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Enhancing IT Service Management Through Process Mining – A Digital Analytics Perspective on Documented Customer Interactions

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1. Introduction

IT service management is crucial to ensure productivity at workplaces by ensuring reliable IT systems and innovative service systems (Peters et al., 2016) thereby fueling digital transformation (MacLean & Titah, 2023). Accordingly, the pressure on IT support, that solve technical customer problems, is steadily increasing despite the adoption of AI-based self-service systems to improve service performance (McKinsey, 2024). Hence, service organizations are desperate to analyze their support agents' problem-solving activities utilizing digital analytics to facilitate high-quality services and manage and coach customer-contact service employees (Hartline & Ferrell, 1996). For this reason, text mining and related AI approaches have already been applied to large amounts of ticket data to classify customer requests (Revina et al., 2020), make knowledge more accessible (Li et al., 2024; Wang et al., 2018) or to assess the quality of services (Agarwal et al., 2016; Reinhard et al., 2023) and predict customer satisfaction (Liessmann et al., 2024). Yet, companies lack an understanding of the actual processes and activities that agents follow to solve customer requests and that standalone text mining methods can not provide (Rizun et al., 2021). Therefore, we refer to process mining (Van der Aalst & Weijters, 2004) as an approach for studying the actual routines of support agents that are inscribed into the ticket documentation. We conduct a systematic literature review and look at an exemplary ticket data set within a single case study to outline a combination of text mining and process mining. Our findings guide practitioners to extract activity catalogs (i.e., a set of recurring activities) and to generate an event log from textual documentation of service processes that track the activities for each ticket. This way our results demonstrate how processual insights can be revealed from documented service interactions and how a lack of data quality hampers digital analytics.

In a world that is increasingly characterized by data and digital processes, innovative analysis methods such as process mining and text mining are becoming the focus of attention. These techniques not only offer the opportunity to extract valuable information from service interactions but also to make processes more efficient and thus improve the quality of services (Ray et al., 2005). Because of this potential, this study is dedicated to bridging the approaches of process mining to the field of IT support services. Instead of merely concentrating on the creation of idealized process models (Garcia et al., 2019) the focus here is on the exploration and analysis of real data and actual processes that are represented as textual records of service interactions between support agents and customers. The derived model supports configuring the overall service system, similar to other approaches to modeling service systems (e.g., Li, 2023; Li & Peters, 2018, 2019; Li et al., 2019, 2020). Our goal is to integrate system data and conversational data as one representation of real-world service interactions and provide a novel approach to applying process mining to the documentation of service interactions in IT support. That type of digital analytics should help service organizations optimize their internal processes, improve the efficiency of customer-facing service processes, and innovate contact-intensive services (Kleinschmidt et al., 2019). Especially, the proposed approach allows to further leverage existing textual data above merely applying text mining methods.

IT support, understood as a socio-technical system, is at the heart of the digital transformation of companies. It combines technological components with human interactions and thus represents an interface where technical problem solutions and human needs meet (Davis et al., 2014; Krcmar, 2015; Li et al., 2018). Helpdesk employees bring invaluable knowledge about recurring problems and effective solution strategies to their daily work. Their in-depth understanding of user concerns and the challenges in the support process is essential for the design of efficient and effective support services. This study therefore examines the question of how the valuable, often implicit knowledge of helpdesk employees, which is documented in IT tickets, can be made explicit, structured, and integrated into the process of continuous improvement of service processes through the systematic application of process mining and text mining techniques.

Prior research has adapted process mining to mining chatbot dialogs (Schloß et al., 2023) or mining bot logs for optimizing robotic process automation (Egger et al., 2024; Leno, 2022). These endeavors aim at optimizing AI-based agents instead of understanding human behavior. However, there is existing literature on extracting intents from conversations to classify new customer intents for example (Chatterjee & Sengupta, 2020). Overall, we identify a lack of knowledge on how to leverage process mining and text mining to investigate actual processes from textual data and a lack of automated approaches to extracting service routines (Das, 2003; Pentland, 1992). Thus, the objective of this study is to investigate:

RQ1: How can process mining, supplemented by the use of text mining methods, contribute to the improvement of IT support services?

RQ2: How can unstructured data from documented IT support tickets be analyzed and evaluated using selected process mining and text mining tools?

To achieve this objective, existing research work and methods in the field of process mining and text mining are examined as part of an extensive literature analysis (Webster & Watson, 2002) to record the current state-of-the-art and existing solution approaches. This theoretical foundation serves as the basis for the subsequent case study of an internal helpdesk of a large healthcare manufacturing company including a dataset of 67.000 support tickets spanning the years 2021 and 2022. Within the case study, state-of-the-art text mining tools are utilized to preprocess the support tickets and extract event logs and activity catalogs to subsequently apply process mining analysis in terms of process discovery, process conformance, and process enhancement.

2. Conceptual Background

Process Mining: The foundation for process mining was laid in 1995 with the aim of using special techniques to extract process models from the data stored in information systems. The pioneers of this approach, such as Cook and Wolf (1995), explored process discovery techniques in software engineering, while others analyzed sequential patterns in workflows to automatically create process models and reduce the need for manual analysis (Garcia et al., 2019; Van der Aalst & Weijters, 2004). Process mining forms a bridge between data science, which aims to transform data into real value, and process science (Vom Brocke et al., 2021) which combines information technology and management science to optimize and manage operational processes (Van der Aalst & Carmona, 2022). Van der Aalst et al. (2012, p. 1) specifies the term process mining as follows: *"The idea of process mining is to discover, monitor and improve real processes (i.e., not assumed processes) by extracting knowledge from event logs readily available in today's (information) systems […]"*.

The objective of process mining is to create a detailed process model from event logs, accurately depicting dynamic process behavior. Event logs, which contain chronological and timestamped information about cases and activities, are essential for process mining. The focus extends beyond performance data to investigating causal and random relationships between activities, providing a comprehensive understanding of process dynamics (Garcia et al., 2019; Van der Aalst & Weijters, 2004).

Process mining can encompass several perspectives: The control flow perspective focuses on the sequence of activities; the organizational perspective analyzes resource information from the log, including the actors involved (e.g., people, systems, roles, and departments) and their relationships; the case and time perspective concentrates on case attributes such as process paths and involved actors, as well as the timing and frequency of events. According to the *Process Mining Manifesto*, three main methods are used in process mining (Van der Aalst et al., 2012), which are also used in this study**:** *(1) Process discovery* generates a process model from event logs without the use of previous information and thus visualizes real process sequences**.** *(2) Process conformance* involves a comparison between an existing actual process model and the associated target process model to evaluate the congruence between the theoretical model and its practical implementation. *(3) Process enhancement* involves expanding and optimizing existing processes based on real process data from event logs.

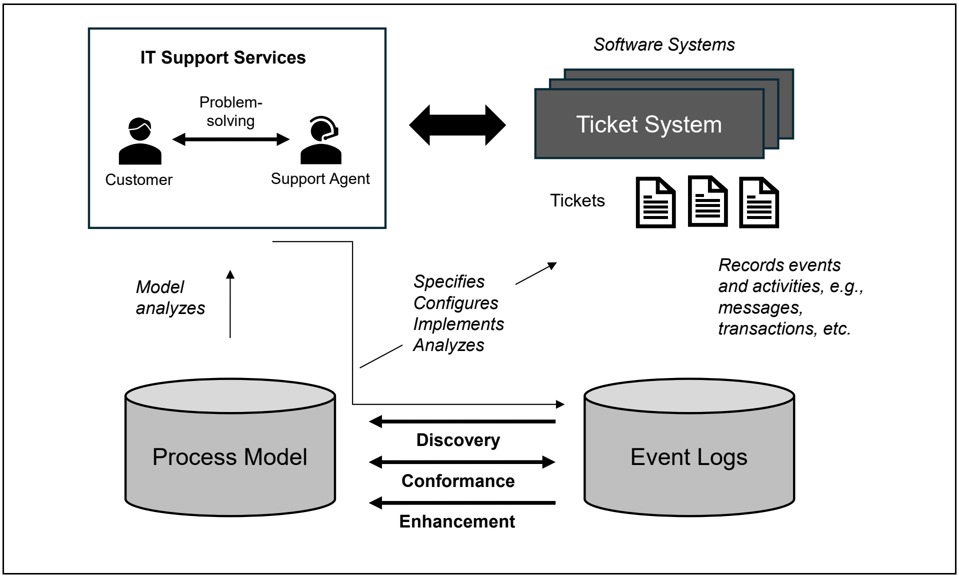

Figure 1: Process Mining in IT support
(Source: Adapted from Van der Aalst et al., 2012, p. 2)

Text Mining: Manually processing and analyzing large amounts of data proves to be time-consuming and prone to errors (Singh et al., 2019). In this context, text mining has established itself as an interdisciplinary field of research that aims to extract valuable knowledge and practically applicable insights from text data (Kao & Poteet, 2007). The aim of text mining is the same as that of data mining but focuses specifically on extracting and obtaining information from various data sources and documents by identifying relevant patterns. In contrast to data mining, which is primarily based on structured data, text mining uses unstructured text collections as a data source to track down patterns. To achieve these goals, text mining draws on methods and techniques from the fields of natural language processing, information retrieval, information extraction, machine learning, computational linguistics, and statistics (Gupta & Lehal, 2009). In the domain of IT support, prior research applied text mining to analyze ticket data in various ways. Liessmann et al. (2024) developed a system or predict customer satisfaction, Rizun et al. (2021) utilized artificial intelligence to assess the complexity of business processes to derive recommendations for automating certain customer requests, and Reinhard et al. (2024) developed a co-agent for providing automated solution suggestions.

This study focuses specifically on the use of text mining in IT support to extract relevant information (i.e., events and activities) from helpdesk tickets. The use of text mining on IT support tickets enables a process mining-based analysis (Figure 1) of lived service interactions and thus serves to deepen the understanding of process flows and supports the creation, analysis, and evaluation of process models using process mining methods.

3. Research Design

This study follows a methodical approach consisting of a systematic literature analysis and a qualitative case study. The literature analysis creates a sound knowledge base by searching scientific databases using precisely defined search strings, based on the method of Brocke et al. (2009) and extended by a backward and forward search according to Webster and Watson (2002). The aim is to identify relevant literature to comprehensively highlight the current state of research and uncover possible research gaps. The empirical investigation in the form of a case study, based on the methodology of Yin (2018) and Eisenhardt (1989), enables the practical verification of theoretical insights by performing a process analysis.

Systematic Literature Review: The aim of the literature search in the context of this study is to identify publications, articles, contributions and books that deal with the application of process mining in combination with text mining methods for analyzing and evaluating process flows in the IT support area. With the help of relevant concepts and technical definitions, a list of search terms was created (e.g. process mining, process modeling, process discovery, text mining, conversational mining, data preprocessing, clustering, IT support, IT service management, etc.), which was used to search scientific databases. The literature search was carried out in recognized scientific online databases using several search strings in English using Boolean operators "AND", and "OR" in various combinations. The literature used for the review covered the period from 2014 to 2024 inclusive to ensure that the sources identified were up-to-date, relevant, and complete. The following is a summary of the literature databases used, the search strings employed, and the number of literature sources identified:

- *Databases:* Emerald, IEEExplore, ResearchGate, Science Direct, Scopus, Springer Link, Web of Science, JSTOR
- *Search strings: ("Text Mining" OR "Conversational Mining" OR "Digital Conversation") AND ("Process Mining" OR "Process Modelling") AND ("IT" OR "ITSM" OR "IT Support" OR "IT Helpdesk" OR "IT Ticket")*
- The overall result of all database queries: n = 246 publications
- Total read at abstract level: n = 125 publications
- Overall relevant for this research: n = 34 publications

To maximize the range of relevant literature sources, the literature search was extended to the Google Scholar search engine. Several rounds of literature searches were undertaken in the named databases. Based on the relevant publications, a forward and backward search was carried out to ensure completeness and to identify further relevant works, whereas older works were included in the backward search and works cited later in the forward search.

Case Study: Case studies are methods of qualitative social research that focus on the in-depth study of a specific object, situation, or phenomenon in its real environment. They are particularly suitable for *how* or *why* questions in research contexts (Yin, 2018). Our single case analysis focuses on a detailed examination of one unique IT support organization. It aims to offer new insights into previously unexplored phenomena by combining methods of text mining and process mining on a set of real-world ticket data.

Our case analysis is based on a data collection of documented IT support tickets. These are around 67,000 tickets from the years 2021 and 2022, which were provided as an extract from a ticket system. This data set includes real service requests with associated problem solutions. The data can be divided into 38 main categories and over 500 subcategories. They log the support processes of users from 78 countries. The tickets contain text-based information (mostly in English) on the solutions to reported problems but are unstructured and sometimes incomplete. The excerpt of the raw data structure can be found in Figure 2.

Category	Description	Example
ticket_number	Ticket number for identifying the ticket	*000001234567*
opened_by_agent	The agent who opened the ticket	*Agent First and Last Name*
short_description	Title or short description of the problem	*LCD Screen is down - Location A*
initial_assignment_ group	The group initially assigned to the incident	*IT Field Services*
assigned_agent	The agent assigned to the incident	*Agent First and Last Name*
main_category	Main category	*Client-Hardware*
subcategory_1	First subcategory	*Monitor/Display*
resolver_group	The group that resolved the ticket	*IT Field Services*
resolver_agent	Agent who resolved the ticket	*Agent First and Last Name*
ticket_type	Type of ticket	*Incident*
region_code	Region code	*EU*
resolution_datetime	Date and time the ticket was resolved	*01.01.2021 10:00:00*
closure_datetime	Date and time the ticket was closed	*01.01.2021 12:00:00*
assignment_group_ history	History of all assigned groups	*Service Desk, Service Desk, IT Field Services, IT Field Services*
work_notes	Agents' work notes on resolving the incident	*Pending for the vendor to replace the hardware.*

Figure 2: Support Ticket Data Structure

Category	Description	Example
additional_comments	Additional comments	*We will arrange for the vendor to replace the hardware tomorrow.*
closure_notes	Notes on closing the ticket and feedback to the user	*The device has been replaced with a new one. It is working fine.*
assignee_history	History of all assigned agents	*First and Last Name of the first/second/third... Agent*

Figure 2: Support Ticket Data Structure (continued)

Due to the nature and complexity of the data, a combination of qualitative and quantitative text analysis approaches was adopted as the method for data collection and analysis. Both qualitative and quantitative evaluations of the ticket data were carried out, supported by the use of specific text and process mining tools such as the *RapidMiner* (https://docs.rapidminer.com/) and *Celonis* (https://www.celonis.com/) software solutions:

- *RapidMiner Studio (Educational Edition): An open-source tool that offers a variety of data mining operators, functionalities, and extensions for comprehensive data analysis* (Sharafi, 2013). Text pre-processing functions (such as tokenization, stop-word filtering, n-gram generation, etc.) and text processing (clustering) were applied to the available data.
- *Celonis (Educational Edition): A proprietary process mining tool that supports various platforms (local, web, or cloud-based)* (Çelik & Akçetin, 2018). In this work, the cloud-based version was used to present the investigated process models in IT support through visualizations of process discovery, process conformance, and process enhancement.

4. Digital Analytics and Service Interactions

In this section, we focus on the discussion of various aspects of process and text mining, particularly concerning text-based content, and its application in IT support. The extensive literature search and analysis made it possible to gain profound insights into the methods for structuring and transforming text data, especially IT support tickets.

4.1 Process Modeling and Mining Based on Text Data

In the context of the daily use of information systems, users leave behind digital behavioral traces (Li et al., 2016) that can be systematically recorded and analyzed using process mining methods. This data is in the form of event sequences or event logs that are generated as part of various process activities. Process models depict these activities and their interrelationships. In addition, human conversations recorded by both information systems and humans can also be interpreted as digital representations of human behavior and used as a data basis for behavioral analyses. The specific digital signatures and characteristic patterns of interpersonal interaction can also be analyzed using process mining techniques, allowing these patterns to be modeled and studied (Compagno et al., 2018).

Several authors (Holstrup et al., 2020; Vakulenko et al., 2019; Wang et al., 2015) investigate the application of process mining algorithms to the analysis of digital, information-seeking conversations consisting of complex message sequences or streams (Holstrup et al., 2020). These conversations, which are not exclusively between users and/or agents, but also interact with alternative information sources such as chatbots, aim to obtain knowledge about defined topics, exchange information, and answer specific queries. Given the characteristics of conversational data as intrinsically intertwined and unstructured manifestations of human language, analyzing them requires transformation into process protocols to ensure compatible processing by process mining algorithms. In research on conversational agents, Schloß et al. (2023) adapted the concept of process mining to model the behavior of customer support chatbots and utilize it as a base for evaluating and improving the chatbot continuously.

However, the exclusive use of process mining methods may be insufficient in certain cases. Process mining focuses primarily on analyzing process-related, sequential events and activities to identify significant patterns. However, other aspects beyond these sequential events can have a significant impact on process modifications (Ceravolo et al., 2024). As a result, contextualizing digital data with complementary information is essential to gain a comprehensive perspective on the dynamics of change (Grisold et al., 2020). In this context, the combination of process mining with qualitative text mining methods (Schmiedel et al., 2019) and/or other data mining methods, such as machine learning (Ceravolo et al., 2024), represents a promising approach to promote a holistic analysis and thus achieve a profound understanding of the change processes (Grisold et al., 2020).

Text mining can also be efficiently applied to various process-related documents to discover certain linguistic patterns and thus generate a comprehensive process lexicon that contains essential activities and data elements of the process. Based on the developed process lexicon, a systematic evaluation and classification of the data stock is carried out concerning its relevance to the process lexicon. The data source evaluated in this way enables experts to draw on relevant data for extraction and subsequent use as the foundation of a knowledge database (Li et al., 2015).

The combination of process mining and text mining offers an innovative approach to in-depth analysis of business processes. This approach, characterized by the systematic collection and analysis of digital behavioral data from information systems, including human conversations, makes it possible to identify hidden patterns and relationships in business processes that go beyond the scope of traditional analysis methods. The synergy between process mining and text mining opens up avenues for more comprehensive and precise analysis by overcoming the limitations of individual methods and providing a holistic picture of business events and their changes.

4.2 Data Analysis in Helpdesks and Ticket Systems

In today's world, IT plays a strategically important role in the secure management of business computerized processes. IT support or helpdesk supports business processes in numerous companies and helps to avoid interruptions in daily business processes (Edgington et al., 2010). IT ticket systems, as socio-technical structures, balance technological and social factors to ensure efficient support. These information systems aim to provide optimal information for economic and efficient decision-making, coordination, control, and monitoring of processes. Technological components include IT tools and infrastructure for tracking requests, diagnosing problems, and communicating with users or digital platforms. The social components are the human actors in IT support (Davis et al., 2014). This interpersonal communication and interaction are of central importance for efficient problem-solving, the effectiveness of IT support, user satisfaction, and teamwork (Jäntti et al., 2012). Communication within the support tickets also serves as an important source of documentation. The processes described there represent a traceable chronicle of interactions and can help to improve support processes.

The creation of IT tickets to solve specific questions or problems is common practice in most companies and follows a clear process. This process begins with the submission of a request by the customer and ends with its resolution. Customer inquiries, problem descriptions, affected systems and/or users, potential effects, and responsible persons are recorded in IT tickets and processed by IT service desks. Incorrect or incomplete information can lead to serious service failures (Rizun et al., 2021). Both structured and unstructured data are generated in ticket systems. This data describes the runtime behavior of the processes and reflects the actual process reality. The ticket resolution process has corresponding logs that are recorded in the ticket system (Gupta et al., 2020). Comments generated during process execution contain unstructured and more or less detailed process information which, once integrated into the process model, enable a comprehensive understanding of the process. The event logs can thus be enriched with the information gained from comments to discover a deeper reality (Gupta et al., 2020).

Text mining technologies can be used in conjunction with process mining methods in ticketing processes and further process modeling to cope with continuously increasing IT complexity and workloads for IT departments (Rizun et al., 2019). Section 4.2 describes the structuring and analysis of the tickets obtained from the case study, including their comments. The ticket processing methods described here are applied accordingly to the case study data.

4.3 Event Logs for Service Interactions

To analyze business processes using process mining, it is necessary to have information about the individual process steps to provide insights into the actual process execution. As already mentioned, the data extracts are provided by the information systems involved, such as ticket systems. The sequences of recorded events, also known as traces, form an event log (Rebmann & Van der Aa, 2021). Regardless of the perspective and purpose of process mining, event logs must fulfill certain minimum requirements so that information about processes can be extracted. The following should be noted: each event in the event log relates to a clearly defined process step or activity, a process instance (case), an initiator, a timestamp, and a sequential sort order (Van der Aalst, 2008). Most process mining tools only require three attributes: the process instance (case), the activity, and the timestamp (Van der Aalst & Carmona, 2022).

However, it is often the case that essential information about process components or specific process steps is not included in standard event logs and therefore remains completely undiscovered. This information is closely linked to the activities and is recorded as part of unstructured, textual data (Rebmann & Van der Aa, 2021). IT service management relies on contextualized problem descriptions from customers and text-based communication between IT staff and other participants. Text data can significantly impact activities, their sequence, and the complexity of business processes. Current research explores enriching event logs with textual data to create a more comprehensive business process model. The complexity of the event log is significantly influenced by the complexity of the text data (Revina & Aksu, 2023). To examine and reduce the complexity of the text data, text mining techniques are often used, which have already been discussed in the previous chapter.

5. Bridging Process Mining and Text Mining

This section presents a case study on applying process mining to IT support data, aiming to optimize business processes. It includes use case selection, text preprocessing with *RapidMiner*, event log preparation, and process mining for discovery, conformance, and enhancement in *Celonis*. The study offers insights into the practical application and potential value of digital analytics for service organizations.

5.1 Text Mining and Data Preparation

5.1.1 Analysis and Preparation

During the data preparation phase, the IT tickets provided were analyzed in detail to understand the process of ticket creation, processing, and resolution. In particular, the comments, work notes, and close notes written by ticket agents played an important role. These not only contain subject-specific solution information but often describe the course of the processing procedure itself.

The analysis revealed that the available data was an excerpt from a ticket system that acted as a central intake point that works together with various international helpdesks and supports users from 78 countries. Depending on the incident and the priority of the problem, tickets are assigned to main categories such as *active directory*, *client hardware*, *databases*, *incident management*, etc., and allocated to a responsible group and a specific agent. In the course of solving the problem, the ticket can be forwarded to other groups for further processing. Agents' comments and notes document solution steps as unstructured, time-stamped text. Once a problem is solved, the ticket is marked "solved". The customer can then close the ticket if satisfied or reopen it if not. Both the initial opening and closing of the ticket are done by the customer. If there is no response, the ticket is automatically closed five days after being marked as solved.

The case study examined is based on an extensive data set of IT tickets. It was crucial to select suitable use cases for analysis and evaluation using process mining tools and text mining tools. In the present case study, one use case refers to the description of the application of process mining and text mining methods to the unstructured data from the IT tickets, whereby the IT ticket serves as the object of investigation and has a specific structure. A total of 60 use cases were selected from the entire collection of documented IT support tickets, comprising 20 use cases from each of the main categories "Client Hardware", "SAP Services" and "Business Applications". The first 20 use cases from the "Client Hardware" category were selected at random. For the second and third group of use cases, only fully completed tickets in English were considered. Special care was taken to ensure that the selected tickets did not contain any empty columns or rows and that the text to be analyzed had the correct character encoding.

5.1.2 Text Pre-Processing and Transformation

Now the practical application of the text mining methods is carried out with the help of the *RapidMiner* software, which was used to analyze selected text data from the IT tickets.

Initially, 60 use cases were selected from the data collection of documented IT support tickets, each of which was divided into three equally sized categories: *client hardware*, *SAP services,* and *business applications*. The *client hardware* group was selected at random. The second and third groups only included fully completed tickets in English. The text data from the columns “work_notes”, “comments” and “clo-se notes” were used for the text mining methods. During the application of text mining methods, however, it turned out that the number of available IT tickets and the associated text data was not sufficient to carry out a meaningful analysis and subsequent evaluation. For this reason, the data set was expanded to 2066 tickets from the *client hardware* category, 3752 tickets from the *SAP services* category, and 2609 tickets from the *business applications* category.

Before analysis, the raw data (comments, notes, and final notes) must be cleaned and formatted for text mining. Using regular expressions, the data was processed with *RapidMiner*, merging it into a single column for easier text clustering. The unstructured text from “work notes”, “comments”, and “final notes” were the main information sources. Cleaning involved handling proper names, abbreviations, unclear formulations, incomplete sentences, and recurring elements from emails and HTML tags. Manual cleansing would have been costly, so automation with case-specific regular expressions was used in *RapidMiner*, though not all variations were covered.

Next, text pre-processing was carried out in *RapidMiner*. The following steps were carried out: The text was first converted to lowercase (Rojas et al., 2018, p. 750). Then, tokenization was performed, breaking the text into individual words and removing punctuation. Tokens that were too long or too short were filtered out. Common but less important words, known as stopwords, were filtered using a list from RapidMiner for the English language (Kumar & Chandrasekhar, 2012, p. 2). Additionally, word sequences (bigrams and trigrams) were analyzed to better capture the semantic structure and increase the dimensionality of the text representation (Schonlau & Guenther, 2017, p. 2). Finally, the tf-idf method was used to transform the text into vectors, weighting tokens based on their frequency in the document and their rarity across the document set (Berry & Kogan, 2010, p. 184; Li et al., 2010, p. 177).

5.1.3 Clustering

Given the selected data set of over 8000 tickets, it proves challenging to manually record all important and relevant activities relating to the IT support processes and the strategies for resolving IT tickets. To automate this process, the k-means clustering method is used. Clustering is one of the methods of unsupervised machine learning, as no classes or groups are predefined in advance. The clustering algorithm aims to independently recognize structures and patterns in the database. The k-means algorithm is based on the text pre-processing steps described in the previous section. At the beginning of the process, the optimal number of k-groups is determined. In this work, the optimal number of k was determined using the Elbow method and subjective judgment. The evaluation of the Elbow method showed no clear preference for an optimal number of clusters between 60 and 80. A subjective evaluation was therefore used. After repeated attempts to select different numbers of clusters to achieve the best possible result, a k-number of 70 proved to be the most suitable. Using the *RapidMiner* operator “Cluster Model Visualizer”, a table was created containing the three most important attributes per cluster. The results served as the basis for the later creation of the sub-activity catalog. An extract of the clusters for the case “SAP services” is represented in Figure 3.

Cluster	Attribute 1	Attribute 2	Attribute 3
Cluster 0	Account	Unlock	Requested
Cluster 1	Systems	Created	Please_help
Cluster 2	Services	Change	Systems
Cluster 3	Password_reset	Reset	Password
Cluster 4	Attachment	Added	List
…	…	…	…

Figure 3: Excerpt from the Cluster Analysis of “SAP Services”

5.1.4 Main and Sub Activity Catalog

To gain a better understanding of the processes taking place within the IT helpdesk, a standardized list of the main activities was created. This describes the respective work steps within service interactions. Two basic types of processes can be identified. On the one hand, there are fixed activities such as “Ticket opened” or “Ticket closed”, which cannot be skipped or omitted, and on the other hand, there are variable activities, which can be regarded as optional. The latter include “solving the problem” and “detailed problem description”, which can be skipped if the work step is trivial and does not require any additional descriptions or further work steps. The creation of the catalog was based on a previous manual examination of IT tickets, as well as an examination using text mining and process mining methods.

Particular attention is paid to the activity “Solving the problem”. Although this is one of the variable processes, in many cases, it can lead to further main activities. The breakdown of this activity depends largely on the complexity of the incident described. Furthermore, it has been observed that extensive problem solutions have led to further branches into so-called sub-activities (Figure 4). A sub-activity represents the lowest level that leads to a concrete problem-solving activity. Due to the sheer number of possible sub-activities, a variety of patterns can be identified based on the clustering approaches that show a solution path to the specific problem. Text mining methods such as text pre-processing and clustering, which were explained in the previous chapters, were used to identify these patterns.

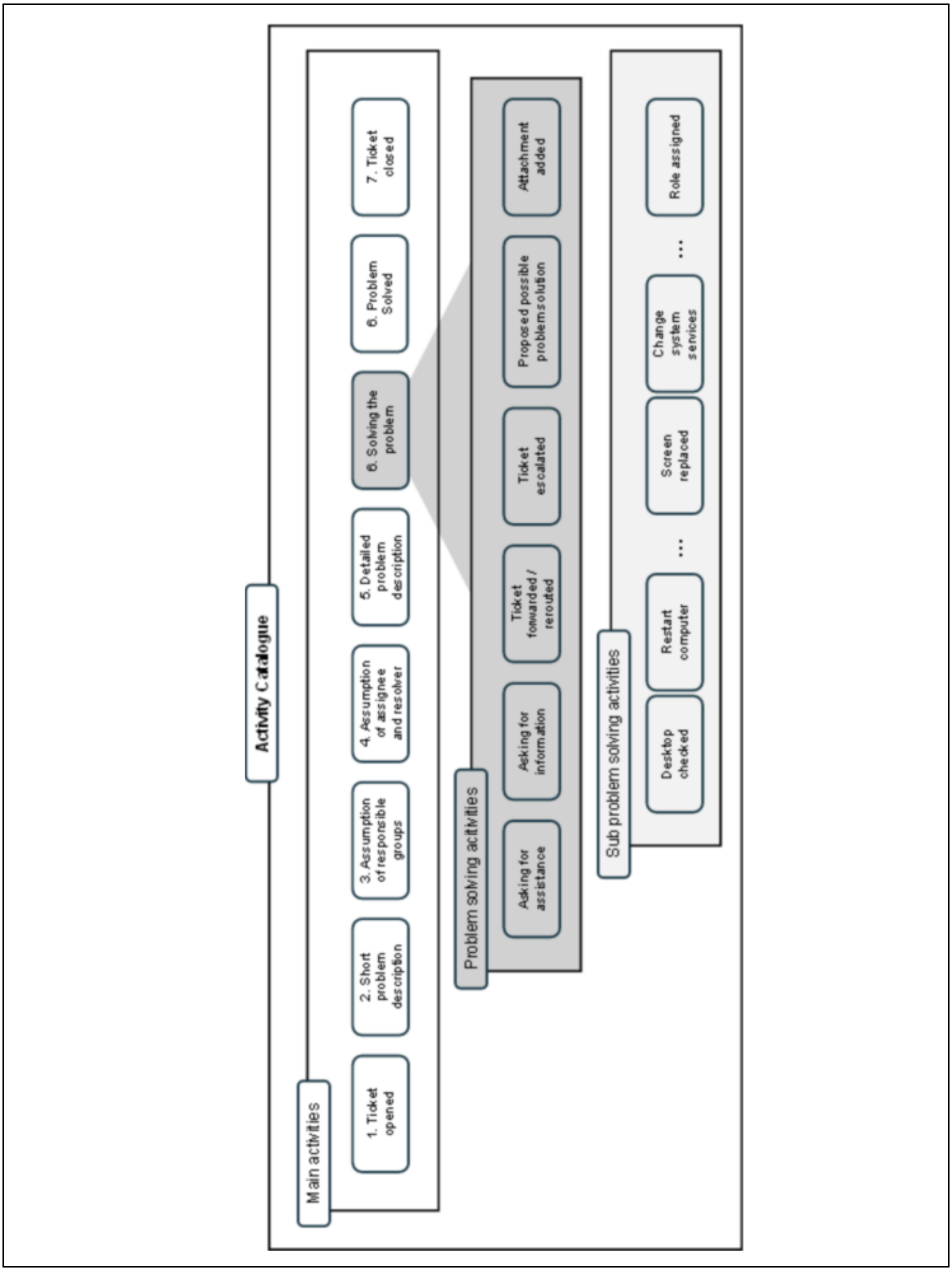

Figure 4: Exemplary Activity Catalog

5.1.5 Event Log

For this case study, an event log was manually compiled from ticket system data. By analyzing the ticket data, process instances, relevant activities, and their sequence were identified. Event logs were enriched with text-based information from agents' comments and notes, adding complexity and deeper insights into the processes. Missing timestamps, essential for process mining, were manually added, and a sorting column ensured the logical, sequential order of the process.

According to the guidelines for creating an event log, a distinction is made between timestamp-based activities, which are provided with an exact timestamp by information systems, and day-based activities, which have no or the same timestamp (Celonis Inc., 2024). In such cases, setting up a sorting column in the event log is crucial. This column allows the system to interpret the correct sequential order of the process activities. Activities with timestamps all receive the same sorting value (in this case the numerical value 10) in the event log, while activities without automatically created timestamps or those with the same timestamps are assigned ascending sorting values. The activity with the lower sorting value is considered to be the one that takes place first. Figure 5 shows an excerpt of the event log.

5.2 Process Mining Analysis

Next, we utilized the derived activities and the extracted event log to perform process mining analysis including (1) process discovery, (2) process conformance, and (3) process enhancement.

5.2.1 Process Discovery

Process Discovery (PD) is a central concept in the field of process mining. It describes the methodology with which process models are automatically generated from the data of an event log. These models depict the actual observed behavior of business processes and thus function as their actual models (Van der Aalst & Carmona, 2022). They not only precisely visualize the observed behavior, but also describe it from the perspective of the control flow, which focuses on the sequence of activities (Van der Aalst et al., 2012). The main objective of PD is to create transparency about the existing processes by making the real processes visible and understandable. In this case study, PD develops are model of the service interactions and touchpoints.

Case ID	Timestamp	Activity	Attribute – User	Attribute – Main category
INC0000017825	2021-01-05 07:34:35	Ticket opened	Agent 14	Client-Hardware
INC0000017825	2021-01-05 07:34:43	Short problem description	Agent 14	Client-Hardware
INC0000017825	2021-01-05 07:35:43	Problem categorization	Unknown agent	Client-Hardware
INC0000017825	2021-01-05 07:35:48	Assumption of responsible groups	Unknown agents	Client-Hardware
INC0000017825	2021-01-05 07:35:53	Assumption of assignee and resolver	Multiple users	Client-Hardware
INC0000017825	2021-01-05 07:35:53	Detailed problem description	Agent 16	Client-Hardware
INC0000017825	2021-01-05 07:35:53	Solving the problem	Multiple agents	Client-Hardware
INC0000017825	2021-01-07 08:06:50	Waiting for vendor to replace PC	Agent 17	Client-Hardware
INC0000017825	2021-01-07 08:36:54	Arranging vendor to replace the PC	Agent 17	Client-Hardware
INC0000017825	2021-01-08 09:36:03	Problem resolved	Agent 17	Client-Hardware
INC0000017825	2021-01-11 10:00:00	Ticket closed	Unknown user	Client-Hardware
INC0000028344	2021-01-05 16:08:52	Ticket opened	Agent 19	Client-Hardware
INC0000028344	2021-01-05 16:08:52	Short problem description	Agent 19	Client-Hardware
INC0000028344	2021-01-05 16:08:52	Problem categorization	Unknown agent	Client-Hardware
INC0000028344	2021-01-05 16:08:52	Assumption of responsible groups	Unknown agents	Client-Hardware
INC0000028344	2021-01-05 16:08:52	Assumption of assignee and resolver	Agent 21	Client-Hardware
INC0000028344	2021-01-05 16:13:14	Solving the problem	Multiple agents	Client-Hardware
INC0000028344	2021-01-05 16:13:14	Detailed problem description	Agent 21	Client-Hardware

Figure 5: Excerpt from the Created Event Log

Case ID	Timestamp	Activity	Attribute – User	Attribute – Main category
INC0000028344	2021-01-05 16:13:14	Bitlocker provided	Agent 21	Client-Hardware
INC0000028344	2021-01-05 16:15:28	Attachment 1 added	Agent 21	Client-Hardware
INC0000028344	2021-01-05 16:15:36	Attachment 2 added	Agent 21	Client-Hardware
INC0000028344	2021-01-05 16:15:46	Attachment 3 added	Agent 21	Client-Hardware
INC0000028344	2021-01-05 16:16:00	Attachment 4 added	Agent 21	Client-Hardware
INC0000028344	2021-01-05 16:17:35	Need to check in range on-site	Agent 22	Client-Hardware
INC0000028344	2021-01-05 16:48:48	User contacted	Agent 23	Client-Hardware
INC0000028344	2021-01-08 15:00:49	Problem resolved	Agent 20	Client-Hardware
INC0000028344	2021-01-13 16:00:13	Ticket closed	Unknown user	Client-Hardware

Figure 5: Excerpt from the Created Event Log (continued)

The process model was generated using the *Celonis* software tool and is based on the previously manually created event log. The model in Figure 6 represents the so-called *happy path*, a process chain that reflects the optimal flow of the process. This path is characterized by the most frequently occurring start and end activities, supplemented by all intermediate activities that have been identified in this particular form and that establish a connection between the start and end points of the process (Celonis Inc., 2022). The "happy path" determined by the software includes 72.8 percent of all activities and 66.3 percent of connections, with an average runtime of 71 days per case.

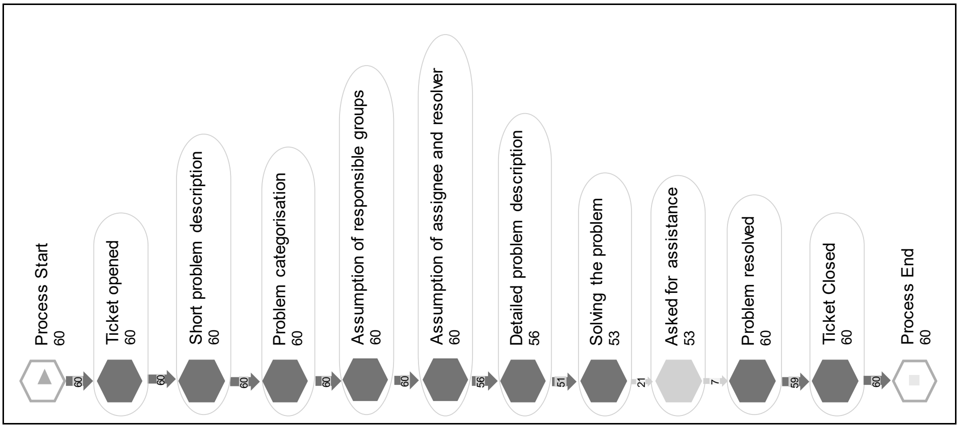

Figure 6: Happy Path

In the process explorer view, the actual process flow can be observed more precisely, which enables a deeper understanding of it. This sequence indicates the so-called *lasagna process* (Van der Aalst, 2011). The aforementioned process is largely structured, the workflows are clearly defined, there are few exceptions and most cases are handled according to a set pattern. Such processes are highly adaptable and allow stakeholders to identify deviations in the processing of certain tickets and unexpected behavior (Van der Aalst, 2011). For example, certain process steps such as "detailed problem description" or "problem resolved" are skipped (Figure 7). Unexpected loops and activities in a waiting state that can slow down the course of the process can also be identified. Furthermore, processes can be identified that have a longer runtime and can therefore be seen as a potential cause of customer dissatisfaction or a weak point in the process. For example, in some cases, it takes an average of 123 days from the ticket escalated to the problem being resolved, 159 days from the ticket being forwarded to the problem being resolved, and 52 days from asking for assistance to the ticket being resolved.

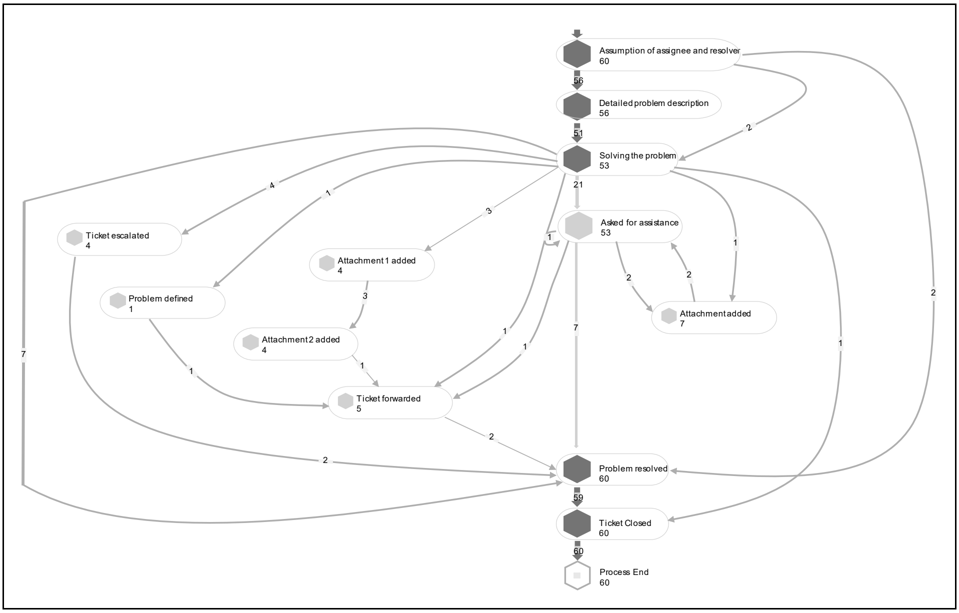

Figure 7: Skipping Process Steps

The *variant explorer* (Figure 8) visualizes the most frequently occurring process variants. By adjusting parameters in the application settings, such as the number of cases per variant or the cycle times, this view enables a multidimensional examination and analysis of the process from different perspectives. A total of 49 process variants were identified, six of which, which together cover 28 percent of all cases, are illustrated in the figure above. In this context, the process step that takes an unusually long 123 days is highlighted.

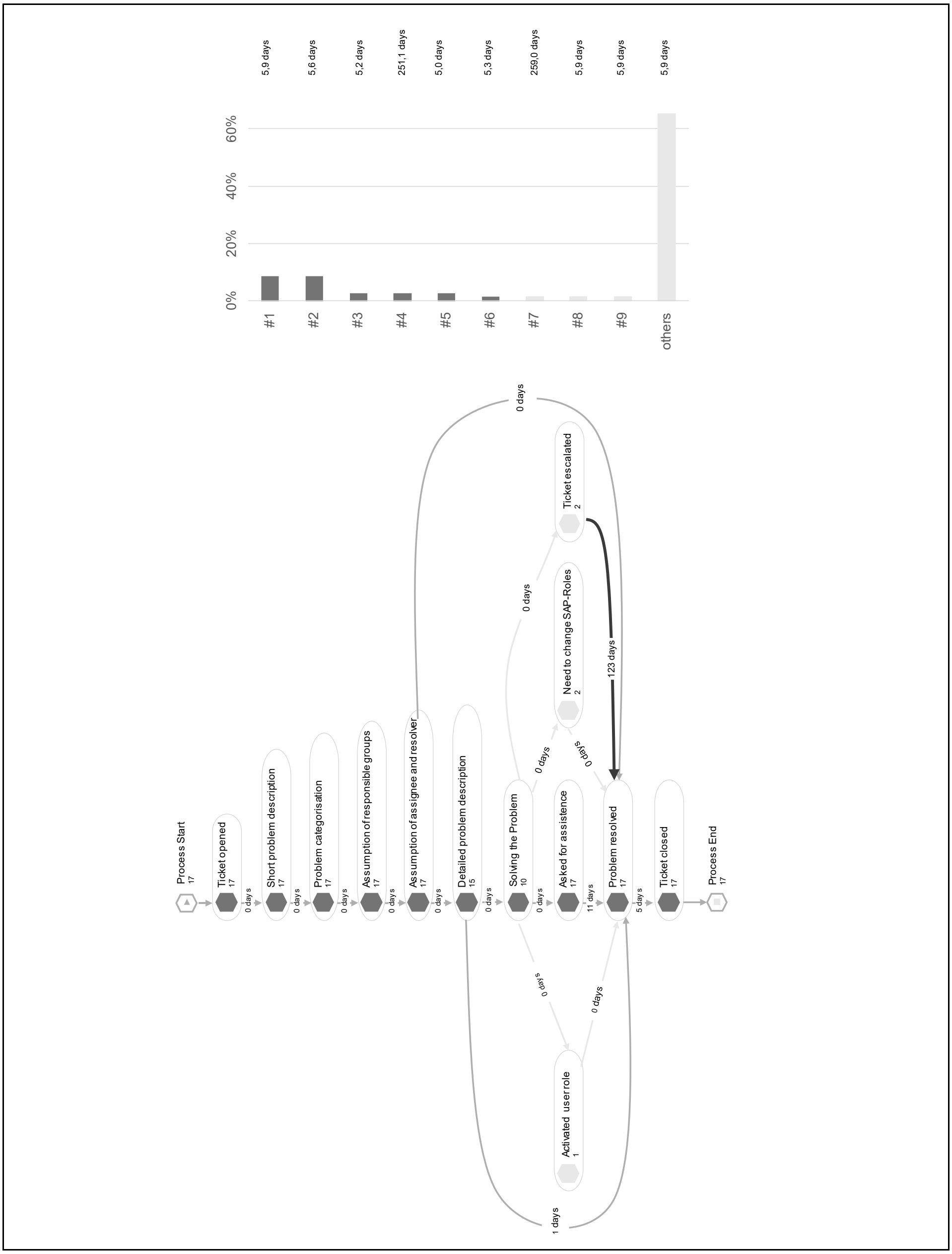

Figure 8: Process Variants

5.2.2 Process Conformance

Process conformance is a method in the field of process mining that aims to compare events in an event log with activities in a process target model and to identify similarities and deviations between the modeled and observed behavior (Van der Aalst, 2011).

The non-conformity of the model can depend strongly on its purpose and does not necessarily mean negative deviations. There is often a positive correlation between non-conformity and flexibility (Van der Aalst, 2011). This is also relevant in this case study, as processes in the IT helpdesk often exhibit a certain degree of flexibility when working out solutions. Therefore, deviations of the actual model from the target model do not necessarily indicate faulty behavior of the process itself. The conformity check can therefore reveal both undesirable and desirable behavior and provide important information for improving the control of the process (Van der Aalst, 2011).

The BPMN target model created with *Celonis* (Figure 9) makes it clear that some process steps are skipped in the normal course of the process. In certain cases, the process step "Solving the problem" is not carried out, as some problems in the IT area can be trivial and do not require a formal problem-solving process. Similarly, the "Asking for assistance" step is not carried out in all cases.

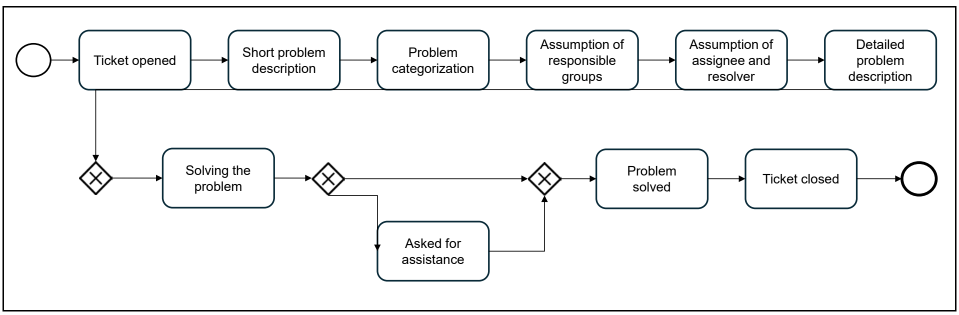

Figure 9: Target Model

The analysis of process conformance should be further extended to sub-activities to enable a more granular analysis of to-be processes.

5.2.3 Process Enhancement

The third category of process mining is process enhancement, which aims to extend or improve existing process models based on information about the actual process documented in an event log (Van der Aalst, 2011).

One possibility for improvement is to revise the existing model to achieve a more realistic representation (Van der Aalst, 2011). For example, the model can be adapted to the extent that deviations in IT support identified during process discovery, such as unexpected loops or identified activities in a waiting state or excessively long throughput times, are placed in the correct order in the model without any time delay.

Furthermore, the process model can be extended by integrating additional data or attributes from the event log to gain a better perspective (2011). The manually created event log contains information on resources, main and subcategories of tickets, type of ticket, and type of first contact. This data can be integrated into the process model and visualized. As a result, additional aspects of the process are taken into account to enable a more comprehensive analysis and identification of improvement opportunities.

The *Celonis* tool offers additional options that enable a change of perspective for better visualization of the process and more precise analyses. For example, an analysis of contact types shows that most contacts are made via self-service. However, incidents reported by email are resolved the fastest. This may be an initial indication that the speed of the ticket solution could potentially be improved if most incidents were reported by email. Furthermore, the throughput times per respective helpdesk group can be used to see whether an increase in personnel is necessary or whether process optimization within this group could be necessary.

6. Discussion

The literature analysis highlights how process mining can improve business processes, especially in IT support, by integrating structured and unstructured data through text mining. Current studies indicate that process models can be developed using both structured performance data and unstructured text data. However, challenges include the complexity of human language and the selection of appropriate methods to transform language data into process models. Despite the ambiguity and context-dependency of text data, process and text mining methods, including enriched event logs, offer new possibilities for business process modeling and investigation. Specific software tools for process and text mining are crucial for analyzing and evaluating service processes. These tools efficiently handle large data sets from IT ticket systems, recognize complex patterns, and increase result reliability. While the literature review provides a broad overview, the case study offers more specific insights.

The case study applied process mining and selected text mining methods to a large IT ticket data set, aiming to gain in-depth insights into process flows. 60 use cases in three categories were analyzed, focusing on various process and text mining techniques. Text mining techniques included tokenization, stop word filtering, n-gram generation, and clustering to cleanse and process unstructured text data from IT ticket comments and notes.

This created a catalog of main and sub-activities, identifying recurring patterns and sub-activities within ticket comments and notes, as well as an enriched event log for process mining. The processed data was analyzed using process discovery, conformance, and enhancement methods to create and compare actual and target process models. The results demonstrate process mining's potential to identify inefficiencies and uncover optimization opportunities.

6.1 Contributions to Literature and Practice

We make contributions to the literature by transferring process mining methods to the field of digital analytics in IT support services. Despite a large number of studies analyzing textual ticket data (Zaidi et al., 2022; Liessmann et al., 2024; Rizun et al., 2021), our study presents a new approach to interpreting and making sense of documented service interactions from a processual perspective. We thereby relate to prior works of Pentland, (1992) and Das (2003) concerning identifying recurring patterns of actions, that we refer to activities and sub-activities in this study. Thereby, we differentiate between service process efficiency on a level of standard ticket processing (i.e., identifying the problem, routing the ticket, etc.) and a deepening level of sub-activities that are related to certain categories of tickets (i.e., resetting a password, activating bitlocker, etc.). Our study contributes a data model for analyzing services concerning their order of events and hence can extract and detect routines and routine change in large unstructured ticket data. We argue that this view will be crucial to also analyze changes regarding the infusion of (generative) AI into customer support services (Reinhard et al., 2024a, 2024b). Process mining can shed light on the real-world consequences of generative AI at the workplaces of service employees (Mrass et al., 2017) and its implications for customer satisfaction. Additionally, future research can understand how service employees shape their workplaces from a perspective of job crafting (Li et al., 2022) that will manifest within various system logs.

Practitioners can easily adapt our approach to analyzing their ticket data considering a process mining logic. The pre-processing pipeline can guide the preparation of large textual data on service interactions that are documented manually or transcribed automatically using speech-to-text technologies. Our main practical contribution lies in deriving an *activity catalog* and enriched *event logs* that represent the foundation of any process mining-related analysis. Especially, the outlined multi-level perspective of activities in IT support services enables service managers and operators to further extend our endeavors to automatically identify activities and sub-activities that are subsequently transferred into event logs. Including ticket categories and other meta-data as additional attributes within the event logs allows them to identify specific target processes, examine variants on sub-activity level, and thus come up with implications for optimizing working steps and instructions to solving certain problems.

To improve the ability to analyze IT support tickets, the development of targeted training programs and workshops for IT support employees would be of essential importance. In particular, these measures should aim to promote precision and consistency in the recording of problems within the ticketing system. Such training could raise awareness of the importance of structured and consistent data collection (Reinhard et al., 2023; Schmidt et al., 2021), which is an essential basis for the successful application of process and text mining methods. Sharing best practices and experiences between organizations could lead to a modular ticketing system (Li et al., 2017; Peters, 2016). This system would allow IT support staff to choose from predefined solutions, improving data consistency and facilitating ticket analysis. Reducing data variability would enhance the effectiveness of the process and text mining techniques in identifying patterns and improving processes, paving the way for fully automated data analysis.

6.2 Limitations and Future Research

The integration of process mining and text mining is promising but methodologically challenging, with several limitations that suggest implications for future research.

Analyzing unstructured text data from IT support tickets is complex and error-prone due to the multi-layered and ambiguous nature of natural language. This difficulty requires expert knowledge for deep data understanding. Cleansing and structuring the data, and addressing incompleteness, and missing timestamps are additional challenges. Future research should focus on developing advanced natural language processing techniques to better handle these complexities. The quality of data significantly affects the analysis. Tickets with less "conversational" problem descriptions, such as those in "Client Hardware", were easier to analyze. In contrast, the "SAP Services" and "Business Applications" categories still had impurities even after data cleansing, resulting in incomplete sub-activity determinations. Future research should aim to improve data cleansing methods and develop techniques to handle varied data quality more effectively.

The case study revealed that the available raw data was often insufficient or completely missing, and descriptions were recorded in different languages, complicating uniform text mining processing. Future research should investigate ways to ensure more comprehensive data documentation by service employees and explore methods for multilingual text processing. Service employees do not completely document their steps and interactions, making data analysis difficult. Implementing automatic transcripts of calls and other service interactions could address this issue. Future research should explore automated documentation techniques to improve data completeness. Tickets only provide an assumption of real service interactions, missing non-digital customer-agent interactions. Future research should consider integrating non-digital interaction data to provide a more accurate representation of service processes. There is no automated generation of event logs and activity catalogs, hindering efficient analysis. Future research should focus on developing automated methods for event log and activity catalog generation. While process discovery is strong, conformance and enhancement are weak. Future research should aim to enhance the capabilities of process mining techniques in these areas to provide a more comprehensive analysis of business processes.

7. Conclusion

This study explored the integration of process mining and text mining to optimize IT support service processes by leveraging knowledge documented in IT tickets. The literature review highlighted the potential of combining process mining, which evaluates event logs, with text mining, which extracts knowledge from unstructured data, identifying key techniques for process modeling and the relationships between actual activities and textual data. A case study demonstrated these methods in IT support scenarios, mapping actual processes and uncovering patterns and inefficiencies. Text mining techniques extracted relevant information from IT tickets, identifying recurring themes and problem-solving strategies. A catalog of activities revealed specific patterns within the tickets. Process conformance analysis revealed discrepancies, suggesting a link between deviations and flexibility. Process enhancements aimed to improve efficiency, processing times, and customer satisfaction. Findings show that integrating process and text mining enhances IT service management by providing a deeper understanding of processes and uncovering inefficiencies. This approach visualizes, analyzes, and optimizes complex process flows, improving service quality. In summary, this study underscores the potential of process and text mining in IT support, offering insights and future research directions for improving service quality. Future research should consider human-centric aspects that are not part of system data and cannot be addressed by process mining alone. This could be achieved, for example, through interviews and qualitative studies that extend computational approaches.

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