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Evaluation of patient transport service in hospitals using process mining methods: Patients' perspective

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Abstract

Designing healthcare facilities and their processes is a complex task which influences the quality and efficiency of healthcare services. The ongoing demand for healthcare services and cost burdens necessitate the application of analytical methods to enhance the overall service efficiency in hospitals. However, the variability in healthcare processes makes it highly complicated to accomplish this aim. This study addresses the complexity in the patient transport service process at a German hospital, and proposes a method based on process mining to obtain a holistic approach to recognise bottlenecks and main reasons for delays and resulting high costs associated with idle resources. To this aim, the event log data from the patient transport software system is collected and processed to discover the sequences and the timeline of the activities for the different cases of the transport process. The comparison between the actual and planned processes from the data set of the year 2020 shows that, for example, around 36% of the cases were 10 or more minutes delayed. To find delay issues in the process flow and their root causes the data traces of certain routes are intensively assessed. Additionally, the compliance with the predefined Key Performance Indicators concerning travel time and delay thresholds for individual cases was investigated. The efficiency of assignment of the transport requests to the transportation staff are also evaluated which gives useful understanding regarding staffing potential improvements. The research shows that process mining is an efficient method to provide comprehensive knowledge through process models that serve as Interactive Process Indicators and to extract significant transport pathways. It also suggests a more efficient patient transport concept and provides the decision makers with useful managerial insights to come up with efficient patient-centred analysis of transportation services through data from supporting information systems.

KEYWORDS
Patient Transport Service, patients' perspective, process improvement, process mining, transport delays

Highlights

- The use case in a German hospital showed that process mining methods allow finding root causes for conformance issues and delays in the patient transport service process.
- Considering a punctuality threshold of 10 min, there was about 9000 h of annual delay and in around 40% of all cases the transporters arrived late at the patients' pick-up location.
- For holistic evaluations the integration of events from different software systems that cover interrelated processes is essential.
- It is crucial to increase the awareness among involved employees regarding process flaws, continuous monitoring and active implementation of improvement strategies.

1 | INTRODUCTION

The expanding patient-oriented perspective in healthcare organisations strengthens the importance of providing efficient and timely healthcare services to the patients. To fulfil this aim, intra-hospital patient transport is one of the great contributors since it is a very high prevalent process. Intra-hospital transport is a service department responsible for internal patient transport, for example, between hospital units, examination departments, functional units, operating rooms, etc. The efficiency of this service and its processes has a remarkable effect on clinical outcomes and patient satisfactions.[1–3] A cross-sectional analysis of 191 incidents during intra-hospital transport reported 31% adverse outcomes.[1] Another study reports that at least one significant complication occurred in 36% of 288 transport cases in brain-injured patients.[4] Increased waiting times and transport duration caused by inefficient processes, contribute to increased costs and patient frustration. Moreover, due to the increasing demand for healthcare services and the ongoing cost burdens on hospitals and other healthcare organisations, there is a strong urge to improve the quality and efficiency of the healthcare processes.

In contrary to other organisations, processes in healthcare are very complex, unpredictable, ad hoc and furthermore have higher impacts on human health and life. Hence, processes can turn out to be much more complex in actual operation than they were originally planned or assumed. Hospital information systems have tremendous amount of data from patients, machines and monitoring systems, which could be converted into useable information enabling value-based decision-makings. However, for a risk averse sector like healthcare, which deals with human lives, the pace of application of analytical methods has been slow.[5] There are numerous applications of analytical methods which have proved their benefits and advantages in analysing operational processes. In this endeavour process mining methods, emerged over the last decade, play an unprecedented role in analysing healthcare processes. They helped many researchers to optimise processes and enhance their efficiency through discovering process complexities and deviations. However, these methods have rarely taken patients' perspective into account.

The main research questions of this paper are: how can process mining help us to evaluate patient transport services and what are the technical prerequisites to come up with efficient patient-centred analysis of transportation services and related information systems. Therefore, the aim of this study is first to evaluate patient transport service process as well as possible causes of inefficiencies and resulting waiting times using process mining methods. For this purpose, a process mining tool is applied to real-world data from a hospital in Germany. The usefulness and the suitability of process mining tools in discovering healthcare processes is elaborated in Section 2.2. Later, improvement concepts including technical requirements for data capturing to enhance the patient satisfaction are suggested. These suggestions are given after consultation with the process managers at the case study hospital. This paper is organised as follows: Section 2 describes the significance of intra-hospital patient transport services and reviews relevant literature on process mining as well as its applications in healthcare and pertinent data challenges. It also highlights the contributions of this paper. Section 3 describes the materials and methods, the case study with the underlying data, the relevant interpretations and the obtained results. Section 4 provides discussions regarding the findings, improvement concepts and the limitations of the study. Finally, the paper concludes in Section 5 and suggests ideas for future work.

2 | RELATED WORK

This section reviews relevant literature. The following literature is chosen to provide a definition of patient transport services and give an overview of common parameters to evaluate their efficiency. This section further gives an introduction to fundamentals of process mining and examines literature on the application of process mining in healthcare. Lastly, data challenges in process mining for healthcare and highlights the contributions of this paper are discussed.

2.1 | Patient transport service

Patient treatment represents the primary process of a hospital, which encompasses all diagnostic and therapeutic tasks from admission to discharge of the patient. All remaining processes which support the primary process by providing the services necessary for treatment are called secondary processes.[6] They can be either medical (e.g., laboratory, pathology) or non-medical (e.g., catering, waste management, patient transport).

One of the secondary processes considered as high-cost secondary activity is the intra-hospital transport service.[7] The efficiency of this service is one of the important factors influencing patients' satisfaction. Patients may not be able to objectively judge the quality of the medical care they receive. However, their satisfaction during their stay in hospitals is massively influenced by waiting times for receiving a service. Suppose that a patient has to be transported to an expensive facility within the hospital, for example, radiotherapy department. Delays in the transport process (apart from the root causes) lead to not only idle times for medical equipment and the technical staff but also decrease patient satisfaction because of long waiting times and possible appointment cancellations.

In literature, transport duration and the associated waiting times are suggested as an important determinant of patients' satisfaction.[8] Efficient patient transport also ensures patient safety and efficient treatment.[9] Chang et al.[10]

identified four safety indicators for patient transport service processes from emergency departments. They highlight duration of transport processes as one of the safety indicators alongside respiratory, circulatory, and equipment. Ulrich and Zhu[3] emphasised also the importance of the transport services and pointed out that inefficient patient transport can lead to transport related clinical complications and affect the patient outcomes. In this regard, Parmentier-Decrucq et al.[11] and Alizadeh Sharafi et al.[12] concluded that inefficient transport processes may lead to significant number of adverse incidents during transporting critically ill patients.

There are different factors influencing the efficiency of the transport services, such as hospital layout and staff effectiveness. There is no doubt that the location of the facilities remarkably impacts the distances to be travelled by patients and nurses. However, for the existing hospital buildings where the location of the facilities cannot be changed, the focus should be on reducing waiting times, enhancing staff effectiveness and properly organising and assigning transport requests.

2.2 | Fundamentals of process mining

Process mining is a method motivated by the aim of extracting non-trivial knowledge from event data about processes, that are supported by information systems. In this context, any operational processes (organisations and systems) can be understood as a process[13] and a process could be defined as a 'coherent series of changes that unfold over time and occur at multiple levels'.[14] The prerequisite for process mining is an event log, which can be considered as a particular view on event data extracted from the process supporting information systems.[13] Within an event log certain information need to be present in order to apply process mining methods. An event log must, as a minimum, contain information per sequentially recorded event, on the executed activity and on the case id that links the event with its information to an individual case.[13,15] Thereby an activity represents a 'well-defined step in the process' and a case reflects a sequence of events.[13,16] To analyse performance related properties a corresponding timestamp per event has to be existing in the event log, too.[13] Possibly events from the event log can contain or can be related to other attributes.[13,16] These can, for example, be resources (like operating persons, related devices and systems, etc.) costs or other data elements (involved locations, sizes of products, etc.).[13,16]

Process mining facilitates discovering process models from event logs and accordingly identifies sequential, time-related patterns and also resource patterns.[17] A process model can be seen as a 'map' describing the life-cycle of a case of a particular type and is in general used to achieve and visualise process insights, to structure discussions between stakeholders, to instruct people, to document for certification procedures, to find errors in systems and procedures, to conduct performance analysis, to specify requirements and configure supporting information systems, etc.[13] Process mining can be applied to any type of organisation and any type of operational processes in case of availability of appropriate data.[13] Nowadays, there are many relevant sub-areas in process mining that can be found in the literature. In the following, we focus in more detail on the three historically most established and fundamental sub-areas[13,16]:

- The first sub-area is process discovery. A discovery technique produces a process model based on the behaviour seen in the event log.
- The second sub-area is process conformance. Conformance checking compares an existing process model with the behaviour from the event log of the same process. This technique helps to check to what extent the discovered process behaviour conforms to the facing process model.
- The third sub-area is process enhancement. The purpose is to extend and improve the existing process model through continuous comparison of information about the behaviour captured in the event log.

Generally, there are different algorithms to discover process models from event logs which can lead to different models, such as Alpha miner,[15] Heuristic miner,[18] Inductive Miner,[19] Spilt Miner[20] and Fuzzy Miner.[21]

Alpha Miner was the first process discovery algorithm and carried out the basis for the development of further algorithms.[13] The main limitation of Alpha Miner is that it is only applicable to event logs without noise.[22] Noises are sporadic and infrequent behaviour in event logs that are not representative for the normal behaviour of the process.[13] Heuristics Miner is an algorithm deals with noise in event logs by introducing frequency-based metrics.[23] Inductive Miner has a special feature to preprocess an event log to construct directly-follows relationships and then discovering process trees.[24] However, Inductive Miner algorithms often lead to oversimplified models.[25] Similar to the Inductive miner, the Split miner extracts directly-follows relations. In contrast to Inductive Miner, the Split Miner is able to discover process models that more accurately represent the process behaviour captured in the event log,[26] yet it often produces complex models that are difficult to interpret. A different approach to the previous ones is the Fuzzy Miner. This algorithm was developed to explore unstructured processes and offers the flexibility to adjust user-defined levels of significance and correlation thresholds.[21] Most of the process mining commercial software algorithms are based on the Fuzzy Miner, such as *Celonis®* Tools[27] and *Fluxicon® Disco*.[28]

To describe process models, there are numerous notations, such as Directly-Follows Graphs (DFGs), Petri nets, Business Process Modelling and Notations (BPMN), and Unified Modelling Language (UML).[29] The three later are sophisticated notations and able to capture concurrent activities. However, they are regarded as too complicated for users and they need considerable computation time.[30,31] In contrast, DFGs offer simplicity and performance which make them more suitable for Commercial process mining tools. Nevertheless, as result of this simplicity, concurrencies and causalities are normally not taken into account.[30] For further details about different notations the reader is referred to van der Aalst[29] and van der Aalst.[32] Commercial tools also offer interactive filters and user-friendliness which make them successful and they are also gaining popularity in healthcare organisations. However, limitations and impacts of DFGs are discussed in Section 4, as they are used for analysis in this paper.

The event log data used in process mining for the discovery of process models contains information about the executed processes, which in general could be extracted automatically and fed into process mining tools with minor time efforts. The major benefit of process discovery is that it provides insights about what has been really executed in volatile environments like hospitals.[33] These advantages make process mining an attractive alternative to conventional process mapping methods, which are mainly based on interviews, and thus, subjective understandings of people about executed processes. The conventional process mapping methods are therefore very time consuming and cannot give us accurate insights about the real processes. Process mining also allows a simple and illustrative generation and demonstration of knowledge about processes, which clearly differs from conventional attempts to investigate abstract and seemingly infinite data tables.[34]

2.3 | Process mining in healthcare

To discover the healthcare processes and detect the deviations from designed schemes, process mining is gaining recently more attention in healthcare. As mentioned, the primary outputs of process mining are process models demonstrating the relationships and frequencies between activities in so called control flow models.[13] Based on the frequencies the most commonly used clinical pathways can be highlighted to gain knowledge about the real course of the healthcare processes to design more efficient processes and layouts.[35,36] Likewise rare variants can be pointed out and investigated to evaluate more deeply the positive or negative outcomes or relations of outliers within the process.[37] In this way, for instance, bottlenecks caused by infrequent behaviour can be analysed or commonalities in non-standard processes can be found.[37]

Process mining can extract knowledge from event logs that may be pulled out of various systems such as hospital information systems, radiology information systems, picture archiving and information systems, laboratory information systems, electronic health records, enterprise resource planning systems, product data management systems, patient logistic systems, etc. Section 3.1 presents the parameters of the data set examined in the case study of this paper and describes the specific fulfilments of the event log requirements introduced in Section 2.2.

In terms of the hospital context, process mining has been mostly applied to medical healthcare processes and clinical pathways.[38] Therefore, in our review we focussed on these two application contexts and selected mainly frequently referred papers published in the last 10 years.

Fernandez-Llatas et al.[39] developed a process mining-based methodology in combination with indoor location systems to analyse and study the behaviour of surgical processes. Rojas et al.[40] applied process discovery to investigate the emergency room processes and determined which activities, sub-processes and interactions lead to longer process duration. Yoo et al.[41] used process mining methods to analyse the effects of the environmental changes such as construction of a new building on process times like waiting time for consultation, required time for each activity, and the entire outpatient processes. Kim et al.[42] applied process mining to discover outpatient care processes. They also compared the machine-driven processes with a domain expert-driven process model and found an accuracy matching rate of 89%.

De Oliveira et al.[43] proposed an unsupervised process mining method to analyse the patient pathways. They focussed on patients suffering from diabetes. Agostinelli et al.[44] analysed patient flows in the departments of outpatient clinic, emergency room, and hospitalisations. Their analysis is done from three different perspectives of control flow, organisational and performance. Halawa et al.[45] proposed an integrated framework which takes the advantages of process mining and simulation to optimise the clinical layout design. They focussed on patient pathways and the frequency of patient visits between spaces. Rismanchian and Lee[46] analysed the clinical pathways in an emergency department and optimised the layout considering three objectives of minimising distances travelled by patients, maximising design preferences and minimising relocation costs. Arnolds and Gartner[47] used process mining methods on clinical pathway data to recognise the significant pathways and then solved the hospital layout planning as quadratic assignment problem.

The use of machine learning techniques in combination with process mining enables us to fully leverage the advantages of process mining techniques to achieve a holistic view of patients' journey. For example, Theis et al.[48] used such an advantage to predict the in-hospital mortality of diabetes ICU patients. This, of course, needs patients' medical history which goes beyond the information captured in the hospital information systems. Using a similar approach Pishgar et al.[49] used admission data and clinical course of hospitalised COVID-19 patients to predict their mortality.

The mentioned studies mostly tended to use process mining to discover process variations and conduct performance analysis to recognise the possibilities for process improvement. Process discovery is the starting point for further explorations and investigations. For this reason, a higher percentage of studies concentrate on just process discovery.[50] Moreover, the applications in healthcare mostly focus on single departments and the application at larger scales for example, multiple departments are less considered.[38]

The application of process mining methods has been rarely used to measure the patient satisfaction. Only a handful of research studies have evaluated patient satisfaction with the help of process mining. They suggest that process mining tools can be used to uncover process deviations to come up with solutions which increase patient satisfactions. For example, Ganesha et al.[51] analysed the event logs for CT tests using the fuzzy miner algorithm to evaluate patient waiting times and suggest that the model can be used to decrease waiting times.

2.4 | Data challenges in process mining for healthcare

Despite the advantages that process mining offers, there are challenges in the healthcare context that should be addressed. Kaymak et al.[52] argued the shortcomings of early process mining methods in medical contexts. They discussed, for example, that the use of process mining might lead to false sequence of medical activities, and thus, medical knowledge must be incorporated into process mining tools. Rojas et al.[53] discussed the challenges and limitations regarding the use of process mining methods in healthcare, for instance, data quality and the importance of the inclusion of medical knowledge as well as integration of data from other resources. Lismont et al.[54] addressed the issues of data irregularity, data abstraction levels, data abundance and data quality in healthcare. Munoz-Gama et al.[50] underlined 10 key challenges in process mining for healthcare. Among other challenges, they also addressed the data quality issues, data privacy in sensitive settings like healthcare facilities and their highly variable processes. It is outlined that raising awareness among healthcare professionals on the use of process mining is crucial and that further studies on real data beyond process discovery need to be undertaken.[50] Further challenges, elaborated by Munoz-Gama et al.,[50] include adopting the patients' perspective to integrate it into hospital information systems or other related systems, and aligning with frequently changing hospital processes.

To overcome the mentioned challenges, process mining experts emphasise on the necessity of continuous integration of expert knowledge and involvement of multidisciplinary teams.[35,50] In order to facilitate quick involvement of stakeholders, it is important to use techniques that do not require substantial process mining expertise. They should provide simple visualisations and be user-friendly.[50] In this regard, Fernandez-Llatas[35] introduced interactive process mining, with the goal of merging data-driven techniques with knowledge-driven approaches to provide an understandable way to investigate the processes. Using interactive process mining methods, process models can be generated, which can evolve to Interactive Process Indicators (IPIs) through coordination steps between the involved parties.[34] IPIs overcome conventional numerical KPIs through contextual and personalised views to support the evaluation of perceptual questions. They also offer the feature to be automatically formalised and learned[34] IPIs provide views on the status of the current processes and can be filtered and adjusted according to specific criteria available in the data.[34] In so called data rodeos, which are recurring joint sessions with all the relevant stakeholders (e.g., data analysts, process managers, executing personnel, patients) involved, interactive analyses of the data and latest process indicators are performed.[34,55] Within and around those interactive sessions, adjustments such as for example, data cleaning, filtering and adding meta data are performed to optimise the IPIs successively to make them understandable and value adding for the hospitals' stakeholders.[35,55]

Ibanez-Sanchez et al.[56] applied IPIs to investigate stroke emergency processes and support the application of value-based healthcare. Lull et al.[55] used IPIs to analyse primary care services based on the hospital information system data in a cardiology outpatient department. Further applications of IPIs in the healthcare domain can be found in Ref. 57. In Section 3.2 IPIs are applied to our use case.

All in all, in the healthcare context the application of interactively designed models as process indicators allow to unify data and knowledge-driven worlds and increase the acceptability of the technology by different healthcare stakeholders, in a way that after application they can understand how their processes are deployed.[58,59] It must be noted that in the healthcare context, patients are the central stakeholders and process mining experts and researchers should take patients' perspective explicitly into account to provide high quality care.[50]

2.5 | Research gaps and paper contributions

The reviewed literature shows that the majority of the research studies in the healthcare context focus on primary processes or evaluation of layout design. Application of process mining methods to analyse the efficiency of patient transport services has not been addressed to the best of our knowledge. Therefore, the main contribution of this study is to apply process mining methods to real data obtained from the patient transport-supporting software system in a German hospital. In this work, process efficiency, delays, transport duration, throughput times between process steps, as well as the identification of problem points and interrelationships of attributes are analysed. The findings can help to evaluate the appropriateness of the transport assignments and to assess patients' satisfaction.

As shown, some of the literature discusses the limitations of the data and process mining techniques in the healthcare domain and from a medical perspective for primary processes. This paper also provides important insights regarding limitation and challenges in using process mining, however, from a managerial point of view and for the patient transport services as a secondary process. Due to the above-mentioned advantages, IPIs are applied to our use case. Additionally, the prerequisites for a holistic data capturing to enable process mining methods for a more patient-oriented analysis of transport services are highlighted.

3 | MATERIALS AND METHODS

In this paper, a real case study is presented to show the capabilities of process mining methods in analysing patient transport processes. The case study is conducted in a German hospital with about 800 beds and approximately annual number of 75,000 inpatient and outpatient cases. An important background information is that the creation of an interface for the reconciliation of transport-related data between the transport-supporting logistics software system and the hospital information system is planned for the future. This interface is intended to support the process managers' goal of optimising the automation of scheduling and disposition of patient transportation assignments, resource-efficient control of transport capacities, increasing the system availability of the transport service, improving adherence to schedules and shortening transport-related waiting times. For this purpose it is necessary to understand how the processes are run in reality. The aim of this case study is to provide guidance on inefficiencies with improvement potential in the current patient transport service processes using process mining analyses. With the data based knowledge, process bottlenecks and inefficiencies that have direct impact on patients' satisfaction and possibly on their clinical outcomes can be recognised. It is crucial to analyse and recognise the process deviations between the as-is (process behaviour discovered in the event log) process based on the log data and the as-planned (assumed or intended process procedure designed prior by the responsible process managers) process via conformance checking. The underlying data helps finding the root causes for the process issues. Ideas concerning operational or managerial changes that possibly lead to process improvements as well as model enhancements will be addressed in the discussions in Section 4.

3.1 | Process information and event log specifications

The patient transport process consists of eight process steps, that are guided and logged by a supporting logistics software system from a German company. The as-planned process of the patient transport service is visualised in Figure 1. The data set analysed was an event log covering the period of the whole year of 2020. The timestamps of the activities were to the precise minute (not to the precise second) within the exported data set.

Currently, transport and route planning in the main operation time of the studied hospital are done manually, under simple technical conditions and planning premises (e.g., an assignment is sent to the next free transporter). The actual complexity of the system remains unrecognised. Given this background, the efficiency of the transport system is dependent on the individual skills of the dispatchers, their experience and the knowledge gained on the basis of available information. Validation and verification of the process is limited to simple visual and logical controls. The adequate control, coordination and optimal resource utilisation does not take place, although the basic technological prerequisites are given by the use of the patient transport-supporting software system and the information it collects.

Containing event information on case id, executed activity and timestamp, the case study data set fulfils the minimum information requirement to be used for process mining analyses (see Section 2.2). In this data set, the case id is an individual number referring to an individual patient transport request.

On the whole, 75,131 completed cases of patient transportation are identified with respectively 601,048 events (eight events with eight different activities per case). There are cases for which there was an initial request and some were multiply requested. When looking at the data of the multiple-requested transports, there were problems with the interpretation of the delay times, as only the first requested target time of the transport was present in the exported data sets. Therefore only the transports that were requested for the first time are considered for the analyses of this use case. After filtering just on the initially requested cases there remain 62,782 cases with 502,256 events to be analysed. Figure 2 shows characteristics of the underlying data set for these cases. This data set is transformed through an R script into a second data set for the analysis. The original data set listed all the case-relevant information, including event-specific information of different events belonging to the case, in columns per case. The reason is that for the used analysis tool, it is necessary that event-specific information is listed in rows per event.

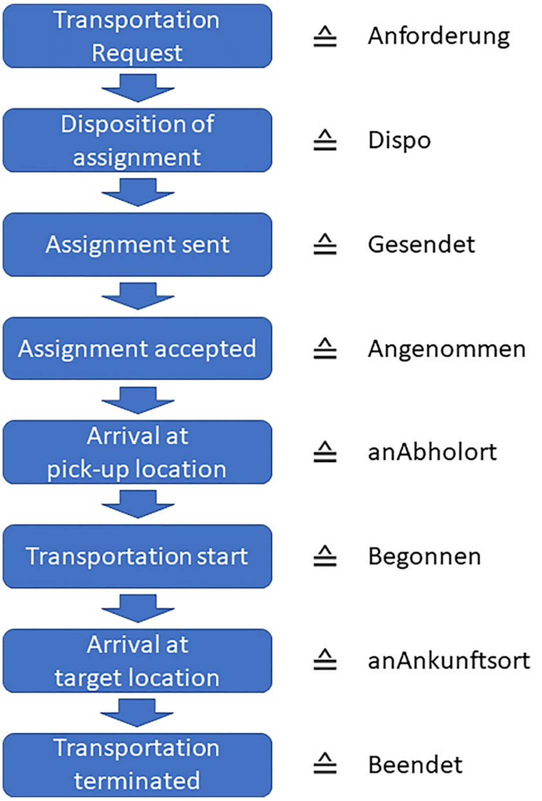

FIGURE 1 Eight process steps from the patient transport service process (on the right, the software designations of the steps, that are based on German, are shown).

The generated second data set finally contained 502,256 rows containing information per event split in four columns with the case id, the activity, the timestamp of the events, a sorting column. In the sorting column a number from '1' to '8' corresponding to the specific activity per event according to the sequence of the process steps in Figure 1 was manually added and matched to each event. The sorting column helps to put the events in a correct order, if timestamps of two or more events appear to be the same. Last but not least, the transformed second data set is linked through the unique case id to all the additional information from the original data set, that is characterised in Figure 2. Together the data sets allow for more comprehensive analysis due to the possibility of conducting attribute-related evaluations.

In the original data set of the completed patient transportations, that were requested only once (see Figure 2), there are 118 case-related attribute categories, like requesting centre, assignment centre, cost centre, last control station, first control station, priority, pick-up location, target location, pick-up house, arrival house, pick-up level, arrival level, pick-up priority, arrival priority, route id, route description, distance, remarks, service provider, operator, tour, type of transport vehicle, patient id, pick-up room number, pick-up room, arrival room number, arrival room, complaint text, complaint category. However, some of them cannot be found consistently for the cases. For the evaluations in Section 3.2 some of the mentioned attribute categories will be utilised to demonstrate the evaluation opportunities that are possible with additional information that go beyond the minimum requirements for an event log (activity, timestamp, case id). In overall 7,408,276 data cells in the original data set (62,782 cases times 118 attribute categories) there were already 1,224,013 cells without information (NULL/NA values). Figure 2 furthermore classifies the attribute categories and sketches the average and median number of entries with relevant information for the outlined attribute categories (subtracting these values from the total of 62,782 gives the number of missing

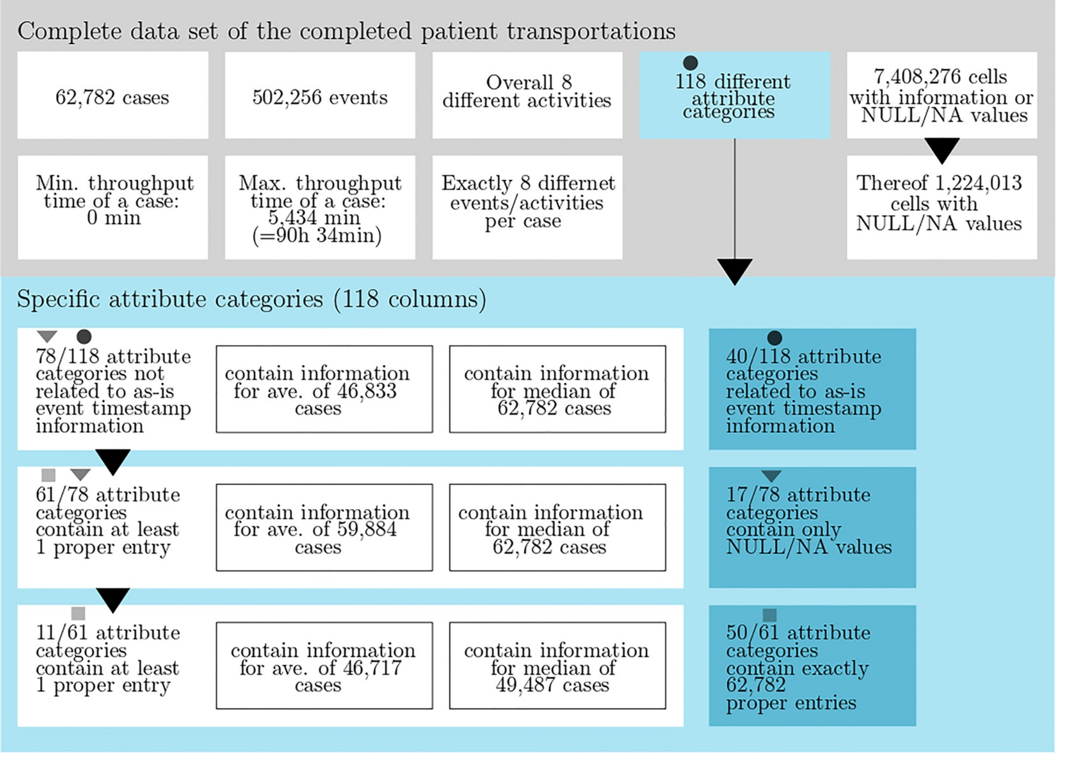

FIGURE 2 Characteristics of the analysis data set of the completed patient transportations, that were requested only once.

attributes on average or median per category cluster). It turned out that there were a total of 78 attribute categories in the 118 columns in the original data set that were not related to the as-is timestamps of the corresponding events of the cases (for example, information on the month, day of the week, calendar week, time differences between process steps already calculated by the software). Seventeen of these 78 attribute categories had no relevant information and the other 61 categories contained more or less information. Precisely, 50 of these 61 attribute categories were completely filled with evaluable information. The remaining 11 of these 78 attribute categories were not consistently filled with information and are therefore only suitable for further investigations to a limited extent.

3.2 | Analysis and results

The event log data are processed with a discovery algorithm to generate the process models and to further analyse the event log data. In this paper, the *Celonis*® *Execution Management System* (https://www.celonis.com/ems/platform/) is used. The reason to choose this tool is that the case study hospital has already deployed it to analyse other processes and the responsible process managers in the here conducted case study were already slightly familiar with it. The *Celonis*® process discovery algorithm is based on the fuzzy miner and utilises features of the heuristic algorithms.[27] It can generate simple visualisations using DFGs. This type of visualisations are easy to interpret for non-experts in the field of process mining at healthcare facilities.[50] However, it is important to be aware of the limitations of DFGs in terms if concurrencies, as mentioned in Section 2.2, in interpreting the results. However, in our case study the activities in reality are directly followed in the patient transport process as depicted in Figure 1 and there are no parallel happening activities. Moreover, to make sure that in case of equal timestamps no concurrency occurs, we added a unique sorting number to each event according to the respective executed activity during data preparation. This means that the order of the activities is specified by the sorting. Therefore, the problem with concurrencies in DFGs were eliminated.

The main focus of the following results is on process discovery and generating comprehension of the underlying process of patient transport. Individual aspects for the conformance checking are also described and ideas for process improvements are suggested.

3.2.1 | Global view

Figure 3 shows a complete process model that contains 100% of the discovered activities as well as 100% of the discovered paths between the activities. The numbers on the paths in Figure 3 indicate the absolute frequency of the relationships between the activities. For our analyses, we use both Key Performance Indicators (KPIs) and IPIs. The *Celonis*® tool provides a powerful visualisation possibility for process models, which helps to build IPIs, for adequate and understandable presentation of the data.[35] These process models make it easier for the process managers to understand the process flaws. For example, Figure 3 provides information regarding process errors in the activity sequences or organisational problems which are discussed in the following.

It is visible that the as-is process model (Figure 3) is unstructured and there are various process deviations from the as-planned process model. An unusual point about the discovered process model is that, according to consultations with the process managers, deviations from the intended sequence of the process steps should not be theoretically possible. Their argument is that there is just one mandatory activity sequence (the as-planned sequence) in the supporting software system which cannot be skipped by the transportation staff. However, the discovered model suggests that there must be problems in the software and log data or it stems from the incorrect working practices with the software system after all.

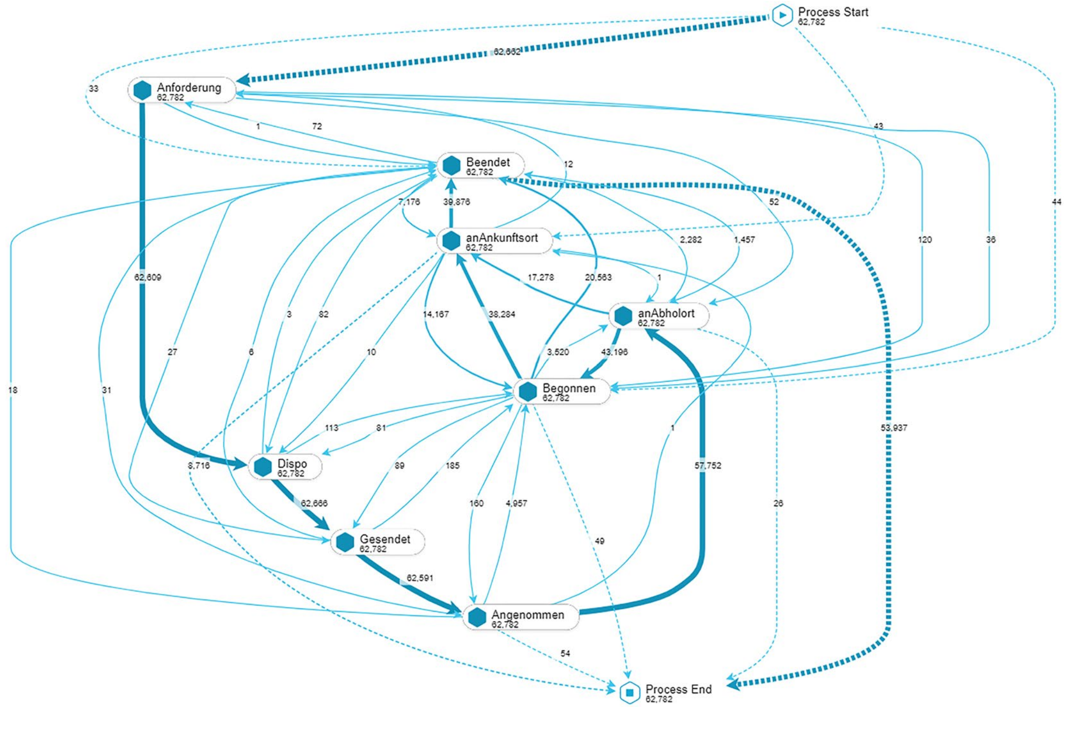

FIGURE 3 Control flow process model of the as-is process with 100% of the activities and 100% of the available paths. The numbers on activities and paths indicate the case count. *Source:* Adopted from *Celonis*®.

The matching rate of the as-is process to the as-planned process is about 61%. This corresponds to 38,208 cases. Another sequence of activities is followed by 14,161 cases (about 23% of all cases) which represents the second most common variant. Figure 4 shows the process model with average throughput times between the activities and with median throughput times for the most and second most common variant.

In comparison to the most common variant (and the as-planned process, see Figure 1), the second most common variant has the activities 'Begonnen' (transportation start) and 'anAnkunftsort' (arrival at target location) swapped.

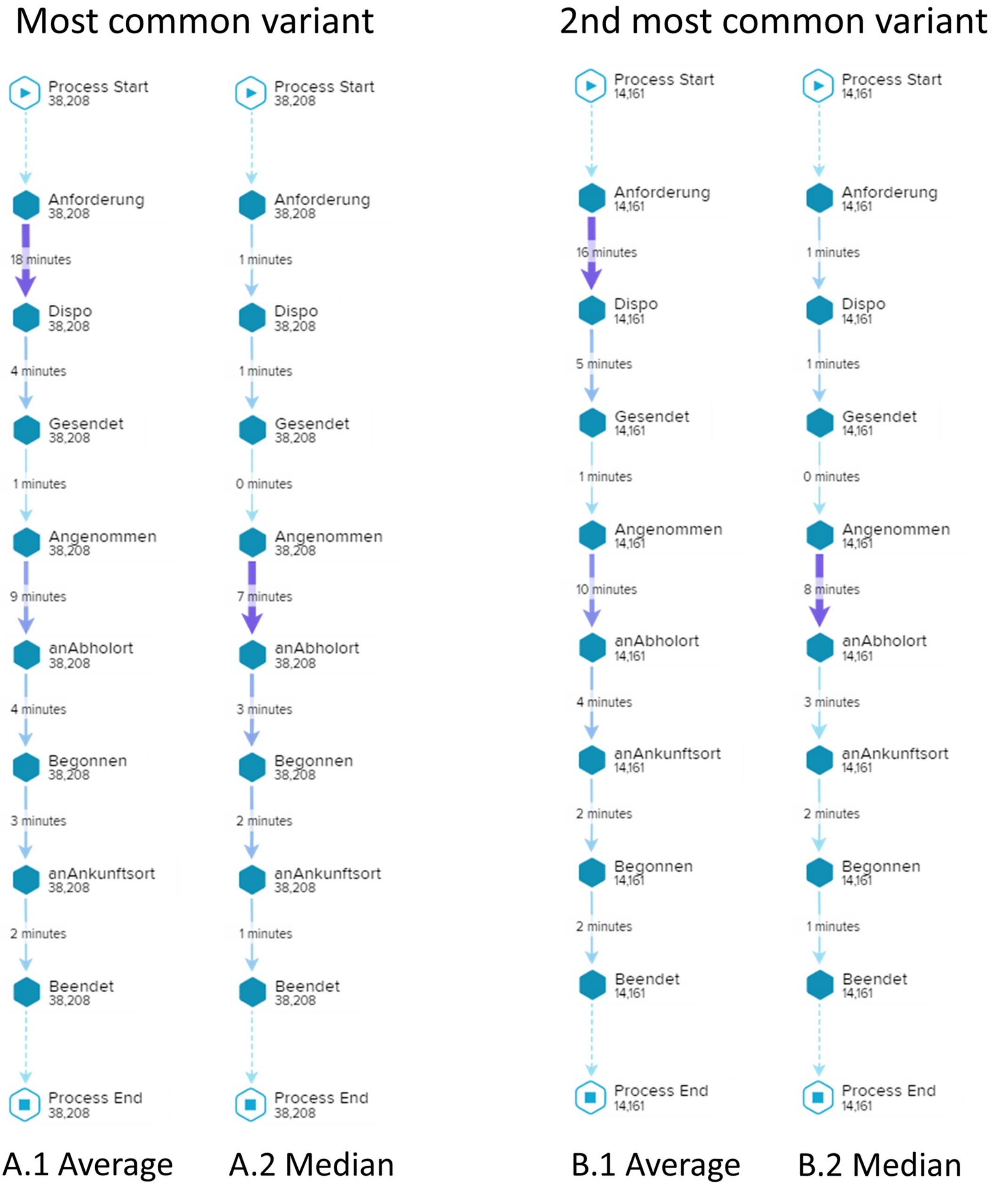

FIGURE 4 The most and second most common control flow model variants of the as-is process. The numbers on activities indicate the case count. The numbers on paths indicate the average (A.1 and B.1) and the median (A.2 and B.2) throughput times between two activities. *Source:* Adopted from *Celonis*®.

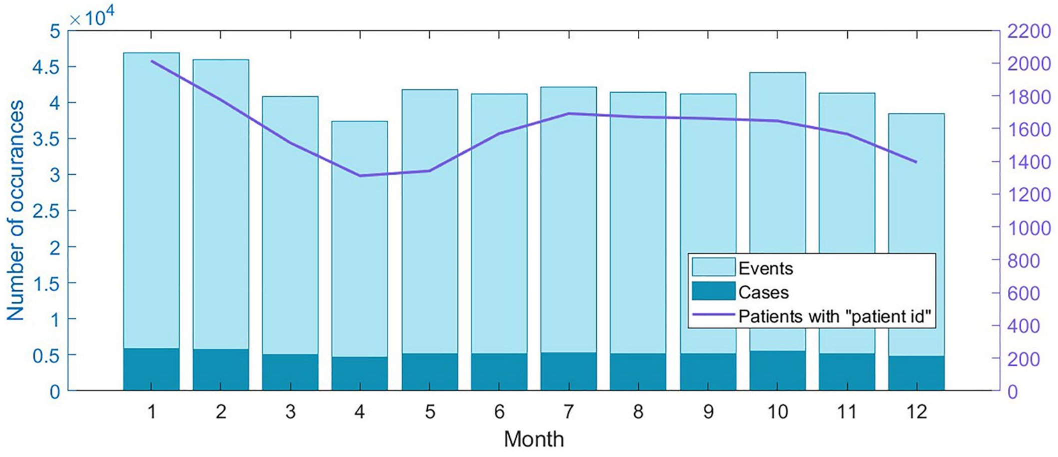

FIGURE 5 Monthly distribution of the number of events (respectively executed activities) and cases for the 502,256 events of the 62,782 cases, as well as monthly number of different patients related to the cases through the attribute category 'patient id'.

Figure 4 provides also an IPI representation for an easy comparison between the mentioned variants. That means in the second most common variant the transportation start seems to be after the arrival at the target location, which is in practice not possible. This indicates, that there is either a data quality issue or the supporting software system was not used correctly. The fact that both variants show large average throughput times between the first two process steps in comparison with small median throughput times between the same activities, implies that there are few outliers that deviate far from the usual data and this raises the average throughput time. In general, there seems to be a large time consumer between the activities 'Angenommen' (assignment accepted) and 'AnAbholort' (arrival at pick-up location), because both variants show within that interval relatively high average and median throughput times.

Figure 5 visualises the monthly distribution of the events. In addition, the number of transport cases and the number of different patients per month are provided. The indicated case number is calculated by dividing the event number by eight, as every case consists of eight different events. There may be cases whose transport process can extend overnight to two different months, but this is neglected here. This also applies to the number of patients designated in Figure 5, which have been allocated case-wise through the attribute category 'patient id' (unique, anonymised patient identifier). Figure 5 shows that, there were during the months of January (month no. 1) and February (month no. 2) clearly above and in April (month no. 4) markedly lower than average events and respectively activities executed. Furthermore, it can be seen that the variability in events and respective case numbers mainly corresponds to the varying number of different patients transported per month. This proves the substantial variability in healthcare settings. Seasonal changes in disease patterns lead to varying patient pathways and medical processes, and consequently different numbers of transport cases. The effects of these changes on care quality and patient outcome should be properly taken into account.

It should be noted that only those patients, that could be counted through their patient id in relation to the cases are depicted in Figure 5. Around 8% of the transport cases are not assigned to a patient id and therefore could not be evaluated. However, in month of May (month no. 5), there is about 21% of transport cases without information on 'patient id'. This clarifies the remarkable disparity between the number of transported patients and the number of executed activities in May in comparison to other months. This issue requires further investigations to find out the underlying reasons. Apart from seasonal changes, it must be scrutinised whether software problems could have led to this specific irregularity.

Figure 6 allows a view on the development of the as-is data conformance with the as-planned process model (see Figure 1). The average conformity rate is, as mentioned before, about 61%. It can be seen that there has been a downward trend in conformity over the course of the year 2020. In December, the process conformity of the data even falls below 50%. This raises once again the question whether it is caused by increasing erroneous working practices or there have been rising logging errors in the supporting software system over time.

It is furthermore possible to detect the conformance violations. Table 1 shows the most common process violations found in the as-is data set. All cases can now be filtered specifically to those where these problems concerning the order of the process steps have been identified. Using such filtering, targeted and deeper investigations on the underlying root causes can be conducted.

To determine the general process delays, the planned times for the completion of the patient transport were compared with the actual timestamps of the termination of the transport ('Beendet'). The delay threshold was set to 10 or more minutes. This specific threshold was set in discussion with the process managers that declared 10 min in delay already as 'critical'. Punctual patient transport is crucial in terms of patient satisfaction, but also in terms of the cost of waiting times for staff at the point of arrival. Approximately 36% (respectively 22,308 cases) of the total cases were delayed by 10 or more minutes. These cases alone led to a total of more than 9000 h of delay over the period of one year. Figure 7 shows the critical day-times per weekday, that are related to the delayed cases. It shows the rounded day-time (the minutes of each timestamp are rounded down to zero, e.g., 14:49 becomes 14:00) of the activity 'Gesendet' (Assignment sent) of all delayed cases.

It is visible that from Monday to Friday the peak of delayed cases have their transportation assignment sent around 12:00 o'clock. The question is whether the resources on the transport service side need to be increased around that time. Although there are fewer delayed cases on Saturdays and Sundays, their peak is also at around 11:00 or 12:00 o'clock. Such evaluations could likewise be carried out on the other seven activities of the process.

In comparison with Figure 8, that also shows the rounded day-time of the activity 'Gesendet' (Assignment sent), but for all 62,782 cases (not only delayed ones), it can be seen that there are two peaks of Assignments sent from Monday to Friday. The first peak is around 08:00 to 10:00 o'clock and the second is around 12:00 to 13:00 o'clock. Although, as Figure 8 shows, there are even higher numbers of orders sent in the morning than at lunchtime, Figure 7 nevertheless shows that it is more likely that orders sent around the lunchtime will ultimately result in delayed cases. Possible contributing factors are insufficient staff presence because of shift changes around this time of day, or even disruptions because of simultaneous transport of meals. Moreover, piling up of the morning delayed cases could also be a trigger for bottlenecks to occur at the second peak of all outgoing orders during lunchtime.

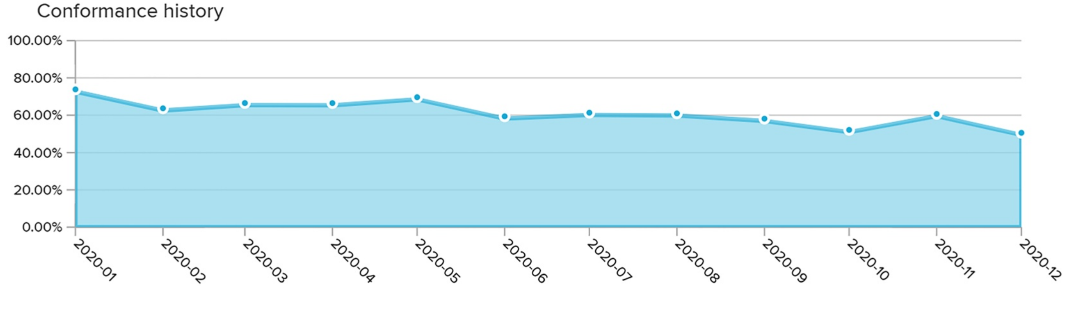

FIGURE 6 Development of process conformity of the as-is data in the course of the year 2020 towards the as-planned process. *Source:* Adopted from *Celonis*®.

TABLE 1 As-is process violations compared to the as-planned process sequence

Percentage of occurrence	Number of cases	Violation
23	14,167	'anAbholort' is followed by 'anAnkunftsort'
10	6395	'Begonnen' is followed by 'Beendet'
8	4957	'Angenommen' is followed by 'Begonnen'
…	…	…

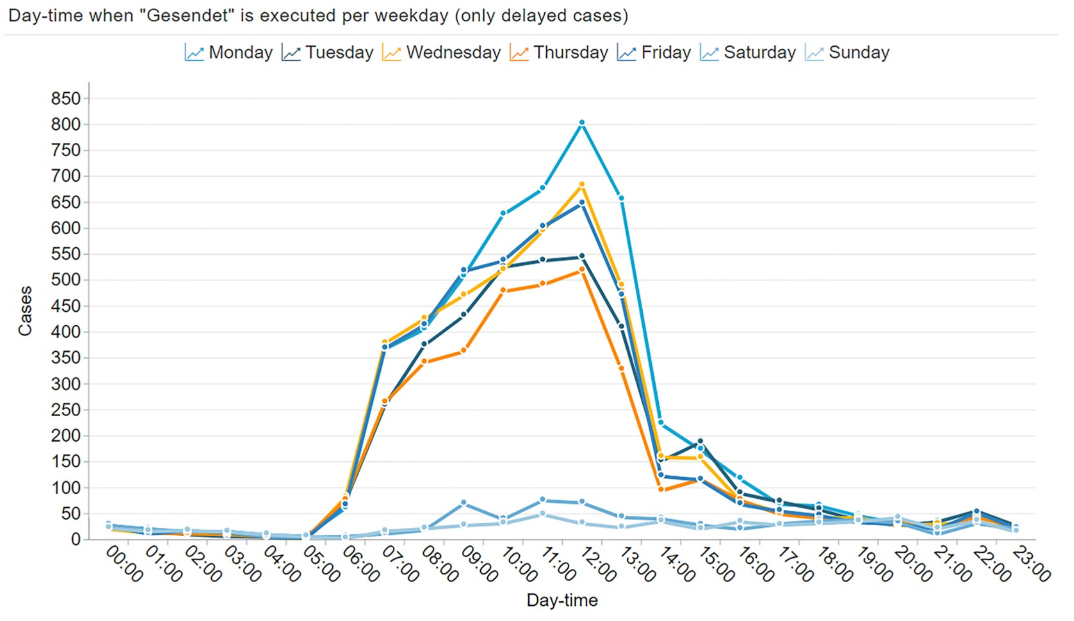

FIGURE 7 Day-time when 'Gesendet' (assignment sent) is executed per weekday of only delayed cases. Shown is the rounded day-time (the minutes of each timestamp are rounded down to zero, e.g., 14:49 becomes 14:00). *Source:* Adopted from *Celonis®*.

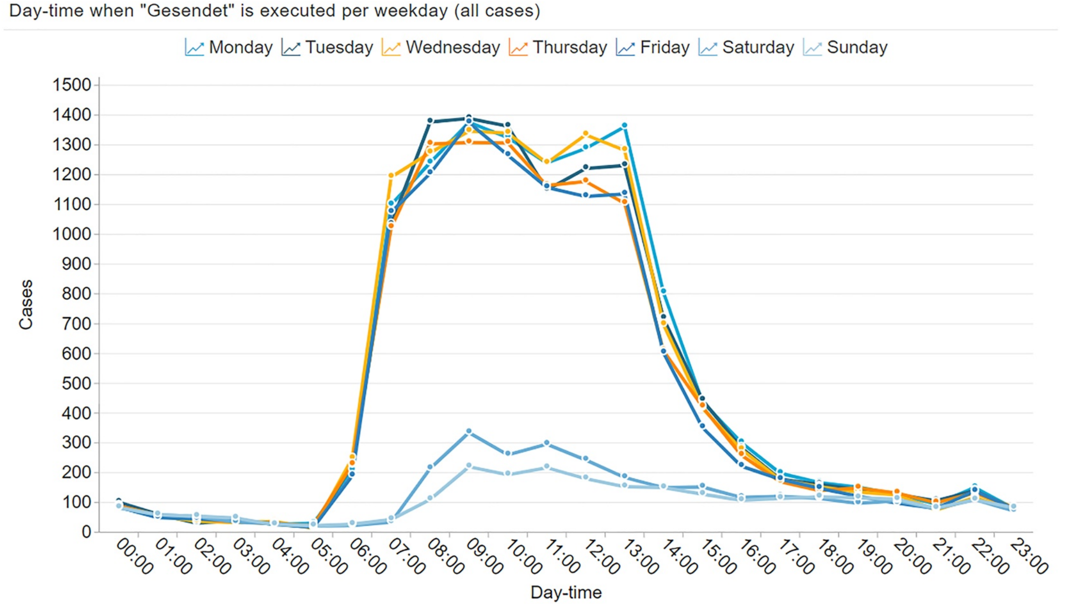

FIGURE 8 Day-time when 'Gesendet' (assignment sent) is executed per weekday of all 62,782 cases. Shown is the rounded day-time (the minutes of each timestamp are rounded down to zero, e.g., 14:49 becomes 14:00). *Source:*Adopted from *Celonis®*.

An important point that must be mentioned here, is the patients' perspective. Considering that the meal trays for the patient at wards are distributed and cleared up at around specific times, the simultaneousness of patients' lunch-times and transport orders is a management issue that should be considered. Patients are unwilling to be transported during their lunchtime, which either causes delays in transportation or a transportation forces them miss or postpone their meals, which either way negatively impacts their satisfaction.

Generally, there is also the possibility of taking a closer look at different process sequences in order to identify problems and their root causes. There are predefined KPIs concerning as-planned throughput times for the time span between 'Anforderung' (transportation request) and 'Begonnen' (transportation start) as well as for the time span between 'Begonnen' (transportation start) and 'Beendet' (transportation terminated). Figure 9 shows histograms for the first mentioned time span and Figure 10 for the second one. It is visible in both Figures that the as-is time spans are for some cases much longer than the as-planned time spans. Furthermore, Figure 9 shows that the as-is time spans deviate more frequently and significantly in an unwanted manner (more cases with longer throughput times in the as-is data compared to the as-planned throughput times for the considered activity interval). In contrast, Figure 10 illustrates that there are many cases where the as-is throughput times are shorter than the as-planned throughput time. Comparing Figures 9 and 10 helps to identify the most problematic activity interval. Figure 9 shows that the median as-is throughput time is higher as the as-planned one and the cases are distributed more in the direction of relatively high throughput times. Figure 10 shows a contrary behaviour. This leads to the assumption that within the interval between the activities 'Anforderung' (transportation request) and 'Begonnen' (transportation start) rather root causes of delays can be found.

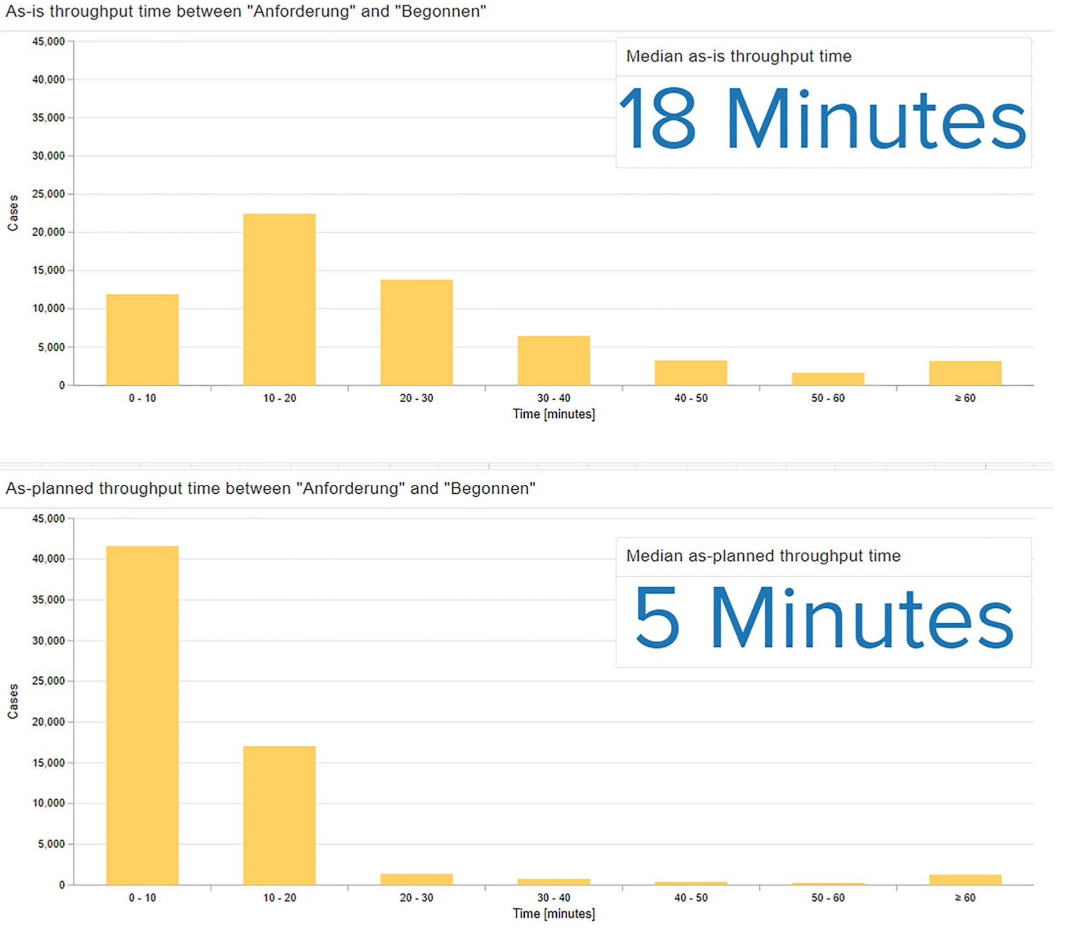

FIGURE 9 Throughput time comparison for the as-is (upper part) and the as-planned (lower part) time span between the activities 'Anforderung' (transportation request) and 'Begonnen' (transportation start). The upper bound of the time spans on the *X*-axis is included in the adjacent bar on the right side. *Source*: Adopted from *Celonis*®.

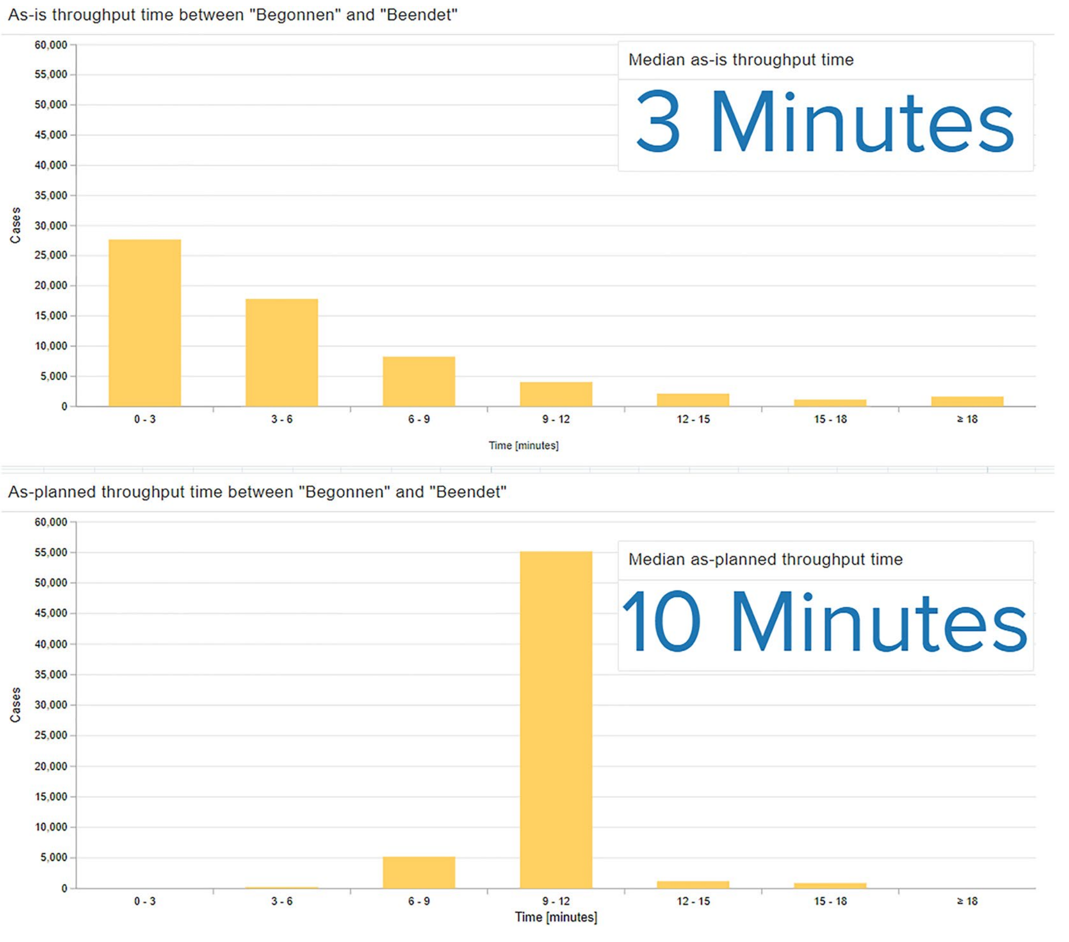

FIGURE 10 Throughput time comparison for the as-is (upper part) and the as-planned (lower part) time span between the activities 'Begonnen' (transportation start) and 'Beendet' (transportation terminated). The upper bound of the time spans on the *X*-axis is included in the adjacent bar on the right side. *Source:* Adopted from *Celonis*®.

To specify this more precisely, Figure 11 shows the distribution of the time delay that is already present at the point of time, when the transporter arrives at the patient's pick-up location where the transportation is getting started. It visualises furthermore that in only around 23% of the cases (respectively 14,396 cases) the transporter arrives before the planned time at the pick-up location. If we take a closer look at exactly these cases, the transporters were nine and less minutes too early in 13,889 cases, that is, in more than 96% of the cases, where the transporter arrived in general too early at the pick-up location. At this point we assume, analogous to the threshold, where we interpreted that a delay of less than 10 min is acceptable, that a premature arrival of less than 10 min would also be within the acceptable boundaries. Transporters who arrive significantly too early at the patient's pick-up location, for example, 10 or more minutes too early (in our case less than 4% of the cases where the transporter arrived in general too early at the pick-up location) can also lead to other bottlenecks in this specific and other cases. The choice of the threshold at which early arrivals by transporters are interpreted as acceptable or not acceptable and the consequences need to be examined more closely. If we set the boundary for punctual pick-ups also to less than 10 min of delay for the arrival of the transporter at the pick-up location, there are another 23,800 cases which we can consider as punctual. Together with the 13,889 cases where the transporter is over punctual in an acceptable way (premature arrival of less than 10 min) we can, in that example, conclude that around 60% of the patients got picked up within an acceptable tolerance threshold. The caused

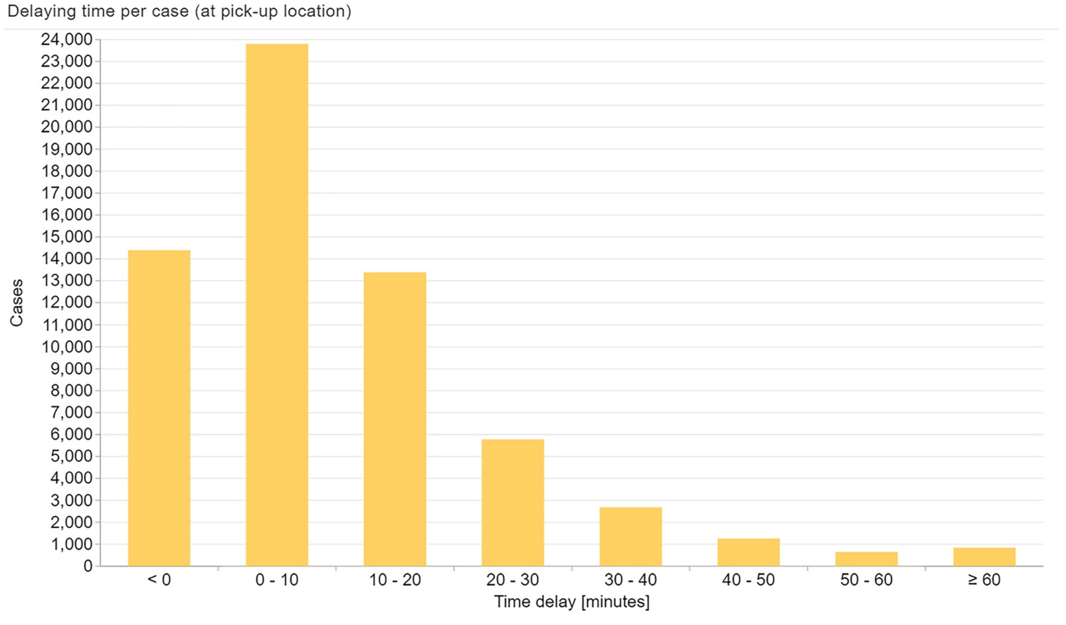

FIGURE 11 Delaying time per case at the location where the transporter arrives to pick the patient up. The upper bound of the time spans on the *X*-axis is included in the adjacent bar on the right side. *Source:* Adopted from *Celonis*®.

waiting time in all the other 40% of the cases can already have a negative impact on the patient's satisfaction even before the transport begins and will significantly retard or influence negatively the rest of the process and related processes.

Similarly, it is possible to evaluate how many minutes late the transporter and patient arrive at the target location (‘AnAnkunftsort’) compared to the planned completion time of the transport. This tends to have a negative impact on waiting staff at the arrival location. Another time span that can be evaluated is the time between the arrival at the target location (‘AnAnkunftsort’) and the end of the transport (‘Beendet’), that corresponds to the handover to personnel at the target location. It should happen as quick as possible to not upset the patient. The waiting time that occurs for the patient after the handover at the target location is not tracked further by the supporting software system, and thus, not available within the analysed data. Another evaluation possibility would be the time span between the transporter arriving at the pick-up location and the transporter starting the transport together with the patient. Long time spans, that might be caused by, for example, patients that are not yet ready for transportation, tend to be annoying for the transporting personnel and block transporting resources.

3.2.2 | Drill down to specific case views

Table 2 shows critical pathways of the patient transport sorted by the number of cases that were delayed at the completion of the transport. The most critical pathway is the way from Station A4.2 in House A (on the fourth floor of House A) to the Endoscopy on the first floor of the same house with a total of 774 cases having a delay of 10 or more minutes. These correspond to about 50% of the patient transports on this pathway (in total 1535 cases) and cause a total delay around 330 h. It can also be seen that the patients on the way back from Endoscopy to the Station A4.2 (444 cases, about 29%) are experiencing delays, too. Table 2 could furthermore be drilled down to the pick-up room or the arrival room within the corresponding locations. Because not all cases contain specific room information, the displayed table is not expanded to include corresponding columns. Figure 12 shows two IPIs for particular selections of transports on the most critical pathway, which provide specifically targeted process knowledge in an illustrative

TABLE 2 Critical pathways in patient transport sorted by the number of delayed cases

Pick-up location	Pick-up building	Arrival location	Arrival building	Delayed cases
Station A4.2	House A	Endoscopy	House A	774
Station A2.1	House A	FUDI EKG	House A	488
Endoscopy	House A	Station A4.2	House A	444
Station B2.2	House B	Radiology	House H	408
Station A2.1	House A	FUDI ECHO	House A	376
Emergency department	House B	Station A4.2	House A	352
…	…	…	…	…

way. To examine more closely this pathway, from pick-up location Station A4.2 to arrival location Endoscopy (both in House A), was coordinated with the process managers, as there seems to be great potential for improvement on that pathway due to the absolute highest number of delays.

Figure 12 shows on the left side the most common variant of the 774 delayed cases (62% coverage and respectively 483 cases) and clarifies which process steps cause high median throughput times. It can be seen that it took the transporter in median around 13 min to get to the pick-up location ('anAbholort') after having accepted the assignment ('Angenommen'). But also the throughput time between the first ('Anforderung') and the second ('Dispo') process step as well as the throughput time between the second and the third ('Gesendet') process step was in median around 7 min. This again supports the assumption, according to Figure 9, that many of the delays arise from longer throughput times of the process interval between the activities 'Anforderung' (transportation request) and 'Begonnen' (transportation start).

What is somewhat irritating about Figure 12 is the fact that according to the data the median transport time between the two locations, which are three floors apart, is only 2 min. The process managers actually suspected the elevators' capacity in House A as the main reason for the delays. However, based on the analysed data, this assumption cannot be confirmed. Considering the fact that three floors are actually travelled, it remains questionable whether the net travel time required for the transport route between the two locations really only took a median of 2 min, as the data suggests. To what extent the discussed time spans account for the final delay in reality has to be further investigated in consultation with the process managers and as well with the process executing staff.

Furthermore, Figure 12 shows on the right side a complete process model that covers all the observed behaviour in the as-is process of the delayed transports on the most critical pathway. In contrast to time-based investigations, general process control flow characteristics can be evaluated based on the model and the therein illustrated case counts. The most frequent process error is related to the fact that, with a total of 291 out of 774 transports, almost 38% of the transports do not go from the start of the transportation ('Begonnen') to the arrival at the target location ('anAnkunftsort'). This is certainly due to the fact that already 213 out of 774 transports (almost 28% of the transports) after the arrival at the pick-up location ('anAbholort') are followed directly by the arrival at the target location ('anAnkunftsort') or by the termination of the transportation ('Beendet') instead of, as intended, by the start of the transportation ('Begonnen'). In addition, undesirably, more than 14% (110 out of 774) of the transports have the arrival at the target location ('anAnkunftsort') as the last activity instead of the termination of the transportation ('Beendet').

In contrast, the complete model shows that there were never any undesired process deviations in the interval from disposition of an assignment ('Dispo') to the acceptance of this assignment ('Angenommen'). There was also only one deviation between the transportation request ('Anforderung') and the disposition of the corresponding assignment ('Dispo'). Thus, up to the acceptance of the assignment of the transportation ('Angenommen') there were barely any process deviations with regard to the sequence of activities. In order to find out why more process errors in the control flow (compared to the as-planned process) increasingly occur at the end of the process, the individual cases and the organisational structures behind them should be examined with a focus on the later process steps. For this purpose, process models can be created that put the resources involved in relation to each other.

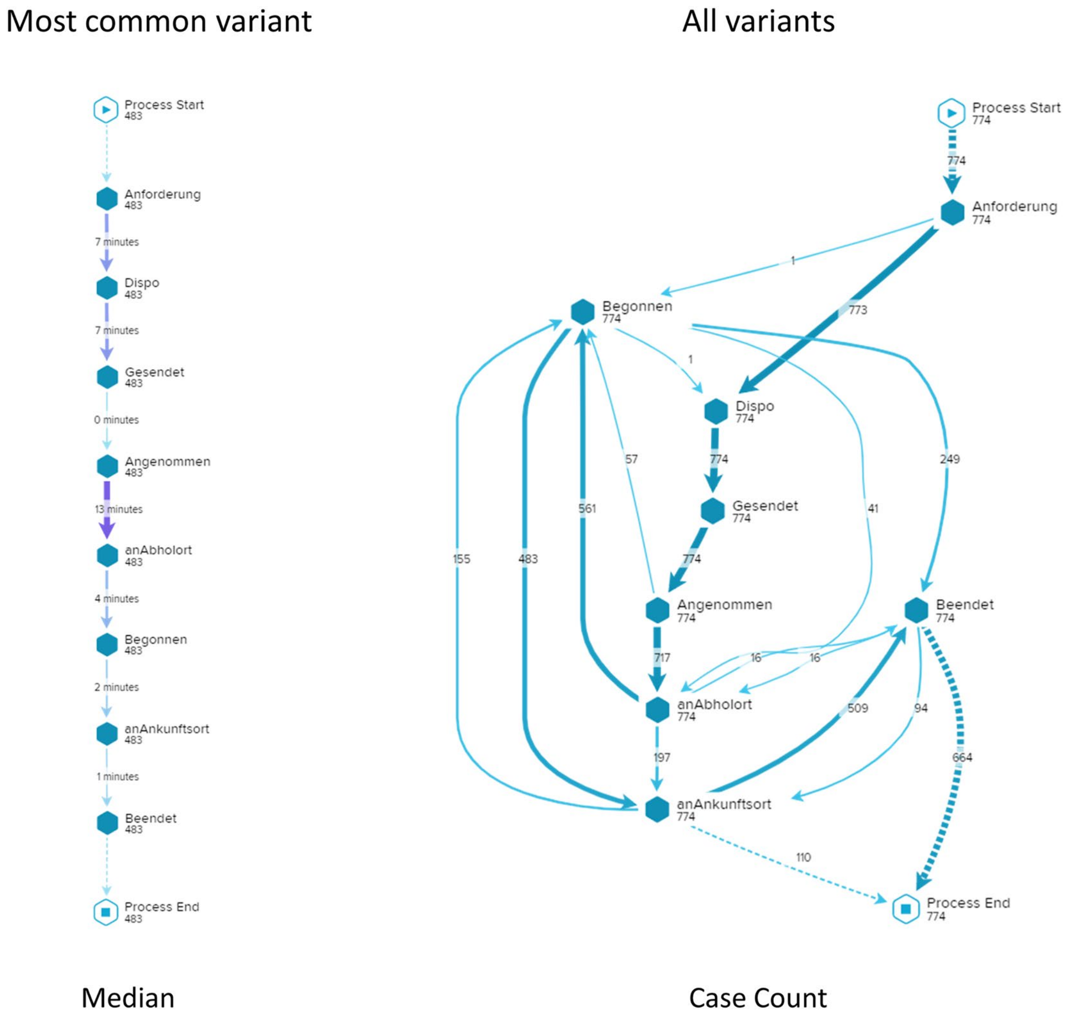

FIGURE 12 Left model: Most common control flow model variant of the as-is process of the delayed patient transports from Station A4.2 in House A to Endoscopy in House A. The numbers on activities indicate the case count of the delayed cases. The numbers on paths indicate the median throughput times between two activities. Right model: Complete control flow model of the as-is process of the delayed patient transports from Station A4.2 in House A to Endoscopy in House A. The numbers on activities and on paths indicate the case count of the delayed cases. *Source:* Adopted from *Celonis®*.

It is also possible to further analyse all the cases (including the ones with no and less than 10 min of delay) on that most critical pathway from Station A4.2 in House A to the Endoscopy in House A. Figure 13 shows the distribution of the delays for all the 1535 cases on that pathway. The used tool from *Celonis®* makes it easy to filter on, for example, the cases that had a delay between 10 and 20 min or the cases that had a delay of more than 60 min and to conduct further investigations.

In addition to their informative value, the mainly presented time-based KPIs serve as intermediate filter steps to ultimately be able to examine the filter-specific process models. These are utilised as IPIs (see Figure 12) that visualise process errors in the activity sequence or organisational and resource-related correlations. The investigations, which are based on the transported knowledge of the interactively generated process models, form the core of process mining analyses. Hence, IPIs have advantages over conventional numerical KPIs in terms of interpretation

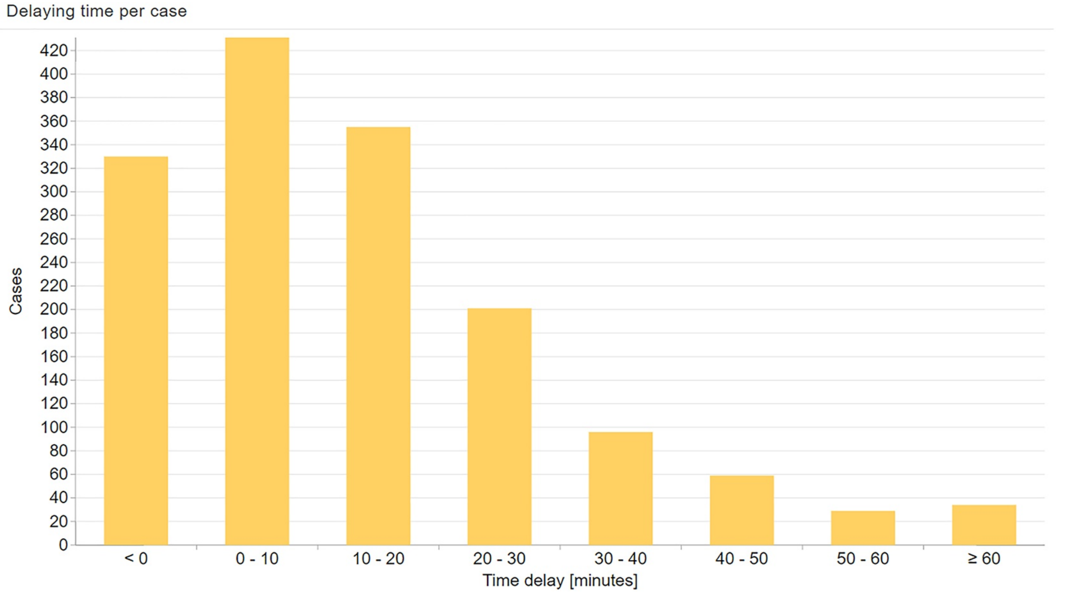

FIGURE 13 Distribution of the delaying time per case on the most critical pathway from Station A4.2 in House A to the Endoscopy in House A (total of 1535 cases). The upper bound of the time spans on the *X*-axis is included in the adjacent bar on the right side. *Source:* Adopted from *Celonis*®.

possibilities and knowledge gains, as they provide a clear overview of correlations between process related components and can be interactively adapted to different questions and objectives.

Generally, process mining can facilitate multi-dimensional analysis of the data. It can help to detect further unusual patterns in processes. All analyses presented so far can be carried out specifically for certain filter groups (according to specified criteria or data attributes) or even for individual cases. However, with more than 62,000 cases, an individual case analysis is only useful in exceptional cases, for example, to estimate extreme outliers. It can be more expedient to filter on cases in a group-wise manner, such as transport route, as shown before, or resources involved (i.e., utilised transport vehicle), pick-up or arrival priority. This procedure helps to identify similar and recurring problems. Further analysis can be done to find out the hourly, daily or monthly distribution of the activities or punctuality of transportations and their correlation with seasonal changes in diseases. Such results can enable us to predict the likelihood if a transportation could be on-time or not. This is crucial to predict and therefore to plan enough time for transports, especially when it comes to critically ill patients.

4 | DISCUSSIONS

Based on the identified research potential and the investigations from the previous sections, this section summarises the findings, proposes improvement concepts, and points out the limitations of the conducted case study.

4.1 | Findings and improvement concepts

Patient satisfaction is a valuable goal of any healthcare organisation and many studies suggest waiting times as the most influencing factor for measuring patient satisfaction. What influences the patient satisfaction is their subjective perception towards the waiting times and not the actual absolute waiting time.[60] Patients' perceptions towards the elapsed waiting times are, of course, influenced by the overall healthcare service quality. What is obvious, is that the patient must receive the right service at the right time with the right quality. In terms of increasing the efficiency of patient transport services and consequently having a positive impact on patients' satisfaction, minimisation of waiting times must be set as an indispensable goal. However, designing systems which help increasing patients' satisfaction demands a holistic view as well as integrated data and process management which are discussed in the following.

Through the data-based analyses with process mining methods, it is possible to find out how waiting times for patients are related to other circumstances. These can be, for example, sub-optimal allocation of assignments to transporters (through automatic or manual disposition), resource bottlenecks or general misplanning at the point of requesting a transport which can cause excessive burdens of the transporters in relation to the actual needs. Also, the lack of satisfaction of the staff involved in the process can have a negative impact on the patients' hospital experience. This can be due to not only their specific waiting times but also the inappropriate combination of transport routes and the resulting increased distances with low patient throughput per transporter.

Considering the data analysis and the obtained results, it can be concluded that there are both organisational and infrastructural elements which influence the waiting times in transport services. Organisational problems are, for example, inappropriate resource planning. Infrastructure issues include, for example, spatial conditions or the availability of elevators. While evaluating the conformity with predefined workflows and temporal requirements, starting points for process improvements can be found by the process mining analyses on real data. Based on the findings, some strategies are suggested in the following to reduce the waiting times.

It was observable that during the lunchtime there are transportation assignments sent to transporters that result finally in delayed cases. Issues here might arise from conflicts between patient transports and simultaneous meal transports. It should be ensured that there are no demand problems with the elevators. For example, adding an elevator might be a better solution in long run. However, there might be construction barriers which hinder adding an elevator. Nevertheless, a reorganisation of operational strategies to more efficient workflows or adjustments of resources during lunchtime can have positive effects on delays and waiting times. For example, the definition of exact rules that determine which elevator(s) must be used for patient transport and which ones for the transportation of meals during lunchtime can be a possible solution.

Another point that should be addressed is having the patients prepared for the transportation. This factor certainly contributes to delays related to the lunchtime. Having the patient ready for transportation requires implementation of comprehensive communications between different hospital units.

In some cases the condition of the patient and the types of examinations allow combining different examinations. This strategy not only can have a positive influence on patients' perception regarding the quality of the services their receive but also reduces waiting times for the overall transport service by reducing travel distances.

It can be understood that transport process delays have strong correlations with specific spatially centralised examination departments, for example, Endoscopy, functional diagnostics (FUDI EKG and FUDI ECHO) and Radiology. Decentralisation of the examination departments will bring an important time gain for the transport services.

Efficient allocation of assignments to the transporters is also an issue of remarkable importance. The evaluations showed that the throughput time between the transporter's acceptance of the transport assignment and the transporter's arrival at the pick-up location has been in median the biggest driver for the total throughput time of the complete process. This also applies to the overall delayed cases.

Furthermore, the initial process phase, such as the interval between requesting a transportation request and the sending of the assignment to a transporter, have a relatively high throughput time. As these steps are currently processed manually within the main operation time of the hospital, automation could lead to significant time savings. However, correlations must firstly be derived on the basis of the available information in order to enable targeted automation of decisions and actions.

Another helpful strategy will be the visualisation of waiting times. Providing the transport services and nursing units with real-time information on waiting times will help them to adapt their operations or to anticipate complications.

In summary, using steady application of analytical methods, such as process mining, is strongly recommended to obtain an overview of the status quo, to identify root causes for process issues and starting points for process improvements as well as to establish consistent feedback loops and automation measures. The interactively developed process models and derived IPIs facilitate the investigation of specific incidents, questions and objectives for the experts as all the related information can be presented at a glance rather than just as solely numerical KPIs.[34,55] An IPI will offer a more enriched view and helps to classify and understand the correlation of the individual numbers shown, as well as allow the measurement and assessment of the effects of process improvement actions.[34,61]

4.2 | Further prerequisites for patient-oriented analysis

At the studied hospital, as shown, evaluations of delays for merely transport activities can already be conducted well, but the resulting waiting times for patients or staff (e.g., from the transport services, examination departments or nursing stations) cannot be easily derived. This stems from the missing relationships between the patient transport process analysed in the case study and previous or subsequent events for all involved individuals. In order to include these interrelationships in analyses and derive a more comprehensive process understanding, knowledge collected from other related processes and their supporting software systems must be integrated. However, a link between the patient transport process to other related processes should not only consider the patient as a case but also, for example, the transporter or other hospital employees and by connecting the different perspectives. In our case study a comparison of the data between the hospital information system and the patient transport-supporting software system is currently not possible automatically due to the missing interfaces. As a result patients can be ordered to different places at the same time. On this basis, proper planning and control of patient flows are impossible. In order to gain a complete understanding of the patient transport service process, to measure its impact on patients' satisfaction and to enable an optimisation, interfaces with consistent linking keys, such as case ids, need to be adopted across several systems, as a basic requirement.

Furthermore, data sets have to be consequently enriched with additional information in certain areas so that the evaluations are more comprehensive and the correlations can become clearer. The case study data set showed that, for instance, many attribute categories not be used for evaluations, because the corresponding information was not gathered equally for all cases in the software system. Attribute categories that should have been filled stringently to enable more detailed evaluations are in our case study, for example, pick-up room, pick-up room number, arrival room and arrival room number.

Finally, open questions remain in the pure data analysis with regard to the unstructured process model that is derived from the data. The reasons for deviations from the strictly prescribed sequence of activities can only be determined through interactive cooperation with responsible process managers, employees involved in the process and software system manufacturer.

5 | CONCLUSIONS

Intra-hospital patient transport is an essential ancillary process which ensures patient satisfaction, patient safety and efficient treatment. The ever-increasing pressure on cost reductions and patient-oriented perspective reinforces the need for development and application of analytical methods to continuously monitor, evaluate and enhance the processes. The recent push towards digitisation of hospitals through the German Federal Government, for example, through the Hospital Future Act (Krankenhauszukunftsgesetz—abbr. KHZG), and the concurrent development of innovative digital and intelligent resource-saving solutions offer extraordinary possibilities to optimise healthcare processes, thereby significantly reducing healthcare costs while improving patient safety and satisfaction. In order to verify the desired impact of digitisation, it is important to analyse data collected in the digitised processes and incorporate the evaluations to improve the operational performance and to ensure and monitor benchmarks.

This study addresses the variability and complexity of the patient transport services in hospitals and proposes the application of process mining to discover and analyse the processes to find process issues. We took first a global view on the patient transport process with all cases within 1 year and then focussed especially on delayed cases and other specific filtered groups. The process models developed interactively using process mining methods serve as IPIs and help us to get a coherent view of the process and to look at specific selected case groups or cases and to set different research priorities. In this way, problems can be identified and solutions can be applied in a targeted manner. However, it must be mentioned that the mere application of process mining methods cannot resolve all the inefficiencies and bottlenecks in the intra-hospital patient transport service processes. It is crucial to increase the awareness among hospital managers and transport staff regarding the process flaws, continuous monitoring of the workflows and active implementation of improvement strategies. Building on the initial analysis addressed within this paper, improvement approaches must be specified in practice by the hospital's process managers and realised by the executing personnel. With constant feedback loops, the effects can be controlled and the process can be continuously improved. Simulation methods can also be used to anticipate situations before implementing specific measures and thus act with foresight. Such approaches also provide the basis for the future use of machine learning methods for consistent process support.

In a future work, all the involved stakeholders must be engaged in evaluating the process data so that holistic and comprehensive solutions can be sought together. It is furthermore important to integrate the subjective experience of patients concerning the investigated processes and the interrelated procedures.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Research data are not shared.

ETHICS STATEMENT

Not applicable.

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