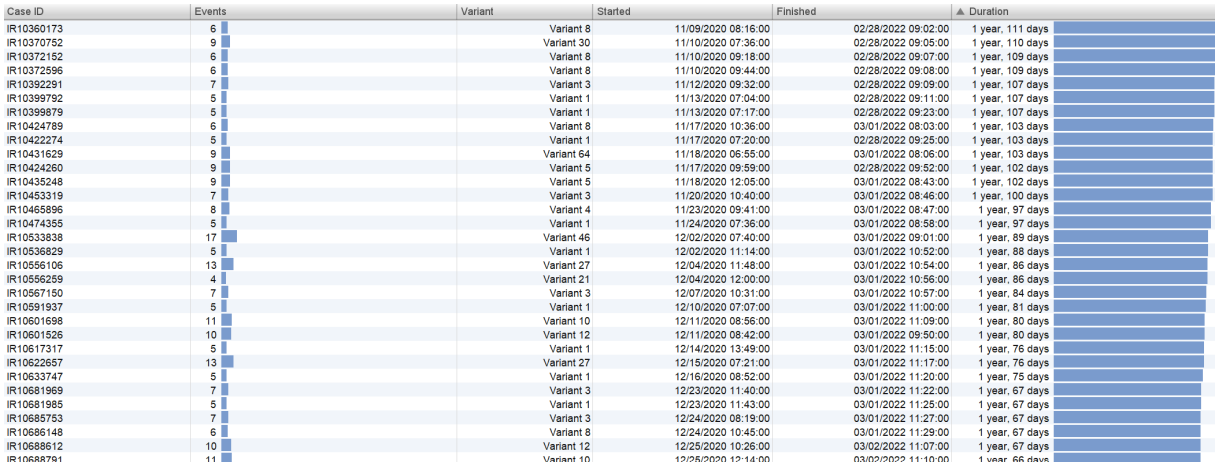


Figure 4.1: Directly-Follows Graph with the incidents flow (since registration until its closure).

Case ID	Events	Variant	Started	Finished	Duration
IR13462095	267	Variant 1,107	01/18/2022 17:36:00	05/02/2022 07:21:00	103 days, 12 hours
IR13598281	266	Variant 1,316	02/05/2022 17:33:00	05/03/2022 07:32:00	86 days, 12 hours
IR13597093	243	Variant 1,313	02/05/2022 08:22:00	05/02/2022 07:27:00	85 days, 22 hours
IR13642221	236	Variant 1,383	02/11/2022 09:12:00	05/17/2022 14:51:00	95 days, 4 hours
IR13661516	232	Variant 1,418	02/14/2022 17:15:00	05/02/2022 09:02:00	76 days, 14 hours
IR13638245	230	Variant 1,378	02/10/2022 17:11:00	05/17/2022 14:40:00	95 days, 20 hours
IR13649201	229	Variant 1,395	02/12/2022 08:06:00	05/17/2022 15:57:00	94 days, 6 hours
IR13657710	223	Variant 1,404	02/14/2022 11:02:00	05/17/2022 15:47:00	92 days, 3 hours
IR13585639	219	Variant 1,301	02/03/2022 15:39:00	04/18/2022 07:03:00	73 days, 14 hours
IR13676121	216	Variant 1,441	02/16/2022 09:18:00	05/02/2022 09:08:00	74 days, 22 hours
IR13623823	215	Variant 1,360	02/09/2022 10:09:00	05/17/2022 14:36:00	97 days, 3 hours
IR13583491	207	Variant 1,297	02/03/2022 12:40:00	05/02/2022 07:23:00	87 days, 17 hours
IR13395632	203	Variant 987	01/10/2022 13:41:00	05/12/2022 09:12:00	121 days, 18 hours
IR13020766	194	Variant 497	11/16/2021 09:39:00	04/23/2022 10:05:00	157 days, 23 hours
IR13292369	192	Variant 797	12/21/2021 15:07:00	04/21/2022 11:21:00	120 days, 19 hours
IR13050558	191	Variant 518	11/19/2021 10:46:00	04/26/2022 21:05:00	158 days, 9 hours
IR13255649	183	Variant 748	12/16/2021 10:11:00	05/23/2022 12:08:00	158 days, 57 mins
IR13330211	183	Variant 851	12/28/2021 09:35:00	04/08/2022 15:26:00	101 days, 4 hours
IR13391558	182	Variant 974	01/10/2022 09:12:00	04/12/2022 13:07:00	92 days, 2 hours
IR13099194	171	Variant 566	11/25/2021 16:41:00	04/12/2022 15:17:00	137 days, 21 hours
IR13102943	165	Variant 567	11/26/2021 08:41:00	04/09/2022 07:58:00	133 days, 22 hours
IR13278675	143	Variant 771	12/20/2021 07:55:00	04/29/2022 11:01:00	130 days, 2 hours
IR13343185	141	Variant 885	12/31/2021 19:20:00	04/27/2022 07:34:00	116 days, 11 hours
IR13341863	141	Variant 882	12/31/2021 08:23:00	04/15/2022 06:48:00	104 days, 21 hours
IR13736966	138	Variant 1,525	02/24/2022 08:12:00	05/25/2022 09:44:00	90 days, 32 mins
IR13432610	132	Variant 1,054	01/14/2022 08:55:00	04/21/2022 10:50:00	97 days, 55 mins
IR13557447	130	Variant 1,258	01/31/2022 16:41:00	05/16/2022 09:31:00	104 days, 15 hours
IR13446432	126	Variant 1,066	01/17/2022 08:18:00	05/27/2022 12:18:00	130 days, 3 hours
IR13661471	121	Variant 1,417	02/14/2022 17:09:00	05/17/2022 16:16:00	91 days, 22 hours
IR13247477	118	Variant 741	12/15/2021 12:32:00	05/24/2022 17:42:00	160 days, 4 hours
IR13387738	118	Variant 966	01/09/2022 13:19:00	05/19/2022 16:53:00	130 days, 2 hours
IR12975081	117	Variant 457	11/09/2021 18:18:00	05/24/2022 09:22:00	195 days, 14 hours

Figure 4.2: Incidents statistics (events, variant, duration, etc)

However, the incident with the largest number of events is not the incident with the longest duration, and in the dataset (see Figure 4.3), it is possible to recognize some incidents taking more than 1 year with few events around 6,9,10 events only. This is probably linked to the timing of a software update or an external issue related to a third-party provider.



Case ID	Events	Variant	Started	Finished	▲ Duration
IR10360173	6	Variant 8	11/09/2020 08:16:00	02/28/2022 09:02:00	1 year, 111 days
IR10370752	9	Variant 30	11/10/2020 07:36:00	02/28/2022 09:05:00	1 year, 110 days
IR10372152	6	Variant 8	11/10/2020 09:18:00	02/28/2022 09:07:00	1 year, 109 days
IR10372596	6	Variant 8	11/10/2020 09:44:00	02/28/2022 09:08:00	1 year, 109 days
IR10392291	7	Variant 3	11/12/2020 09:32:00	02/28/2022 09:09:00	1 year, 107 days
IR10399792	5	Variant 1	11/13/2020 07:04:00	02/28/2022 09:11:00	1 year, 107 days
IR10399879	5	Variant 1	11/13/2020 07:17:00	02/28/2022 09:23:00	1 year, 107 days
IR10424789	6	Variant 8	11/17/2020 10:36:00	03/01/2022 08:03:00	1 year, 103 days
IR10422274	5	Variant 1	11/17/2020 07:20:00	02/28/2022 09:25:00	1 year, 103 days
IR10431629	9	Variant 64	11/18/2020 06:55:00	03/01/2022 08:06:00	1 year, 103 days
IR10424260	9	Variant 5	11/17/2020 09:59:00	02/28/2022 09:52:00	1 year, 102 days
IR10435248	9	Variant 5	11/18/2020 12:05:00	03/01/2022 08:43:00	1 year, 102 days
IR10453319	7	Variant 3	11/20/2020 10:40:00	03/01/2022 08:46:00	1 year, 100 days
IR10465896	8	Variant 4	11/23/2020 09:41:00	03/01/2022 08:47:00	1 year, 97 days
IR10474355	5	Variant 1	11/24/2020 07:36:00	03/01/2022 08:58:00	1 year, 97 days
IR10533838	17	Variant 46	12/02/2020 07:40:00	03/01/2022 09:01:00	1 year, 89 days
IR10536829	5	Variant 1	12/02/2020 11:14:00	03/01/2022 10:52:00	1 year, 88 days
IR10556106	13	Variant 27	12/04/2020 11:48:00	03/01/2022 10:54:00	1 year, 86 days
IR10556259	4	Variant 21	12/04/2020 12:00:00	03/01/2022 10:56:00	1 year, 86 days
IR10567150	7	Variant 3	12/07/2020 10:31:00	03/01/2022 10:57:00	1 year, 84 days
IR10591937	5	Variant 1	12/10/2020 07:07:00	03/01/2022 11:00:00	1 year, 81 days
IR10601698	11	Variant 10	12/11/2020 08:56:00	03/01/2022 11:09:00	1 year, 80 days
IR10601526	10	Variant 12	12/11/2020 08:42:00	03/01/2022 09:50:00	1 year, 80 days
IR10617317	5	Variant 1	12/14/2020 13:49:00	03/01/2022 11:15:00	1 year, 76 days
IR10622657	13	Variant 27	12/15/2020 07:21:00	03/01/2022 11:17:00	1 year, 76 days
IR10633747	5	Variant 1	12/16/2020 08:52:00	03/01/2022 11:20:00	1 year, 75 days
IR10681969	7	Variant 3	12/23/2020 11:40:00	03/01/2022 11:22:00	1 year, 67 days
IR10681985	5	Variant 1	12/23/2020 11:43:00	03/01/2022 11:25:00	1 year, 67 days
IR10685753	7	Variant 3	12/24/2020 08:19:00	03/01/2022 11:27:00	1 year, 67 days
IR10686148	6	Variant 8	12/24/2020 10:45:00	03/01/2022 11:29:00	1 year, 67 days
IR10688612	10	Variant 12	12/25/2020 10:26:00	03/02/2022 11:07:00	1 year, 67 days
IR10688791	11	Variant 10	12/25/2020 12:14:00	03/02/2022 11:10:00	1 year, 66 days

Figure 4.3: Incidents statistics (ordered by duration)

4.2.3 Variant Analysis

The Disco Tool was also used to proceed with the analysis of variants and to identify the number of cases, events per variants as well as their median and mean durations. Disco can order the variants from the one with the most of the cases, to the one with the fewest cases, as shown in Figure 4.4.

Starting with Variant 1, it is the one with the cases with a total of 5 events, this lead a total of 1182 cases with a median duration of 15 days and 15 hours, and a mean duration of 42 days and 10 hours.

Additionally, while observing the number of statistics, there is a total of 2051 variants being recognized. From variant 345 to variant 2051, it is possible to recognize only 1 case and a non-consistent number of events, as well as the values obtained for the median and mean duration.

It is important to note that the most relevant variants are the ones that present the largest number of cases.

Variant	▲ Cases	Events	Median duration	Mean duration
Variant 1	1,182	5	15 days, 15 hours	42 days, 10 hours
Variant 2	357	5	15 days, 19 hours	16 days, 9 hours
Variant 3	320	7	17 days, 23 hours	76 days, 2 hours
Variant 4	259	8	24 days, 21 mins	32 days, 17 hours
Variant 5	173	9	24 days, 2 hours	71 days, 2 hours
Variant 6	165	5	15 days, 6 hours	28 days, 19 hours
Variant 7	163	8	19 days, 7 hours	19 days, 14 hours
Variant 8	135	6	16 days, 16 hours	38 days, 3 hours
Variant 9	129	7	17 days, 19 hours	19 days, 10 hours
Variant 10	99	11	27 days, 2 hours	77 days, 1 hour
Variant 11	96	8	19 days, 15 hours	19 days, 19 hours
Variant 12	90	10	25 days, 18 hours	83 days, 10 hours
Variant 13	80	9	15 days, 3 hours	17 days, 4 hours
Variant 14	79	6	16 days, 2 hours	17 days, 3 hours
Variant 15	74	9	18 days, 20 hours	27 days, 22 hours
Variant 16	71	8	20 days, 3 hours	22 days, 17 hours
Variant 17	51	8	24 days, 6 hours	31 days, 14 hours
Variant 18	48	7	17 days, 11 hours	26 days, 17 hours
Variant 19	47	15	43 days, 16 hours	47 days, 15 hours
Variant 20	43	5	15 days, 19 hours	15 days, 22 hours
Variant 21	42	4	14 days, 3 hours	28 days, 15 hours
Variant 22	40	12	22 days, 22 hours	37 days, 11 hours
Variant 23	37	10	29 days, 21 hours	32 days, 3 mins
Variant 24	36	14	84 days, 22 hours	85 days, 5 hours
Variant 25	34	11	24 days, 1 hour	26 days, 6 hours
Variant 26	33	7	20 days, 16 hours	98 days, 2 hours
Variant 27	31	13	27 days, 2 hours	80 days, 13 hours
Variant 28	31	7	16 days, 18 hours	17 days, 10 hours
Variant 29	27	10	19 days, 2 hours	24 days, 35 mins
Variant 30	22	9	24 days, 10 hours	112 days, 10 hours
Variant 31	19	13	33 days, 3 hours	33 days, 11 hours
Variant 32	19	10	66 days, 1 hour	45 days, 23 hours

Figure 4.4: Process variants and their statistics (events, median duration and mean duration

Further statistics, the distribution and trend of the variants can be analyzed in Figure 4.5.

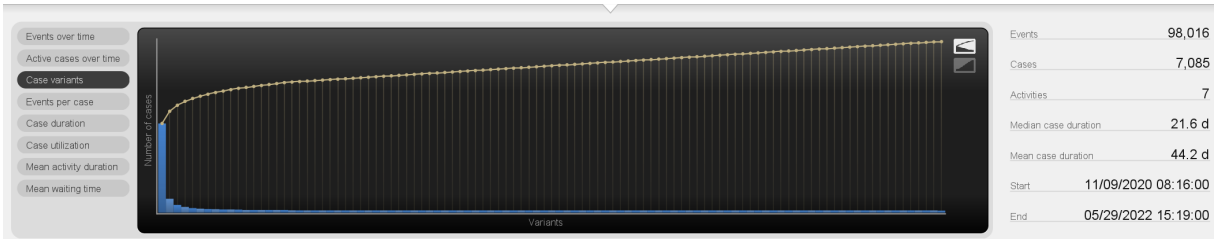


Figure 4.5: Case Variants

Furthermore, it is possible to observe the statistics distribution of the Case duration (Figure 4.6) as well as the number of events per case (Figure 4.7).

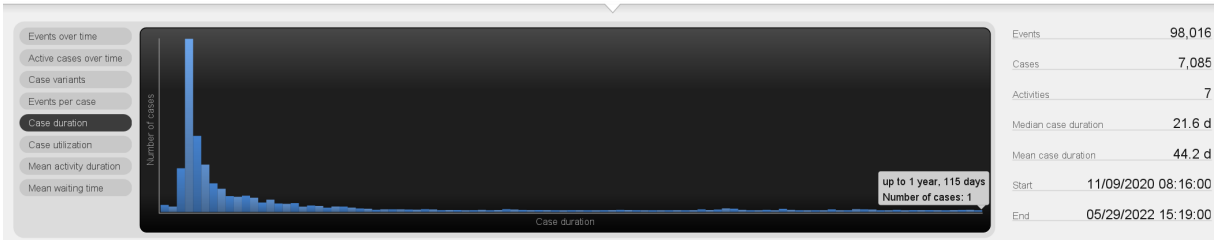


Figure 4.6: Case Duration (days)

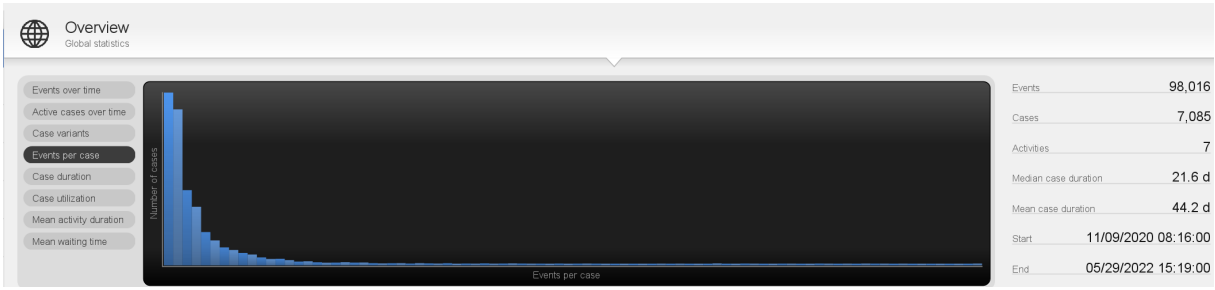


Figure 4.7: Events per Case

4.2.3.1 Variant Statistics Analysis

This subsection evaluates the **mean**, **standard deviation for each variant index**, and they are fundamental for the computation of the service level targets proposed in the next section.

One can observe that there is a significant amount of variants found. This indicates that support teams manage incidents using various approaches or process flows. That is to say, there are many paths that an incident can follow. This reinforces the fact that defining a simple service level target (for example, for incident resolution) is not realistic or accurate since different incidents may have different life cycles. Therefore, it becomes clear that SLAs are not very dynamic or adaptive.

The **Time To Respond** is one of the main concerns since we observe a **mean** of 3 days and 9 hours. By experience, we can assume this exceeds acceptable time limits. Having a customer waiting for a response for almost 4 days is not acceptable. Even if we have in the dataset incidents logged during holiday periods and moments where the customer does not reply on time, we cannot be comfortable with the response times given.

All of these metrics refereed, can be analyzed in Figure 4.8.

	count	mean	std	min	25%	50%	75%	max
Variant index	21257.0	7.867009	6.842353	1.0	2.0	5.0	12.0	25.0
Severity	21257.0	2.384438	0.500394	1.0	2.0	2.0	3.0	3.0
SLA	21257.0	83.02959	29.976307	15.0	60.0	60.0	120.0	120.0
Time_To_Respond	21257	3 days 09:03:09.969421837	10 days 06:48:04.234833955	0 days 00:01:00	0 days 00:04:00	0 days 00:15:00	0 days 21:28:00	437 days 22:49:00
Time_To_Respond_Seconds	21257.0	291789.969422	888484.234834	60.0	240.0	900.0	77280.0	37838940.0
Time_To_Respond_Minutes	21257.0	4863.166157	14808.070581	1.0	4.0	15.0	1288.0	630649.0
Time_To_Respond_Hours	21257.0	81.0531	246.801187	0.02	0.07	0.25	21.47	10510.82

Figure 4.8: Mean, Standard Deviation for each variant

4.2.3.2 Top Variant Analysis

From the next subsection, it is possible to understand that 54.34% of the cases are in the top 25 variants. Using only this subset and computing an aggregation under the top variants index for time to close in minutes and time to close in hours, it is possible to note that, for each variant, we present very high values. This means that the teams taking the incident's part may not want to respect metrics in terms of time. It can also happen that sometimes certain customers are not getting proper responses in time, which normally downgrades customer expectations and increases dissatisfaction. Table 4.9 presents some of these alarming numbers.

	Time_To_Close_Minutes						Time_To_Close_Hours					
	mean	std	min	max	median	count	mean	std	min	max	median	count
Variant index												
1	61122.747039	130828.828078	52.0	679807.0	22516.0	1182	1018.712394	2180.480430	0.87	11330.12	375.270	1182
2	23618.459384	5008.594324	20176.0	100923.0	22787.0	357	393.640924	83.476553	336.27	1682.05	379.780	357
3	109594.046875	179679.891208	216.0	681097.0	25884.5	320	1826.567469	2994.664827	3.60	11351.62	431.405	320
4	47146.220077	62390.750855	2535.0	666666.0	34641.0	259	785.770386	1039.845835	42.25	11111.10	577.350	259
5	102379.606936	151696.216134	1342.0	673913.0	34760.0	173	1706.326936	2528.269866	22.37	11231.88	579.330	173
6	41464.363636	91697.300968	335.0	601066.0	22013.0	165	691.072667	1528.288705	5.58	10017.77	366.880	165
7	28244.846626	5118.057823	20419.0	73537.0	27785.0	163	470.747485	85.301181	340.32	1225.62	463.080	163
8	54943.385185	131451.115888	1188.0	685486.0	24037.0	135	915.722741	2190.852074	19.80	11424.77	400.620	135
9	28010.333333	7913.560471	20279.0	53482.0	25662.0	129	466.838605	131.893299	337.98	891.37	427.700	129
10	110962.262626	157332.449356	4090.0	640933.0	39054.0	99	1849.371111	2622.207213	68.17	10682.22	650.900	99
11	28548.708333	3620.058519	21381.0	40614.0	28283.0	96	475.812083	60.334487	356.35	676.90	471.385	96
12	120141.422222	155811.691922	1738.0	640868.0	37161.5	90	2002.357778	2596.861325	28.97	10681.13	619.360	90
13	24724.137500	12022.028788	20295.0	107054.0	21819.0	80	412.068875	200.366740	338.25	1784.23	363.650	80
14	24699.620253	4381.771171	20276.0	42924.0	23175.0	79	411.659873	73.029509	337.93	715.40	386.250	79
15	40214.513514	50382.892074	20291.0	437588.0	27155.0	74	670.241892	839.714604	338.18	7293.13	452.580	74
16	32760.478873	14003.186559	20265.0	80224.0	28992.0	71	546.007606	233.386569	337.75	1337.07	483.200	71
17	45514.254902	63229.237411	21696.0	482441.0	35000.0	51	758.571176	1053.820205	361.60	8040.68	583.330	51
18	38511.458333	63855.612694	20327.0	383001.0	25198.5	48	641.857708	1064.259899	338.78	6383.35	419.975	48
19	68643.340426	10463.104015	51834.0	104870.0	62996.0	47	1144.055532	174.383972	863.90	1747.83	1049.930	47
20	22954.860465	2548.350994	20212.0	30326.0	22775.0	43	382.580698	42.472191	336.87	505.43	379.580	43
21	41256.523810	99215.728057	2988.0	650816.0	20381.5	42	687.609048	1653.594863	49.80	10846.93	339.690	42
22	53964.900000	87508.519798	2660.0	521651.0	33069.0	40	899.414750	1458.474858	44.33	8694.18	551.150	40
23	46085.297297	21595.500300	23139.0	160375.0	43035.0	37	768.087027	359.926047	385.65	2672.92	717.250	37
24	122724.888889	20103.070709	48872.0	154166.0	122335.5	36	2045.415000	335.051197	814.53	2569.43	2038.925	36
25	37867.205882	16626.245553	20452.0	89529.0	34677.0	34	631.120000	277.104102	340.87	1492.15	577.950	34

Figure 4.9: Time to close in minutes and hours after aggregation

4.3 Service Level Targets Analysis

After the usage of Disco to discover the process variants, that data was exported in a CSV-formatted file and treated (using Python) to try to compute improved service level targets based on **variants**, instead of pure **mean** or **median** metrics taken from the entire dataset containing all cases. In a CSV file, each event is usually stored in a single line, and the fields are separated by some punctuation symbol, usually a comma (,). If the comma is used as a decimal symbol or as a digit grouping symbol, then it is common to separate the fields by a semicolon (;) instead [12]. In the Load dataset process, we should read the CSV using the pandas library. After that, the dataset should be converted to a datetime start timestamp, a complete timestamp, and time to respond. Exceptionally, the time to respond should be converted to a timedelta to be able to be used.

The statement of the code is mentioned on Listing 4.1.

Listing 4.1: Reading and formating the event log

```
scenario = "datasets/Thesis_Final.csv"
df = pd.read_csv( scenario )
df["Start␣Timestamp"] = pd.to_datetime( df["Start␣Timestamp"] )
df["Complete␣Timestamp"] = pd.to_datetime( df["Complete␣Timestamp"] )
df["Time_To_Respond"] = pd.to_timedelta( df["Time_To_Respond"] )
df = df[ df[ "Time_To_Respond_Seconds" ] >= 1 ]
```

4.3.1 Service Target based on Global Median

To suggest a value to define for the resolution times for the incidents, the data was assessed using key statistical indicators, including the average, standard deviation, and median.

	count	mean	std	min	25%	50%	75%	max
Duration	9094	47 days 04:52:34.004288542	70 days 15:34:27.141023326	0 days 00:02:43	15 days 04:24:06.500000	21 days 09:26:43	46 days 08:23:13.250000	476 days 00:45:45
Duration_Seconds	9094.0	4078354.004289	6104067.141023	163.0	1311846.5	1848403.0	4004593.25	41129145.0
Duration_Minutes	9094.0	67972.566703	101734.452777	2.7	21864.1	30806.75	66743.2	685485.8
Duration_Hours	9094.0	1132.876237	1695.573996	0.0	364.4	513.45	1112.4	11424.8

Figure 4.10: Statistics for case resolution times

Usually, a company will define targets taking into account the mean or the median (50%). Consequently, from the results obtained on Figure 4.10, one would suggest, as a naive proposal, a target of 513.45 hours, approximately 21 days for the resolution time, as the median value was used to derive the result. The median is a value closer to reality since it is less affected by outliers or large variations than the mean.

4.3.2 Service Target based on Variant Median

As an alternative, we discover, using Disco, process variants on the event log. Process variants refer to different ways of defining a sequence under the activities within the business process creating opportunities to identify patterns, deviations and ways to optimize the processes with

the benefit of process mining.[3] As part of this work, there were several tests conducted to define the variants to understand the best approach to define the service targets for resolution time.

The definition in Python is shown on listing 4.2:

Listing 4.2: Filtering top n variants

```
n_variants = 10
top_n_variants = df[ df['Variant index'] <= n_variants ]
```

The analysis of variants is used to understand how much time it takes to close the incidents by seconds, minutes, and hours. These metrics were used to compute the optimal service targets, Listing 4.3.

Listing 4.3: Variants remaining

```
all_cases = pd.DataFrame(df.groupby(["IncidentID","Variant index"])['
    Complete Timestamp'].last() - df.groupby("IncidentID")['Start Timestamp'
    ].first())
all_cases.columns = ["Time_To_Close"]
all_cases["Time_To_Close_Seconds"] = round(all_cases["Time_To_Close"].dt.
    total_seconds(),1)
all_cases["Time_To_Close_Minutes"] = round(all_cases["Time_To_Close_Seconds
    "]/60,1)
all_cases["Time_To_Close_Hours"] = round(all_cases["Time_To_Close_Minutes"
    ]/60,2)

### Just the top N Variants
top_n_variants_incidents = pd.DataFrame(top_n_variants.groupby(["IncidentID
    ","Variant index"])['Complete Timestamp'].last() - df.groupby("
    IncidentID")['Start Timestamp'].first())
top_n_variants_incidents.columns = ["Time_To_Close"]
top_n_variants_incidents["Time_To_Close_Seconds"] = round(
    top_n_variants_incidents["Time_To_Close"].dt.total_seconds(),1)
top_n_variants_incidents["Time_To_Close_Minutes"] = round(
    top_n_variants_incidents["Time_To_Close_Seconds"]/60,1)
top_n_variants_incidents["Time_To_Close_Hours"] = round(
    top_n_variants_incidents["Time_To_Close_Minutes"]/60,2)
```

To understand how many variants are used under the cases, the calculation can be made using a line of code (Listing 4.4.

Listing 4.4: Variant analisys

```
round(top_n_variants_incidents.shape[0]/all_cases.shape[0]*100,2),"% of
    cases in top", n_variants, "variants")
```

[3] https://medium.com/@abelnkwachi/process-mining-variant-analysis-with-python-b6e51535ff9a

From the figure 4.11, it is possible to understand that there is a total of twenty-five variants containing 54.34% of the cases. Please refer to figure 4.12 where it is possible to note the mean, standard deviation, minimum, and maximum value.

	Time_To_Close_Minutes						Time_To_Close_Hours					
	mean	std	min	max	median	count	mean	std	min	max	median	count
Variant index												
1	61122.747039	130828.828078	52.0	679807.0	22516.0	1182	1018.712394	2180.480430	0.87	11330.12	375.270	1182
2	23618.459384	5008.594324	20176.0	100923.0	22787.0	357	393.640924	83.476553	336.27	1682.05	379.780	357
3	109594.046875	179679.891208	216.0	681097.0	25884.5	320	1826.567469	2994.664827	3.60	11351.62	431.405	320
4	47146.220077	62390.750855	2535.0	666666.0	34641.0	259	785.770386	1039.845835	42.25	11111.10	577.350	259
5	102379.606936	151696.216134	1342.0	673913.0	34760.0	173	1706.326936	2528.269866	22.37	11231.88	579.330	173
6	41464.363636	91697.300968	335.0	601066.0	22013.0	165	691.072667	1528.288705	5.58	10017.77	366.880	165
7	28244.846626	5118.057823	20419.0	73537.0	27785.0	163	470.747485	85.301181	340.32	1225.62	463.080	163
8	54943.385185	131451.115888	1188.0	685486.0	24037.0	135	915.722741	2190.852074	19.80	11424.77	400.620	135
9	28010.333333	7913.560471	20279.0	53482.0	25662.0	129	466.838605	131.893299	337.98	891.37	427.700	129
10	110962.262626	157332.449356	4090.0	640933.0	39054.0	99	1849.371111	2622.207213	68.17	10682.22	650.900	99
11	28548.708333	3620.058519	21381.0	40614.0	28283.0	96	475.812083	60.334487	356.35	676.90	471.385	96
12	120141.422222	155811.691922	1738.0	640868.0	37161.5	90	2002.357778	2596.861325	28.97	10681.13	619.360	90
13	24724.137500	12022.028788	20295.0	107054.0	21819.0	80	412.068875	200.366740	338.25	1784.23	363.650	80
14	24699.620253	4381.771171	20276.0	42924.0	23175.0	79	411.659873	73.029509	337.93	715.40	386.250	79
15	40214.513514	50382.892074	20291.0	437588.0	27155.0	74	670.241892	839.714604	338.18	7293.13	452.580	74
16	32760.478873	14003.186559	20265.0	80224.0	28992.0	71	546.007606	233.386569	337.75	1337.07	483.200	71
17	45514.254902	63229.237411	21696.0	482441.0	35000.0	51	758.571176	1053.820205	361.60	8040.68	583.330	51
18	38511.458333	63855.612694	20327.0	383001.0	25198.5	48	641.857708	1064.259899	338.78	6383.35	419.975	48
19	68643.340426	10463.104015	51834.0	104870.0	62996.0	47	1144.055532	174.383972	863.90	1747.83	1049.930	47
20	22954.860465	2548.350994	20212.0	30326.0	22775.0	43	382.580698	42.472191	336.87	505.43	379.580	43
21	41256.523810	99215.728057	2988.0	650816.0	20381.5	42	687.609048	1653.594863	49.80	10846.93	339.690	42
22	53964.900000	87508.519798	2660.0	521651.0	33069.0	40	899.414750	1458.474858	44.33	8694.18	551.150	40
23	46085.297297	21595.500300	23139.0	160375.0	43035.0	37	768.087027	359.926047	385.65	2672.92	717.250	37
24	122724.888889	20103.070709	48872.0	154166.0	122335.5	36	2045.415000	335.051197	814.53	2569.43	2038.925	36
25	37867.205882	16626.245553	20452.0	89529.0	34677.0	34	631.120000	277.104102	340.87	1492.15	577.950	34

Figure 4.11: Statistics of Time to Close the Incidents for n=25 variants

While analysing the results for the top 25 variants, we observed that the median values for most of them align closely with the previously proposed target of 513.45 hours. However, there are some variants where this target does not serve well as an SLA target, as it would consistently result in missed targets.

For example, variant 19 shows a median resolution time of 1049.93 hours more than double the proposed value. These types of variants typically involve complex issues that require collaboration across multiple teams. Factors such as delays in coordination and challenges in retrieving logs or data significantly impact resolution times. Applying a generic SLA to such cases would be unrealistic and not reflective of the true nature of the work involved. Each variant should be considered individually when defining SLA targets.

On the other hand, there are also cases like variant 21, which has a median of 339 hours, well below the 513.45-hour benchmark. This shows that a single SLA value cannot adequately represent the wide range of case complexities.

Initially, we began the analysis with all variants above 54.34%However, going forward, we will narrow the focus and concentrate on different computation steps for a more targeted and effective evaluation.

4.3.3 Summary

The Global Gap prefixed variables presented in Table 4.1 are metrics calculated and supported by the potentially proposed resolution time based on a target using the median for the total incidents. This metric is achieved by subtracting the proposed time from the real time spent on the incident. This produces an error, which we will evaluate in the next section using the RMSE.

Below, we are sharing a sample of the metrics for the top 10 variants for incidents that were calculated taking into account the mean/median of the total time (minutes/hours) for the incidents.

Global Mean Hours	1132.88
Global Mean Minutes	67972.57
Global Median Hours	513.45
Global Median Minutes	30806.75

Table 4.1: Incident resolution statistics based on total incidents

The Variant Gap prefixed variables presented in Figure 4.13, are calculated based on each variant's Mean/Median, as presented in Figure 4.12, by subtracting the resolution time for each incident on each corresponding variant; therefore, every variant has its own variant gap metric values. Below is a table with the mean with a red rectangle, which corresponds to the **Variant Mean per Variant**, and the median with a green rectangle, which corresponds to the **Variant Median per Variant**. This data was used to proceed with the calculations for the Variant Gap prefixed metrics.

	Time_To_Close_Minutes						Time_To_Close_Hours					
	mean	std	min	max	median	count	mean	std	min	max	median	count
Variant index												
1	61122.747039	130828.828078	52.0	679807.0	22516.0	1182	1018.712394	2180.480430	0.87	11330.12	375.270	1182
2	23618.459384	5008.594324	20176.0	100923.0	22787.0	357	393.640924	83.476553	336.27	1682.05	379.780	357
3	109594.046875	179679.891208	216.0	681097.0	25884.5	320	1826.567469	2994.664827	3.60	11351.62	431.405	320
4	47146.220077	62390.750855	2535.0	666666.0	34641.0	259	785.770386	1039.845835	42.25	11111.10	577.350	259
5	102379.606936	151696.216134	1342.0	673913.0	34760.0	173	1706.326936	2528.269866	22.37	11231.88	579.330	173
6	41464.363636	91697.300968	335.0	601066.0	22013.0	165	691.072667	1528.288705	5.58	10017.77	366.880	165
7	28244.846626	5118.057823	20419.0	73537.0	27785.0	163	470.747485	85.301181	340.32	1225.62	463.080	163
8	54943.385185	131451.115888	1188.0	685486.0	24037.0	135	915.722741	2190.852074	19.80	11424.77	400.620	135
9	28010.333333	7913.560471	20279.0	53482.0	25662.0	129	466.838605	131.893299	337.98	891.37	427.700	129
10	110962.262626	157332.449356	4090.0	640933.0	39054.0	99	1849.371111	2622.207213	68.17	10682.22	650.900	99

Figure 4.12: Variant statistics for the first 10 variants per mean and median

4.4 Evaluation

The evaluation phase applies the RMSE to critically assess the data and confirm its adequacy for this work. Figure 4.13 below shows how this was achieved. From this figure, it is evident that some Global Gap values are negative. This indicates that the incident required more time than the corresponding Global target. The same interpretation applies to the Variant Gap; when the actual resolution time exceeds the established variant mean or median, the result is negative.

While positive values in both cases indicate that the incident was resolved in less time than the respective target.

Global_Minutes_Mean	Global_Minutes_Median	Global_Hours_Mean	Global_Hours_Median	Global_Gap_Minutes_Mean	Global_Gap_Minutes_Median	Variant_Gap_Minutes_Mean	Variant_Gap_Minutes_Median	Global_Gap_Hours_Mean	G
63702.190402	31170.0	1061.703146	519.5	-621783.809598	-654316.0	-630542.614815	-661449.0	-10363.066854	
63702.190402	31170.0	1061.703146	519.5	-620286.809598	-652819.0	-629045.614815	-659952.0	-10338.116854	
63702.190402	31170.0	1061.703146	519.5	-620261.809598	-652794.0	-629020.614815	-659927.0	-10337.696854	
63702.190402	31170.0	1061.703146	519.5	-617394.809598	-649927.0	-571502.953125	-655212.5	-10289.916854	
63702.190402	31170.0	1061.703146	519.5	-616104.809598	-648637.0	-618684.252961	-657291.0	-10268.416854	
...	...	...	...	...	...	...	...	...	
63702.190402	31170.0	1061.703146	519.5	43467.190402	10935.0	40887.747039	2281.0	724.453146	
63702.190402	31170.0	1061.703146	519.5	43458.190402	10926.0	40878.747039	2272.0	724.303146	
63702.190402	31170.0	1061.703146	519.5	43439.190402	10907.0	21201.363636	1750.0	723.983146	
63702.190402	31170.0	1061.703146	519.5	63640.190402	31108.0	61060.747039	22454.0	1060.673146	
63702.190402	31170.0	1061.703146	519.5	55031.190402	22499.0	38475.220077	25970.0	917.183146	

Figure 4.13: Global Gap, Variant Gap, Global Compliance, Variant Compliance metrics

It was defined as Global Compliance for the mean/median to understand how many incidents would be above or below the proposed service target resolution times.

A

Global_Compliance_Hours_Mean	count
Below Global Mean	3415
Above Global Mean	435

B

Global_Compliance_Hours_Median	count
Below Global Median	2747
Above Global Median	1103

Figure 4.14: Global Compliance for the mean or median of the incidents

From the 4.14, it is possible to understand that most of the incidents are below the mean and median. Furthermore, the number of incidents below the global compliance mean is higher than those below the global compliance hours median, indicating fewer cases fall below the median compared to the mean.

This is justified by the mean being influenced by all the incidents, including a few highly complex incidents that take significantly longer to resolve.

Together with the Global Compliance metrics, the Variant Compliance metrics were computed, which represent the number of incidents above/below the variant mean/median.

A

Variant_Compliance_Hours_Mean	count
Below Variant Mean	3046
Above Variant Mean	804

B

Variant_Compliance_Hours_Median	count
Below Variant Median	1932
Above Variant Median	1918

Figure 4.15: Variant Compliance for the mean or median of the incidents

From the 4.15, it is noticeable that the Variant Median represents the central value among the variant compliance times. As expected, being the median, it provides a balanced point where approximately half of the values lie below and half above, reflecting the middle behaviour of the variants.

Although the Variant Compliance Hours Mean is influenced by the variability in the incident flow, as different cases may follow distinct incident resolution paths with different durations.

However, while comparing the Global Compliance to the Variant Compliance, the latter offers a more realistic perspective. This is because each case can exhibit unique behaviour, resulting in its own process variance. While some cases may share the same variant, many will follow different paths, making variant-level compliance a more accurate reflection of the actual process execution.

4.4.1 Assessing with the Root Mean Square Error

To continue the evaluation, we analysed the RMSE of the Global Gap and Variant Gap metrics, which indicated how far the actual results deviated from expected outcomes.

From Tables 4.2 and 4.3 becomes clear that the RMSE values for the proposed service targets based on process variants are smaller than the ones based on global mean or median for the entire event log. This value becomes even smaller as the number of variants increases.

	Number of Variants			
	25	**50**	**75**	**120**
Global Gap Minutes Mean	112189.12	111927.54	110117.88	108309.05
Variant Gap Minutes Mean	108268.38	107453.66	105559.18	103382.85
Global Gap Minutes Median	115087.13	115293.69	113538.51	111869.19
Variant Gap Minutes Median	115495.63	115092.4	113093.38	110835.03
Percentage number of cases	54.34 %	60.85 %	64.19 %	67.72 %

Table 4.2: RMSE for Global Gap and Variant Gap in Minutes

	Number of Variants			
	25	**50**	**75**	**120**
Global Gap Hours Mean	1869.82	1865.46	1835.3	1805.15
Variant Gap Hours Mean	1804.47	1790.89	1759.32	1723.05
Global Gap Hours Median	1918.12	1921.56	1892.31	1864.49
Variant Gap Hours Median	1924.93	1918.21	1884.89	1847.25
Percentage number of cases	54.34 %	60.85 %	64.19 %	67.72 %

Table 4.3: RMSE for Global Gap and Variant Gap in Hours

4.5 Process Improvement

4.5.1 Proposing Service Level Targets (SLT) Per Variant

Nowadays, adapting agreement targets to the specific characteristics of each process variant is essential for more accurate and realistic service definitions, contributing to stronger business

relationships.

The proposed SLT for each process variant is determined using a baseline that falls below the median, ensuring a more realistic benchmark. This decision was taken under the considerations delivered by the previous subsection 4.4.

Although the RMSE shows better results for the mean, this will not be a fully viable solution since the mean is affected by incidents that take longer to resolve. In realistic terms, the median is the best approach since it will not be affected by outliers.

As shown in Tables 4.3 and 4.2, the variant approach performs better in its respective context. Although the difference in RMSE values may not be large, the key point is that the Global Gap approach aggregates all incidents into a single model. This is not ideal, as each incident may follow a different process flow, making a one-size-fits-all approach less accurate. An example of the proposed approach applied to the first 25 variants is presented in Table 4.4, which then can be helpful to formulate and design realistic and yet accurate SLAs.

Variant	Propose Resolution Time (Minutes)	Propose Resolution Time (Hours)
1	22516	375.270
2	22787	379.780
3	25884	431.405
4	34641	577.350
5	34760	579.330
6	22013	366.880
7	27785	463.080
8	24037	400.620
9	25662	427.700
10	39054	650.900
11	28283	471.385
12	37161	619.360
13	21819	363.650
14	23175	386.250
15	27155	452.580
16	28992	483.200
17	35000	583.330
18	25199	419.975
19	62996	1049.930
20	22775	379.580
21	20382	339.690
22	33069	551.150
23	43035	717.250
24	122335	2038.925
25	34677	577.950

Table 4.4: Proposed SLT per variant.

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Chapter 5

Conclusion

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This chapter outlines the conclusions of this work by identifying limitations encountered during the development process and delineating possible areas of future research.

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Chapter 5
Conclusion

5.1 Conclusions

This study provides clear evidence of how dynamic agreement targets can be adjusted using process mining techniques.

By looking into the main problems that many organizations deal with, this work highlights how these issues can affect both performance metrics and the expectations of the customers who rely on those services.

Therefore, we propose a dynamic approach to adjust Service Level Targets (SLTs) based on insights derived from process mining.

We worked with real data from a multinational company that lacked an established SLA. Instead, SLA expectations were based on informal, subjective decisions rather than on calculated metrics or a clear understanding of incident workflows. This gap highlighted the need for a more data-driven approach to SLA definition and monitoring. The dataset was carefully prepared to determine whether incidents had been closed, to define clear and meaningful attributes for each column, and to assess whether including repeated incidents would add value to the analysis.

After preprocessing, a complete dataset with well-defined attributes was generated and analysed using the Disco tool. The main objective was to understand the incident flow, extract process variants, and evaluate statistical patterns—such as the duration of the longest and shortest incidents and the time taken to resolve them.

The analysis revealed a total of 2,051 process variants. However, only 25 of these accounted for approximately 55% of the data. As a result, the focus of the study was narrowed to these 25 most representative variants to ensure a more targeted and meaningful evaluation.

After processing and analysing the variants, Python code was used to compute descriptive statistics for key attributes, including Variant Index, Severity, agreement targets, and Time to Respond. The analysis included calculating the count, standard deviation, mean, median, minimum, quartiles, and maximum for each attribute to better understand their distribution and variability across the dataset.

Consequently, we develop code in Python to calculate both the Global Gap and Variant Gap prefixed metrics, along with their respective compliance metrics, to assess whether performance was above or below the defined targets.

The results showed that the metrics based on Global Gap Mean RMSE were 108309.05 minutes (equivalent to 1805.15 hours), while the metrics based on Variant Gap Mean RMSE were slightly lower at 103382.85 minutes (1723.05 hours). Regarding median values, the equivalent Global Gap Median RMSE reached 111869.19 minutes (1864.49 hours), and the Variant Gap Median RMSE was 110835.03 minutes (1847.25 hours).

Although the mean-based RMSE values appear more favorable, they are significantly influenced by outlier incidents with unusually long resolution times. From a practical perspective,

the median offers a more robust and representative measure, as it is less sensitive to extreme values and better reflects typical performance.

Moreover, the Global Gap aggregates all incidents into a single model, which may obscure important differences in process behaviour. Since incidents often follow distinct process flows, a variant-specific approach provides greater accuracy and interpretability, making it a more suitable method for performance evaluation and SLA compliance analysis.

Based on the RMSE calculations for both the Variant Gap and Global Gap, the results indicated values exceeding 1,500 hours. This substantial duration highlights the overall time discrepancies observed in the dataset and underscores the need for further investigation into the underlying process inefficiencies contributing to such extended resolution times.

The extended resolution times may be related to the complexity of the issues being handled, which often leads to delays caused by troubleshooting and when key steps need to be transferred over teams.

Additionally, one of the key findings of this analysis is the presence of structural inefficiencies within the current process design. The frequent handovers and dependencies between teams contribute significantly to delays in incident resolution. These inefficiencies suggest that the company would benefit from a thorough review and optimization of its cross-team workflows. Without such improvements, incidents are likely to remain unresolved for extended periods as they circulate among multiple teams.

Moreover, reflecting on the purpose of the previous questions at the beginning of this work, it is possible to answer the research question, taking into account the baseline of the work developed under the previous chapter (Chapter 4).

As described in section 1.3 under **RG1**, the following insights were obtained in response to **RQ1**:

RQ1. Which factors could influence the choice of implementing SLTs within SLAs in business relationships?

Well-defined SLTs play a crucial role in shaping business relationships. Among the key components of SLAs, response time and resolution time stand out as significant factors. Faster response times contribute directly to building customer trust, as they reflect the company's commitment to reliability and efficiency in service delivery. Timely problem resolution demonstrates efficiency and reinforces the perception of reliability and professionalism, enhancing customer trust.

From the section 4.4, resolution time emerges as a key factor influencing the decision to implement agreement targets. Improved resolution times are directly associated with better performance outcomes.

Additionally, in relation to **RG2** and **RQ2 - What could be dynamically adjusted enterprise service targets based on process and data mining methods?**, the analysis conducted in this work, incident resolution time emerges as a critical factor that can be dynamically adjusted to improve service performance. By categorizing specific types of issues within defined process variants, it becomes possible to extract and analyse relevant data to estimate the average resolution time for each category. This enables a more tailored and data-driven approach to SLA definition.

Likewise, response time also plays a significant role in shaping overall service quality and customer satisfaction. Therefore, establishing a reliable and representative metric such as the Variant Global Median (refer under 4.5 is essential for accurately defining incident expectations and aligning agreement targets with realistic operational capabilities.

In addition to addressing the defined research questions, this work makes relevant scientific and practical contributions, as described under 1.3.3.

The first contribution **C1** contributes to the field of Service Level Management by demonstrating the integration of process mining techniques into the definition and evaluation of SLT. Using Disco to analyse the incident flows, the study identified 2,051 variants, but only 25 accounted for most of the cases, showing the importance of evaluating performance at the variant level. Python and pm4py were used to compute descriptive statistics and to create the Global Gap and Variant Gap RMSE metrics. The results showed that variant-based RMSE values were lower and more representative, while the global approach tended to hide important differences between how incidents were processed. Overall, the findings suggest that a structured, variant-focused process mining approach offers a clearer and more accurate way to assess performance and SLA compliance.

The second contribution **C2** shows that process mining enables the identification of key inefficiencies such as frequent handovers, complex process variants, and prolonged resolution times. The concentration of incidents in a small number of variants and RMSE values exceeding 1,500 hours highlight significant performance gaps, demonstrating the value of variant-based and median-driven metrics in defining realistic SLTs and supporting informed process optimization decisions.

Overall, these contributions demonstrate that the integration of process mining into Service Level Management provides tangible benefits for practitioners seeking to design more effective, transparent, and adaptable SLAs.

5.2 Limitations

This subsection will discuss some limitations of this work.

5.2.1 Internal Validity

Research studies with limited datasets contain the risk of taking wrong conclusions and obscure trends in the incident management with adaptive agreement targets. Additionally, incidents that are very different in terms of area and behaviours can lead to inconsistent data due to a comparison of different data.

Consequently, external factors, including changes in companies' policies or technology advancements, can also influence study outcomes uncertainly.

For instance, it is vital to guarantee proper methodology in data gathering and analysis in order to reduce errors caused by measurement biases, and make conclusions based on the reviewed research replicable. Taking care of these threats to internal validity then serves to strengthen the credibility as well as soundness of an SLR's deductions about ticketing system procedures.

This threat to internal validity can be illustrated by the following example:

- **Dataset taken under COVID period:** The dataset has data from the COVID years, during which many of the teams experienced layoff, one possible cause to observe a long time under each team when taking an incident might be related to this as an external factor influencing the amount of time between each status.

5.2.2 Construct validity

The studies in the literature review were obtained from relevant literature databases, including journals, proceedings, and books, following a well-defined research protocol. The research protocol specified the study objectives, research questions, search strategy, and search strings used, while also establishing inclusion and exclusion criteria and outlining the data extraction and quality assessment procedures. This comprehensive approach helps mitigate potential bias in the selection and inclusion of studies.

However, it is worth noting that the dataset is limited to studies conducted in recent years, as the topic of SLAs with process mining is still emerging. Specifically, the dataset includes data from 2017 onwards, which may impact the depth and breadth of available information.

One of the threats to construct validity is the small number of articles available for analysis, with only eleven articles forming the basis of this research. This limited pool of data could potentially impact the robustness and generalization of the findings, underscoring the need for further research and data to strengthen the construct validity of this study. Despite this limitation, the identified studies offer valuable insights into the integration of process mining in SLAs, opening avenues for future investigations in this evolving domain.

The dataset used contains data; however, changes within the company over time may have impacted it. If a more recent dataset were used, the results of the dynamic analysis could differ. The sample used in the company is mainly focused on one department and does not reflect the overall behaviour of the organization. It is, in fact, concentrated on one of the company's largest areas

5.2.3 External Validity

One of the external validity threats impacting this work is the consideration that some of the relevant studies could not be included in our search. Regardless of the efforts to include all the possibilities of research with the use of an optimized search string. The limited number of libraries used, which only included three (ACM, Scopus, IEEE Xplorer), may have resulted in reducing the conclusions. Also, the restriction on the number of years could have removed an important article with good conclusions and data, as well as the restriction on language could have eliminated some studies that were not in English. Readers should keep these limitations in mind when interpreting the findings and remain open to the existence of additional research that could provide further insights beyond the scope of this work. If a team has different procedures for handling a case and processing it, this could influence the response times across teams.

5.2.4 Conclusion Validity

A rigorous research protocol employs well-defined criteria and methodologies for selecting studies from leading literature databases, designed to minimize bias in both study selection and data extraction. However, the restriction of the dataset to studies conducted from 2017 onwards may limit the breadth and depth of available information, potentially influencing the comprehensiveness of our review.

A concern regarding construct validity arises from the relatively small number of articles and incidents from the event log included in our analysis. This limited dataset could potentially impact the robustness and generalization of our conclusions.

5.3 Future work

Due to lack of data and time, several topics remain open for discussion after this work. The following areas are suggested to be addressed in the future:

- Utilization of other and different datasets to better understand how the identification of the global gaps behaves, and what could be improved in the development part.
- Utilization of a short dataset and compare it with a big dataset to understand what different results are expected, focusing on obtaining the SLT value based on the global gap.
- Analyse characteristics of the process variants, assess their relationships and compute weighted service level targets.

Bibliography

[1] W. Van der Aalst. *Process mining: Data science in action*. Springer Berlin Heidelberg, Jan. 2016, pp. 1–467. ISBN: 9783662498514. DOI: 10.1007/978-3-662-49851-4.

[2] W. van der Aalst and A. ter Hofstede. *Workflow Patterns The Definitive Guide*. Tech. rep. 2016.

[3] J. N. Adams, D. Schuster, S. Schmitz, G. Schuh, and W. M. P. van der Aalst. "Defining Cases and Variants for Object-Centric Event Data." In: (Aug. 2022).

[4] E. Aktas and F. Ulengin. "Penalty and reward contracts between a manufacturer and its logistics service provider." In: *Logistics Research* 9.1 (Dec. 2016). ISSN: 18650368. DOI: 10.1007/s12159-016-0136-9.

[5] S. Alter. "Work system theory: A bridge between business and IT views of systems." In: *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. Vol. 9097. Springer Verlag, 2015, pp. 520–521. ISBN: 9783319190686. DOI: 10.1007/978-3-319-19069-3.

[6] A. Altomare and E. Cesario. "A Comparative Analysis of Data-Driven Consolidation Policies for Energy-Efficient Clouds." In: *Proceedings - 2017 25th Euromicro International Conference on Parallel, Distributed and Network-Based Processing, PDP 2017*. Institute of Electrical and Electronics Engineers Inc., Apr. 2017, pp. 535–538. ISBN: 9781509060580. DOI: 10.1109/PDP.2017.54.

[7] P. Avgeriou and ACM Digital Library. *Proceedings of the 16th European Conference on Pattern Languages of Programs*. ACM, 2012, p. 250. ISBN: 9781450313025.

[8] AXELOS. *ITIL Foundation: ITIL 4 Edition*. First. Part of Williams Lea Tag. London, England: TSO (The Stationery Office), 2019. ISBN: 9780113316076.

[9] S. Baskoro and W. D. Sunindyo. "Predicting Issue Handling Process using Case Attributes and Categorical Variable Encoding Techniques." In: *Proceedings of 2019 International Conference on Data and Software Engineering, ICoDSE 2019*. Institute of Electrical and Electronics Engineers Inc., Nov. 2019. ISBN: 9781728149929. DOI: 10.1109/ICoDSE48700.2019.9092617.

[10] J. Caldeira, F. Brito e Abreu, J. Cardoso, and J. P. dos Reis. "Unveiling process insights from refactoring practices." In: *Computer Standards and Interfaces* 81 (Apr. 2022). ISSN: 09205489. DOI: 10.1016/j.csi.2021.103587.

[11] A. Carrera-Rivera, F. Larrinaga, and G. Lasa. *Context-awareness for the design of Smart-product service systems: Literature review*. Nov. 2022. DOI: 10.1016/j.compind.2022.103730.

[12] Diogo R Ferreira. *A Primer on Process Mining Practical Skills with Python and Graphviz*. 2017.

[13] J. Dugmore. *The ISO/IEC 20000 Service Management Handbook: Training - Implementation - Certification*. First published in the UK in 2012. Stevenage, Hertfordshire, UK: ConnectSphere, 2012. ISBN: 9781908772046.

[14] M. Dumas, F. Fournier, L. Limonad, A. Marrella, M. Montali, J.-R. Rehse, R. Accorsi, D. Calvanese, G. De Giacomo, D. Fahland, A. Gal, M. La Rosa, H. Völzer, and I. Weber. "Augmented Business Process Management Systems: A Research Manifesto." In: (Jan. 2022).

[15] B. Estrada-Torres, P. H. P. Richetti, A. Del-Río-Ortega, F. A. Baião, M. Resinas, F. M. Santoro, and A. Ruiz-Cortés. "Measuring performance in knowledge-intensive processes." In: *ACM Transactions on Internet Technology* 19.1 (Feb. 2019). ISSN: 15576051. DOI: 10.1145/3289180.

[16] Gerard Blokdijk and Ivanka Menken. *The Service Level Agreement SLA Guide: SLA Book Templates for Service Level Management and Service Level Agreement Forms-Fast and Easy Way to Write your SLA*. Tech. rep. 2008.

[17] W. Hussain and O. Sohaib. "Analysing Cloud QoS Prediction Approaches and Its Control Parameters: Considering Overall Accuracy and Freshness of a Dataset." In: *IEEE Access* 7 (2019), pp. 82649–82671. ISSN: 21693536. DOI: 10.1109/ACCESS.2019.2923706.

[18] ISACA. *COBIT 2019 Framework: Introduction and Methodology*. Schaumburg, IL, USA: ISACA, 2018. ISBN: 9781604207637.

[19] M. Junaid, A. Sohail, R. N. B. Rais, A. Ahmed, O. Khalid, I. A. Khan, S. S. Hussain, and N. Ejaz. "Modeling an optimized approach for load balancing in cloud." In: *IEEE Access* 8 (2020). ISSN: 21693536. DOI: 10.1109/ACCESS.2020.3024113.

[20] B. Kitchenham and P. Brereton. "A systematic review of systematic review process research in software engineering." In: *Information and Software Technology* 55.12 (2013), pp. 2049–2075. ISSN: 09505849. DOI: 10.1016/j.infsof.2013.07.010.

[21] J. J. Lee and R. Ben-Natan. *Integrating Service Level Agreements Optimizing Your OSS for SLA Delivery*. 2002.

[22] Maikel L. van Eck(B), Xixi Lu, Sander J.J. Leemans, and Wil M.P. van der Aalst. "A Process Mining Project Methodology." In: *International Conference on Advanced Information Systems Engineering: CAiSE 2015: Advanced Information Systems Engineering* 1626 (1999), pp. 41–56. DOI: 10.1007/3-540-48738-7.

[23] F. Mannhardt, P. Arnesen, and A. D. Landmark. "Estimating the impact of incidents on process delay." In: *Proceedings - 2019 International Conference on Process Mining, ICPM 2019*. Institute of Electrical and Electronics Engineers Inc., June 2019, pp. 49–56. ISBN: 9781728109190. DOI: 10.1109/ICPM.2019.00018.

[24] F. Mannhardt, M. De Leoni, H. A. Reijers, and W. M. Van Der Aalst. "Data-driven process discovery - Revealing conditional infrequent behavior from event logs." In: *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. Vol. 10253 LNCS. Springer Verlag, 2017, pp. 545–560. ISBN: 9783319595351. DOI: 10.1007/978-3-319-59536-8{_}34.

[25] Z. Milosevic, A. Goodchild, and C. Herring. *Business Contracts for B2B*. Tech. rep. 2000.

[26] D. Pati and L. N. Lorusso. "How to Write a Systematic Review of the Literature." In: *Health Environments Research and Design Journal* 11.1 (Jan. 2018), pp. 15–30. ISSN: 21675112. DOI: 10.1177/1937586717747384.

[27] C. Peoples, Z. Tariq, A. Moore, M. Zoualfaghari, and A. Reeves. "Using Process Mining to Formalise Service Level Agreement (SLA) Allocation." In: *Proceedings - 2021 IEEE SmartWorld, Ubiquitous Intelligence and Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Internet of People, and Smart City Innovations, SmartWorld/ScalCom/UIC/ATC/IoP/SCI 2021*. Institute of Electrical and Electronics Engineers Inc., 2021, pp. 671–676. ISBN: 9781665412360. DOI: 10.1109/SWC50871.2021.00100.

[28] A. Revina and Aksu. "An approach for analyzing business process execution complexity based on textual data and event log." In: *Information Systems* 114 (Mar. 2023). ISSN: 03064379. DOI: 10.1016/j.is.2023.102184.

[29] Rob Addy. *Effective IT Service Management*. 2007.

[30] A. K. Swain and V. R. Garza. "Key Factors in Achieving Service Level Agreements (SLA) for Information Technology (IT) Incident Resolution." In: *Information Systems Frontiers* (2022). ISSN: 15729419. DOI: 10.1007/s10796-022-10266-5.

[31] W. Tan, L. Huang, M. Y. Kataev, Y. Sun, L. Zhao, H. Zhu, K. Guo, and N. Xie. "Method towards reconstructing collaborative business processes with cloud services using evolutionary deep Q-learning." In: *Journal of Industrial Information Integration* 21 (Mar. 2021). ISSN: 2452414X. DOI: 10.1016/j.jii.2020.100189.

[32] J. Xu, R. He, W. Zhou, and T. Li. "Trouble Ticket Routing Models and Their Applications." In: *IEEE Transactions on Network and Service Management* 15.2 (June 2018), pp. 530–543. ISSN: 19324537. DOI: 10.1109/TNSM.2018.2790956.

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Appendix A.

Article's Review

A.1 Article's List

A.1.1 Predicting Issue Handling Process using Case Attributes and Categorical Variable Encoding Techniques

Objective: This article will propose a new approach to predicting issues through the use of predictive models by handling processes on Service Level Agreements (SLAs) [9]. The researchers discuss the poor SLAs, which highly impact the support management systems, presenting challenges for project managers.

Description: This study, supported by P3MI Institut Teknologi Bandung, addresses the challenges of software maintenance. Support quality is typically assessed using Service Level Agreements (SLAs); however, project managers find it hard to monitor SLAs related with software complexity or bugs. Researchers believe that this is one of the important reasons to have predictive predictions to manage SLAs. Unfortunately, authors found that most of the predicting issue resolution times neglect the dynamic changes that can happen in bug resolution processes. Techniques such as Naïve Bayes, Support Vector Regression (SVR), and Hidden Markov Models (HMM) have been used to estimate the remaining time for issue resolution. One of the techniques used to improve prediction accuracy is Artificial Neural Networks (ANN), which combine machine learning with process mining. Authors propose a new methodology involving three stages: log enrichment, index-based encoding, and categorical variable encoding. Log enrichment will be important to derive variables from duration and next activities under the prediction analysis. Index-Based encoding separates event sequence data into static (case attributes) and dynamic (event attributes) components, creating a feature vector that incorporates both data types. Categorical variables are encoded using four techniques: ordinal encoding, which does not increase the number of columns; and one-hot, sum, and backward difference encodings, which expand the dimensionality based on the number of classes. For prediction analysis, the activity variable is encoded using an index-based approach, and the next activity

is encoded using one-hot encoding. Consequently, results showed an enhanced predictive performance by improving the prediction of the next activity by 8.7% and remaining duration by 1.9%. In the remaining duration prediction, one-hot and sum encoding achieved a Mean Absolute Error (MAE) of 19.72, while one-hot encoding reached an accuracy of 65.38% in predicting the next activity. Based on this work, it is possible for future researchers to explore additional data sources and compare performance among different cases to further refine it.
Relation to our work: The focus of this work aligns closely with that of this work. Our work will focus on enhancing the SLAs in a business context with the use of Process Mining, and this exact work done by other researchers shows the exact same thing.

A.1.2 Using Process Mining to Formalise Service Level Agreement Allocation

Objective: This article validates the proposed SLA process using process mining techniques by identifying contradictions and trying to suit the SLAs processes under different customers' requirements, including the no technical knowledge ones [27].
Description: The article proposes a process that assigns a score combined with customer prioritization to households based on their classifications. Researchers have developed a process of SLA generation using Heuristic Minor by assigning SLAs based on what is known about the customer. The main contribution of this article was based on a ranking engine with score mapping and the optimization of characteristics, household profiles, disposable income, and online behavior by categorizing households. After careful examination using process mining, it enabled ways of optimizing the process and made it more efficient. The effectiveness of service classifications will be examined when customers provide responses that do not reflect their current circumstances, either through error or omission. If a client provides inaccurate or hidden personal details, this process will evaluate how this impacts their SLA proceeding with the examination of the risks to their rating and the potential for assigning them an unsuitable service. Additionally, researchers will consider the consequences of the client skipping activities due to time constraints, including effects on their classification and the resources allocated to their SLAs. Overall, researchers aim to optimize cost efficiencies for both customers and service providers and to enhance the SLA assignment process through continuous improvement.
Relation to our work: The learning approach implemented in this study differs from the work developed under our study. Researchers had proposed a new methodology with a scoring system integrated with heurist model derived from process mining. However, the findings from this study are aligned with the same goal as this work, which is to improve the Service Level Agreement with the use of process mining.

A.1.3 Analysing Cloud QoS Prediction Approaches and Its Control Parameters: Considering Overall Accuracy and Freshness of a Dataset

Objective: This article proposes an improvement on the SLA management by evaluating control parameters and data with the use of prediction methods [17].
Description: The main goal of this related work is to avoid SLA violations by predicting violations for each SLO and Quality of Service (QoS). The researchers analyzed the accuracy of six common algorithms: simple exponential smoothing, simple moving average, weighted

moving average, Holt-Winter double exponential smoothing, extrapolation, and autoregressive integrated moving average (ARIMA). These algorithms have been used under different testing control parameters. By exploring the impact of data freshness on the accuracy of simple exponential smoothing in a cloud QoS dataset. The Predictive Performance indicates that it is dependent on both the control parameters employed and the characteristics of the dataset, thus assisting service providers in selecting the most effective approaches to handling SLAs and minimizing their penalties. To sum up, this article evaluated the prediction accuracy of various methods, considering both overall accuracy and data freshness by examining variations in control parameters and managing SLAs efficiently.
Relation to our work: This paper had a focus mainly on evaluating the prediction accuracy of various methods for SLA violations. This can contribute to this work, since some approaches specific to preventing SLA violations can be used.

A.1.4 Trouble Ticket Routing Models and Their Applications

Objective: The main goal of this article is to minimize time and errors associated with the manual ticket assignment, increase resolution success rates, and reduce processing delays that could lead to SLA violations [32].
Description: This article is focus in investigating strategies for optimizing the routing of trouble tickets in system maintenance to enhance efficiency and adherence to SLAs. At the same time, it intends to overcome the obstacles with the manual routing, which can lead to errors and potential SLA breaches due to the delays. Researchers had introduced three routing models by using historical data on problem descriptions and resolution sequences by developing algorithms to automate ticket assignments to the most suitable expert groups, thereby reducing processing times and improving resolution success rates. After conducting several experiments, researchers have shown that this model helps to reduce the number of steps needed to resolve the tickets and enhance successful resolutions. This study showed that problem descriptions are the key to route accuracy. While the method follows a linear routing strategy, the research suggests exploring non-linear approaches that assign tickets to multiple expert groups simultaneously.
Relation to our work: This related work provides valuable insights for optimizing ticket routing processes, particularly by using process mining techniques. It offers a foundation for effectively assigning the appropriate SLA to tickets, enhancing the overall efficiency and accuracy of the routing process.

A.1.5 A Comparative Analysis of Data-Driven Consolidation Policies for Energy-Efficient Clouds

Objective: This article intends to compare virtual machine consolidation strategies in cloud data centers using predictive data mining models to enhance energy efficiency, minimize migrations, and reduce SLA violations [6].
Description: This study investigates Virtual Machine (VM) consolidation in cloud data centers to reduce power consumption by efficiently allocating VMs across fewer physical servers while meeting SLAs. By employing data-driven predictive models to forecast future resource

needs, such as CPU and RAM, using real-world data and comparing different consolidation strategies based on decision tree models, the research assesses their impact on energy efficiency, migrations, and SLA compliance. The goal is to optimize energy use and enhance consolidation practices through advanced predictive techniques.
Relation to our work: Although this related work does not directly align with our study, it offers valuable insights that we can apply. Specifically, it addresses SLA compliance in relation to VM migrations, including how to quantify and compare these aspects. This research is particularly relevant as it emphasizes practical, hands-on methods for calculating SLA compliance and managing violations in a scenario of VMs.

A.1.6 Estimating the impact of incidents on process delay

Objective: This article focuses on linking incident data to process delays regardless of the imprecise timing of incidents to estimate delays caused by external incidents using process mining. Above all, this research used a large dataset from the Norwegian railway system [23].
Description: This article aims to achieve a new method to estimate delays caused by external incidents using process mining to identify variations such as delays within processes. To address the gap of ignoring external factors such as system malfunctions or resource shortages, a method has been created that employs **Markov Chain Monte Carlo (MCMC)**. This method estimates the impact of incidents on process delays, focusing on an extensive dataset of over 120 million events from the Norwegian railway system and tested under 50,000 incidents. A key contribution of this study is the integration of external incident data into process mining, by offering a more in-depth view of process delays. This method reveals how infrastructure failures may contribute to substantial delays, and provides meaningful insights into the impact of predictive maintenance.
Relation to our work: While this study is not directly related to SLA prediction, it provides a foundational framework for process mining techniques and their variants. It can serve as a valuable baseline for understanding and refining process mining calculations relevant to SLA investigations.

A.1.7 Method towards reconstructing col- laborative business processes with cloud services using evolutionary deep Q-learning

Objective: This article focus under improving business process reconstruction by using algorithms to reinforce learning techniques for dynamic optimization using Q-Learning. Additionally, this article will evaluate performance under cloud workload by taking advantage of model convergence, QoS, and efficiency under diverse cloud service selection scenarios [31].
Description: This article wants to enhance business process as a service by reconstructing the architecture. Under this study, it aims to suggest new models of deep Q-Learning to address limitations faced in business processes while taking into consideration Quality of Service (QoS) optimization and efficiency in dynamic cloud environments.
Relation to our work: While this study deals only with a perspective of adjusting the business with process mining, the same can be used under this study to apply later on this work such as the mining processes used and how they were adjusted to the work.

A.1.8 Modeling an optimized approach for load balancing in the cloud

Objective: This article plans to optimize approaches for load balancing in cloud based on hybrid load balancing algorithms, classify different types of cloud data, ensuring that there is an increase in throughput, and reducing the number of service level agreements (SLA) [19].
Description: This research focuses on improving load balancing in cloud computing using machine learning and techniques of process mining. This study proposes a new algorithm based on the CSO algorithm with Support Vector Machines (SVM). Consequently, this algorithm will improve the throughput, response time, migration time, and prevent SLA violations.
Relation to our work: This work will help in understanding new algorithms with process mining, the impact on response times, SLAs, and in the business.

A.1.9 An approach for analyzing business process execution complexity based on textual data and event log

Objective: The main goals of this work will be to enrich the understanding of event log (EL) based complexity common in BPM with textual data (TD) based complexity, identify metrics, and study the relation between TD and EL, understand how textual data can contribute to EL prediction, exploring and adapt the approach for applying to the real world [28].
Description: Nowadays, companies tend to support their work on vast information systems to manage business processes (BPs), generating large amounts of structured event logs and unstructured textual data, which are important to understand and improve operational efficiency. This study introduces a new approach of integrating textual data with event logs to analyze and predict Business Process Execution Complexity (BPEC) derived from Natural Language Processing (NLP) using machine learning techniques. After this, it will correlate complexity metrics extracted from event logs to provide a global look at the process execution. Moreover, this study confirms that combining textual and event log data provides deeper insights into process complexity and shares new approaches for business process improvement.

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