

# Mining Processes in Dentistry

Ronny S. Mans  
School of Industrial  
Engineering  
Eindhoven University of  
Technology  
P.O. Box 513, NL-5600 MB  
r.s.mans@tue.nl

Hajo A. Reijers  
School of Industrial  
Engineering  
Eindhoven University of  
Technology  
P.O. Box 513, NL-5600 MB  
h.a.reijers@tue.nl

Michiel J.I.M. van  
Genuchten  
Open Digital Dentistry  
genuchten@ieee.org

D. Wismeijer  
Department of Oral Function  
and Restorative Dentistry  
Academic Centre for Dentistry  
Amsterdam, Amsterdam, The  
Netherlands  
d.wismeijer@acta.nl

## ABSTRACT

Business processes in dentistry are quickly evolving towards “digital dentistry”. This means that many steps in the dental process will increasingly deal with computerized information or computerized half products. A complicating factor in the improvement of process performance in dentistry, however, is the large number of independent dental professionals that are involved in the entire process. In order to reap the benefits of digital dentistry, it is essential to obtain an accurate view on the current processes in practice. In this paper, so called process mining techniques are applied in order to demonstrate that, based on automatically stored data, detailed process knowledge can be obtained on dental processes, e.g. it can be discovered how dental processes are actually executed. To this end, we analyze a real case of a private dental practice, which is responsible for the treatment of patients (diagnosis, placing of implants and the placement of the final restoration), and the dental lab that is responsible for the production of the final restoration. To determine the usefulness of process mining, the entire process has been investigated from three different perspectives: (1) the control-flow perspective, (2) the organizational perspective and (3) the performance perspective. The results clearly show that process mining is useful to gain a deep understanding of dental processes. Also, it becomes clear that dental processes are rather complex, which require a considerable amount of flexibility. We argue that the introduction of workflow management technology is needed in order to make digital dentistry a success.

## Categories and Subject Descriptors

H.4.1 [Information Systems Applications]: Office Automation—*workflow management*; J.3 [Computer Applications]: Life and Medical Sciences—*health*; H.2 [Database Management]: Process Mining

## General Terms

Measurement

## Keywords

Process mining, Workflow management, Dentistry

## 1. INTRODUCTION

For a long time, dentistry has been mostly carried out in the analogue world: patient information was recorded on paper, communications between the dentist and the lab took place by phone or fax, impressions of patients’ teeth were poured in plaster to create models, models of the final restoration were waxed, and analogue articulators were used. In the last years, a new phase has been entered where certain steps of dental processes are done digitally. However, these steps are still “digital islands” in an overwhelmingly “analogue sea”. Some examples are: Instead of impressions a scan is made using an intra-oral scanner. A crown is designed on a CAD station instead of a wax-up. Yet, a physical model from an analogue impression is still needed in order to test the fit of a crown.

It can be anticipated that through the application of digital dentistry further improvements can be achieved. For example, considerable benefits for patients can be obtained, such as better fitting prosthetics (due to limited loss of precision in the digital process), less rework, and more comfort. Various cost savings can also be expected, since less material is required for intermediate, analogue steps. Furthermore, less toxic materials will be required in the lab.

To arrive at an accurate estimation of the overall benefits of digital dentistry it is paramount to develop an understanding of the entire chains of operations that are required for various treatments. After all, many innovations in digital

dentistry go beyond the walls of the traditional practices and are therefore difficult to assess. A characteristic of the dental domain is that its processes often involve many independent business entities of dental professionals, where each of the parties has a limited understanding of the activities that take place elsewhere. This is where we believe that workflow management and process mining are relevant. Both technologies and their associated techniques can contribute to a better understanding of the benefits of digital dentistry. In particular, the development of digital dentistry requires that processes are streamlined, which can go hand in hand with the application of workflow management. In turn, process mining can contribute to develop an understanding of what really happens within workflows that run across all partners, and where improvement opportunities exist.

In this paper, we focus on process mining [1], which aims at extracting process knowledge from so-called *event logs*. Such logs may originate from all kinds of systems, such as generic enterprise information systems, as well as practice management systems of dentists, or order tracking systems used at dental labs. Typically, event logs contain information about the start and completion of process steps, along with related context data (e.g. actors and resources). Up to now, process mining has been applied in a wide variety of settings, such as high-tech manufacturing, financial processes, and hospitals. Since process mining uses factual execution data it allows for obtaining an objective view on how processes are *really* executed. Moreover, it allows for obtaining quantitative insights into these processes (e.g. performance information). In this way, there is a clear difference between process mining and more traditional ways of investigating business processes. For example, by conducting interviews there is always the risk that highly subjective information is gathered.

The purpose of this paper is to demonstrate the *usefulness* of process mining for the domain of dentistry. That is, for a selected dental process we show how process mining can be applied to identify the steps that are taken in the entire process, as well as their timing behavior. Moreover, we can discover which people are involved in the process and how they collaborate. To this end, in Section 4, we use several mining techniques, which also illustrates the diversity in these. To date, we are not aware of any applications of process mining in dentistry. Various applications of process mining in the healthcare domain are known [1, 10, 14, 15, 17, 18, 22, 29]. However, these works are limited to a single business entity (i.e. a hospital), whereas in dentistry multiple business entities are usually involved. As will be discussed, this brings extra challenges along. Moreover, we elaborate on a methodology for how process mining can be applied in order to discover different perspectives of a dental process.

The remainder of this paper is organized as follows. Section 2 provides a background on process mining. In Section 3, we elaborate on the method that is used in order to be able to apply process mining for a selected dental process. In Section 4, the ensuing results are presented. Finally, a conclusion and outlook are provided in Section 5.

## 2. PROCESS MINING

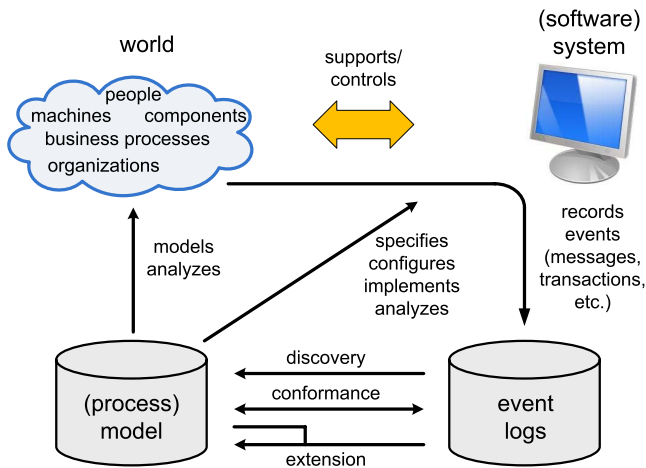
Process mining is applicable to a wide range of systems. The only requirement for process mining to be applicable is that the system produces event logs, thus recording (parts of) actual behavior. An interesting class of information systems that produce event logs are the so-called Process-Aware Information Systems (PAISs) [9]. Examples are classical Workflow Management Systems (WFMSs) (e.g. Staffware), ERP systems (e.g. SAP), case handling systems (e.g. BPM|One), Product Data Management (PDM) systems (e.g. Windchill), Customer Relationship Management (CRM) systems (e.g. Microsoft Dynamics CRM), middleware (e.g., IBM's WebSphere), hospital information systems (e.g., Chipsoft), etc. These systems in general provide very detailed information about the activities that have been executed.

However, not only PAISs are recording events. Also, a wide variety of other systems does so. For example, in a dental practice, a practice management system is used which records for each patient the services that have been delivered as well as the appointments that have taken place. In a dental lab, an order tracking system may be used which records all steps that have been taken to deliver a dental product, along with the time of their completion. Since in dentistry typically multiple business entities (e.g. a dentist and a dental lab) are collaborating in order to arrive at a final product, typically the systems used are limited to the work practices of one business entity only. This means that information in the separate systems is not related.

The goal of process mining is to extract information (e.g., process models) from the recordings of various systems, i.e., process mining describes a family of a-posteriori analysis techniques exploiting the information recorded in event logs [1]. Typically, these approaches assume that it is possible to sequentially record events such that each event refers to an activity (i.e., a well-defined step in the process) and is related to a particular case (i.e., a process instance). Furthermore, process mining techniques can use additional information such as the performer or originator of the event (i.e., the person/resource executing or initiating the activity), the timestamp of the event, or data elements recorded along with the event (e.g., the size of an order).

Process mining addresses the problem that most process /system owners have a limited insight into what is actually happening. In practice, there is often a considerable gap between what is prescribed or supposed to happen, and what actually happens. Only a thorough assessment of real behavior, which process mining strives to deliver, can help to establish a realistic vision on the operational process, which is a hard requirement for effectively developing a supporting IT system or redesigning that process. *The idea of process mining is to discover, monitor and improve real processes (i.e., not assumed processes) by extracting knowledge from event logs.* Three basic types of process mining can be distinguished (as shown in Figure 1): (1) *discovery*, (2) *conformance*, and (3) *extension*.

**Discovery:** The first type of process mining is discovery, i.e., deriving information from some event log without using an a priori model. Based on an event log various types of models may be discovered, e.g., process models, business



**Figure 1: Three types of process mining: (1) Discovery, (2) Conformance, and (3) Extension.**

rules, organizational models, etc. For example, many techniques have been developed to discover the control-flow perspective, e.g. expressed in terms of Petri nets [3, 28, 26], Heuristics nets [27], Event-driven Process Chains (EPCs) [8], Activity graphs [5, 6], Control-Flow Graphs [7], ADO-NIS workflow models [11], and ADEPT models [12]. However, process mining is not limited to the control-flow perspective. There are also process mining techniques which put the focus on other perspectives, e.g., the organizational perspective [2, 13, 24], the performance perspective [23], and the data perspective [20].

**Conformance:** For this category of process mining, the event log is used to check if reality conforms to a model [21]. For example, there may be a guideline indicating that the time between placing and exposing an implant must be at least four weeks. Conformance checking may be used to detect deviations from this rule, to locate and explain these deviations, and to measure the severity of these deviations.

**Extension:** This class of process mining techniques assume that there is an a-priori model. This model is extended with a new aspect or perspective, i.e., the goal is not to check conformance but to enrich the model with the data from the event log. An example is the extension of a process model with performance data, i.e., an a-priori process model is used in which the bottlenecks are detected.

Note that there is a clear difference between process mining and Business Intelligence (BI) tools in use. BI tools focus on performance indicators such as the number of final restorations placed, the length of waiting lists, and the success rate of surgery. As such, BI tools do *not* show the *end-to-end process* and *cannot zoom into selected parts* of this process [1]. By contrast, process mining looks inside the process at different abstraction levels.

The ProM framework and tool set has become the de facto standard for process mining. ProM ([www.processmining.org](http://www.processmining.org)) is a “plug-able” environment for process mining using MXML, SA-MXML, or XES as input format. ProM 5.2 was released in 2009. ProM 6 (released in November 2010) provides a completely new architecture and user-interface to

overcome some of the limitations of earlier versions of ProM. In this paper, we use both ProM 5.2 and ProM 6.

### 3. METHOD

In this section, we elaborate on the *method* that is used to apply and evaluate process mining in the dental domain. First, the selected dental process is introduced in Section 3.1, along with the raw data that has been obtained from this process. As will be discussed in Section 3.2, a preprocessing phase is required. In Section 3.3, we briefly elaborate on the kind of results we wish to obtain and the mining techniques that will be used in order to achieve these results.

#### 3.1 Single Crown Implant Process

As already indicated in the introduction, many independent business entities of dental professionals can be involved in the entire dental process. Moreover, these dental professionals each tend to have their own specific IT applications which are typically not synchronized. In order to still apply mining, the following, novel approach has been used for collecting data.

We focused on a medium-sized private dental practice in the Netherlands where several dental specialists are working. Here, we selected a group of patients with an implant-borne, single crown restoration. For this so-called “single crown on implants” process it was known that there was a collaboration with exactly one dental lab. This allowed us to follow for all involved patients the steps that are performed in the private dental practice as well as in the dental lab.

To allow for mining the entire process, two different data sets have been obtained. First, for the dental practice we have extracted all the appointments that have taken place for a group of 55 patients that received a complete treatment in the years 2008 up til and including 2010. This resulted in a log consisting of 811 events, where each event refers to either the start or end of an appointment. Second, at the dental lab a log has been extracted which contained for the period starting in 2008 until and including 2011 all the dental products that were produced for all the patients treated at the dental practice. Note that for each dental product it was recorded which steps were taken to obtain the final product. This resulted in a log of more than 2,500 dental products that consisted of more than 40,000 events. The textual information in both logs were all recorded in Dutch.

#### 3.2 Preprocessing

Despite two different logs becoming available through the previously described step, some further preprocessing is required to start the mining proper. (Note that in the sequel all event names have been translated from Dutch into English.)

First, for the dental practice the log contained many different event names. A closer inspection revealed that many different event names referred to the same subject. This is due to the fact that for the appointments a free text field was used to allocate a subject to the appointment. For example, for the event names “impl cons: 15 min earlier!!”, “card! impl cons: 15 min earlier!!”, “card !! impl cons: 15 min earlier!!”

a few characters differ but they all refer to the concept of an implant consultation. Additionally, it may also be the case that event names are completely different but still refer to the same subject. For example, the event names “pain after impl Friday” and “mrs is afraid of infection” refer to the situation that a problem has occurred after the placing of an implant.

To arrive at a situation where the names of the events all refer to a correct subject, we developed a new plug-in in ProM which consisted of the four following steps. First, the event names are selected which occur most frequently in the log. Second, for each selected event name, the corresponding correct subject is provided manually. As a third step, the plug-in proposes a subject for each remaining different event name. This is done based on finding the closest string similarity between the event name in question and the top most occurring event names for which already a mapping has been provided. If desired, the proposed subject can be changed manually. Afterwards, each event name is mapped to the correct subject. For our log we have chosen to select the first 30 event names that occurred most frequently. For the example above, this had as consequence that the events having as names “impl cons: 15 min earlier!”, “card! impl cons: 15 min earlier!”, “cart !! impl cons: 15 min earlier!” are all mapped to the “impl cons” event name. As a result, for the dental practice we ended up with a log which only had 32 different event names.

As a second preprocessing step, we addressed the challenge of how to integrate the two logs. At the dental practice, the name of the patient is used as identifier for each process instance. However, this does not imply that at the dental lab the same name can be used as identifier for the product that is made for the patient. For example, for patient “J Jansen” at the lab the identifier “Jansen 1550” was used. In the end, to trace the path that is followed by each patient in the dental practice and in the lab, it was necessary to manually link each patient in the dental practice with the corresponding product in the lab. This resulted into one log consisting of 55 patients, 1542 events, and 61 different event names.

### 3.3 Mining

To apply process mining to the dental process in question, and evaluate its use, an *explorative approach* was used that is not limited to a single perspective. That is, for all patients we concentrated on the paths followed for patients, i.e. the control-flow perspective. Also, we focussed on the discovery of organizational aspects (resource perspective), as well as the discovery of performance related information (performance perspective). Moreover, in order to obtain process knowledge two classes of process mining techniques needed to be applied, being “discovery” and “extension”. Next to that, for each mining algorithm used, specific details about the algorithm are provided.

As a methodological step, all results that were obtained with process mining were validated with the process owners in question, which also served the purpose to interpret the findings.

## 4. RESULTS

In this section, we focus on the results that were obtained for the control-flow, organizational, and performance perspectives. Note that the presentation of these results also allows the demonstration of the diversity of process mining techniques available. In conformance with our approach, we clearly distinguish between two kinds of results for each perspective. First, there are the results that have directly been discovered by process mining. Second, the results are presented that were obtained during the validation.

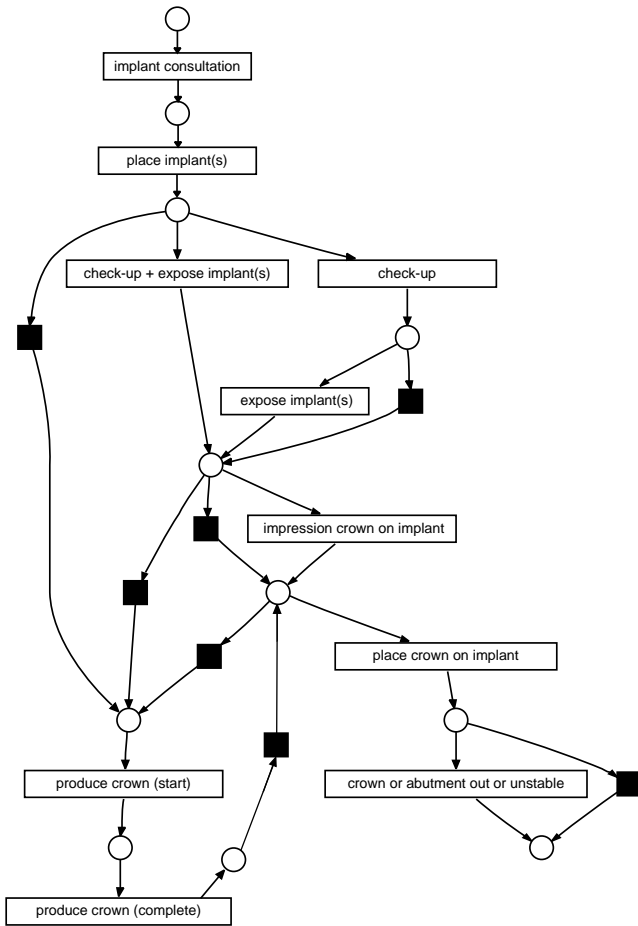
### 4.1 Control-Flow Perspective

One of the most powerful mining techniques is *control-flow mining*, which automatically derives process models from event logs. The generated process model reflects the actual process as observed through real process executions. If we generate process models from the logs we obtained, they give insight into the paths that are followed by patients both in the dental practice and in the dental lab. Until now, there are several process mining algorithms such as the  $\alpha$ -mining algorithm, Heuristics mining algorithm, region mining algorithm, etc [1, 4]. As a first mining algorithm, we used the Heuristics mining algorithm, since it can deal with noise and exceptions, and enables users to focus on the main process flow, instead of on every detail of the behavior appearing in the event log [1].

Figure 2 shows a part of the process model obtained by the Heuristics mining algorithm. Although, the model focusses on only the “complete” events and the main paths followed, it is quite ‘spaghetti-like’. This demonstrates that the process is less structured and requires quite some flexibility in executing the actual procedure. Even more importantly, although such a model can be understood by process analysts, it is mostly not at all comprehensible to professionals working in the field (e.g. a dentist or a dental lab owner). To arrive at a comprehensible model, we applied the following strategy. First, for the events related to the dental practice only these events were selected that occur in more than 10% of the process instances. Second, for the lab, we only identify a start event when the lab starts producing a certain product and an end event when the lab finishes producing the respective product. Note that the name of both the start and event refer to the product that is made. In this way, for the dental practice we just concentrate on the most important events and their ordering. Also, by only focusing on a start and end event for each product that is made in the lab, it can be specifically seen in the entire process when the work in the lab is performed. The two above mentioned filtering steps resulted in a log consisting of 55 cases, 211 events, and 10 different event names. Compared to the previous log, the overall number of events and the number of different event names significantly decreased.

The result can be seen in Figure 3. Here it needs to be noted that the model shown is a Petri net [19]; white rectangles represent work tasks, whereas black rectangles are only added to accurately describe the flow of work. The reader who is not familiar with Petri nets may refer to [19]. The model has been obtained by first applying the Heuristics mining algorithm and afterwards the obtained Heuristics net is converted into a Petri net. Later in the paper we will use this same model for presenting performance related information about the process. Note that although the discovered





**Figure 3: Petri net obtained for the filtered log. White rectangles represent tasks, whereas black rectangles are only added to accurately describe the flow of work.**

Petri net may look simple this does not mean that the discovered model could have been obtained manually, e.g. by inspecting the event log.

An important aspect that needs to be considered for a discovered net is whether it is representative for the behavior seen in the event log. An important quality indicator is the *fitness* metric, which has been implemented in the “conformance checker” plug-in of ProM [1]. This metric is based on the amount of missing and remaining tokens during log replay, i.e. it quantifies to which degree a log complies with a given process model. A fitness value of “1.0” indicates that the model is able to parse all the events of each case whereas a fitness value of “0.0” indicates that not any event of a case can be successfully parsed. For the discovered model in Figure 3, the fitness value is “0.95”, which indicates that it is highly representative for the behavior seen in the log.

The process that has been discovered for the “single crown on implants” process is the following. First of all, regarding the working process of the dentist there is an implant consultation (task “implant consultation”) in which the placing of an implant and the final restoration is discussed. This meet-

ing is followed by the placing of the implants (task “place implant(s)”). Afterwards, either a check-up meeting takes place (task “check-up”) or a check-up takes place together with the exposure of the implant (task “check-up + expose implant(s)”). Note that after the check-up meeting there is also the option to expose the implant in an individual meeting (task “expose implant(s)”) or not. As part of placing the final restoration, first an impression is made (task “impression crown on implant”) followed by the placing of the crown itself (task “place crown on implant”). Finally, for some patients a problem occurs in the sense that there is a problem with the crown or abutment (task “crown or abutment out or instable”). Here, the “crown or abutment out or instable” transition corresponds to the individual appointment that takes place in order to solve the problem. The start and beginning of the production of the crown by the lab is represented by the “produce crown (start)” task and “produce crown (complete)” task respectively. As can be seen, the production of the crown can start at different places in the place but ends before the placement of the crown.

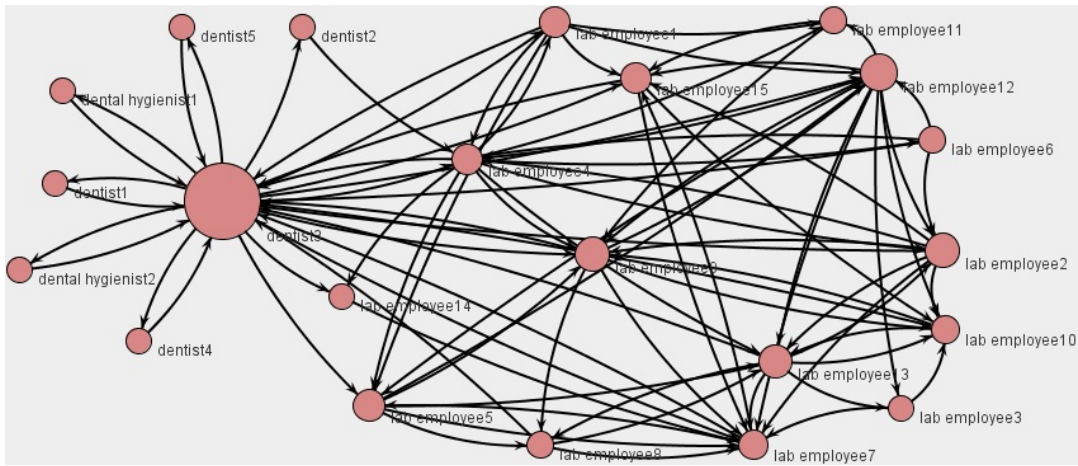
The model shown in Figure 3 has been validated with the owner of the process. The owner confirmed the truthfulness of the process as it has been discovered. In addition, it was stressed that for the lab an impression is always needed. For the model this has as meaning that the making of the impression is made during the “impression crown on implant” task or it is made as part of either the “place implant(s)”, “expose implant(s)”, “check-up”, or “check-up + expose implant(s)” tasks.

## 4.2 Resource Perspective

There are several process mining techniques that address the organizational perspective, e.g., organizational mining, social network mining, mining staff assignment rules, etc. [2]. Here, we elaborate on social network mining to provide insights into the collaboration between people in the entire process for the dental practice as well for the lab. The Social Network miner allows for the discovery of social networks from process logs. The generated social network allows for the analysis of social relations between persons involving process executions. Figure 4 shows the derived social network. To create the network, we used the “handover of work” metric [2] that measures the frequency of transfers of work among people working in the process. Note that for deriving the social network we used the original log for which the corresponding Heuristics net is shown in Figure 2. In this way, we can analyze all the recorded, direct handovers of work between people.

The people that are highly involved in the process appear as larger dots in the figure. The results are useful to detect whether people are highly involved in the process or that they only collaborate with a few people. Note that the names of the people have been anonymized due to confidentiality issues. Also, the name of a dot indicates the role being played by a person.

From the mining result it immediately becomes clear that person “dentist3” is highly involved in the process. About this observation, we had a discussion with the process owners in order to interpret the results. They agreed with the main results. Additionally, the discussion also led to the following



**Figure 4: Social network for both the dental practice and the dental lab. The red dots represent people involved in the process. A dot with prefix “dentist” represents a dentist whereas the prefixes “dental hygienist” and “lab employee” respectively represent a dental hygienist and a lab employee.**

insights. That is, a closer inspection revealed that “dentist3” is the main person responsible for the dental practice on the placing of the implants, as well as the placement of the final crown. Moreover, via arcs “dentist3” is connected with persons “dentist5”, “dental hygienist1”, “dentist1”, “dental hygienist2”, “dentist4”, and “dentist5”. For each of these persons there are no connections with other persons in the network. Also, “dentist3” is connected with “dentist2” for which there is only one connection with another person in the network. Here, the discussion made us understand that these persons all work for the dental practice and are colleagues of “dentist3”. In particular, “dental hygienist1” and “dental hygienist2” are dental hygienists and the involvement of “dentist1”, “dentist2”, “dentist4”, and “dentist5” is related to the fact that even though they are dentists they sometimes perform a task in case a patient has a problem. So, the remaining persons in the network are working for the dental lab. Also, if “dentist3” would be removed from the diagram there would be two almost disconnected clusters of persons. In this way, the network clearly shows that for the “single crown on implants” process there are two different organizations involved and that there is a clear divide between the organizational roles involved.

Finally, another interesting result that can be seen in the network is that both “lab employee7” and “lab employee10”, both working for the lab, have many incoming arcs. A discussion with the process owners revealed that this is due to the fact that these persons are responsible for the making of the bill, which is typically the last task that is done for a product that is made in the lab; work is handed over to them last.

### 4.3 Performance Perspective

Process mining also provides several performance analysis techniques. For this purpose, we made use of the *extension* type of process mining. That is, the Petri net model shown in Figure 3 was used for an enhanced analysis.

Figure 5 shows the results of a performance analysis based on the mined model shown in Figure 3 and its corresponding

log. The analysis is performed by the “Performance Analysis with Petri net” plug-in. In particular, the plug-in projects timing information on places and transitions. It graphically shows the bottlenecks and all kinds of performance indicators, e.g., average/variance of the total throughput time or the time spent between two tasks. Furthermore, in case of a choice within the process, it is shown how often the alternative was followed.

In Figure 5, the coloring of the places visualizes how much time a case spends in the place waiting for the next task. A pink color denotes a high waiting time (more than 14 days), a yellow color denotes a medium waiting time (between 7 and 14 days), and a blue color denotes a low waiting time (lower than 7 days). For example, the place between the “implant consultation” and the “place implant(s)” task has a pink color as the average waiting time is “59.37” days (standard deviation “53.93”). Another place in the process for which there is a high waiting time is the place after the “check-up” task. Moreover, the place between the “produce crown (start)” task and the “produce crown (complete)” task is colored yellow, which means that the work done by the lab also requires quite some time. In fact, the average waiting time spent in this place is “11.91” days (standard deviation “5.63”). Note that for a place much more timing related information is calculated (e.g. synchronization time, minimum, and maximum values for them).

Also for the tasks in the process, performance related information was calculated with the plug-in. In Table 1, for several pairs of tasks, performance related information is presented concerning the time between these tasks. For example, it can be seen that the average time between the “place implant” and “expose implant” tasks is “81.6” days, the standard deviation is “36.72”, and the minimal and maximal value is “41.72” and “181.98” days respectively. Regarding the choices in the process it can be seen, for example, that for 4% of the patients, the check-up is combined with the exposing of the implant. Also, after the check-up for 30% of the patients following this path the implant(s) are exposed.



Tasks	Average	St Dev	Min	Max
“place implant(s)” and “check-up”	8.16	2.65	5.74	17.79
“place implant(s)” and “expose implant(s)”	81.6	36.72	41.72	181.98
“place implant(s)” and “impression crown on implant”	86.71	49.3	40.81	238.99
“check-up” and “expose implant(s)”	70.04	34.96	35.07	169.19
“expose implant(s)” and “impression crown on implant”	11.55	15.37	1.0	49.22
“impression crown on implant” and “place crown on implant”	15.84	3.26	13.0	25.79

**Table 1: Several statistics about the time that is spent between two tasks. For each pair of tasks, the average (Average), minimal (Min), and maximal (Max) time between them is provided. Also, the corresponding standard deviation (St Dev) is provided.**

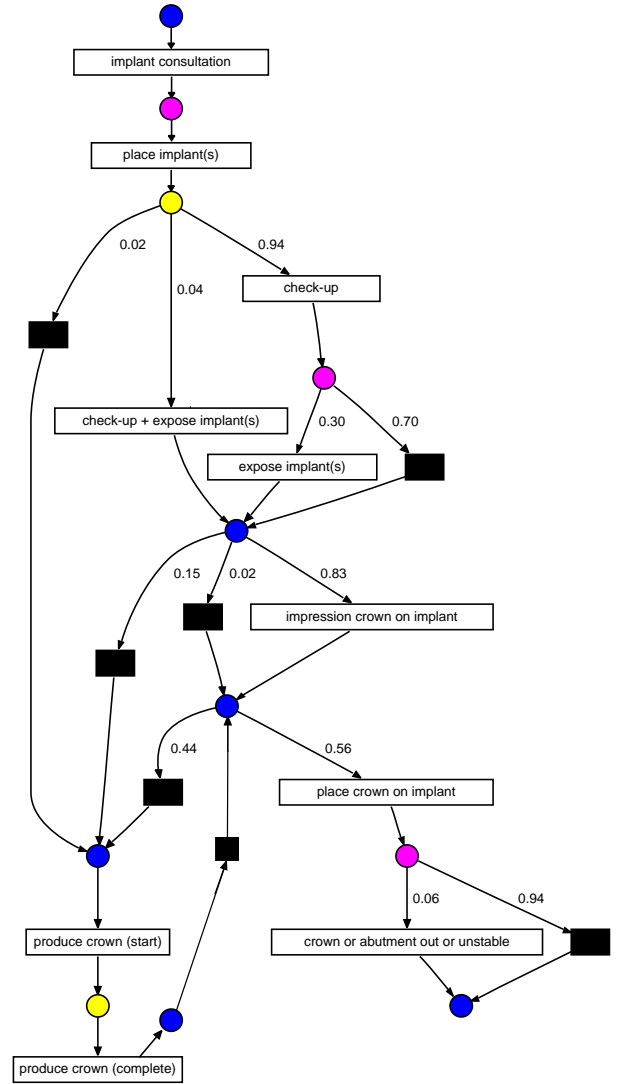
The above mentioned results were presented to the people involved in the process, who confirmed that these values are realistic. Moreover, they showed a great interest for the exact timing information that was obtained. This is due to the fact that in dentistry sometimes there is mandatory waiting time between tasks. For example, imagine the time that is necessary to allow for the healing of a wound. This also shows that for places for which there is a high waiting time, it can not be automatically assumed in dentistry, that potentially for them a lower waiting time can be realized. For example, the high waiting time in the place after the “check-up” task is actually artificially created and should not be seen as an inefficiency.

## 5. CONCLUSION AND OUTLOOK

In this paper, we have concentrated on the usefulness of process mining in dentistry. In particular, we have focused on the “single crown on implants” process as it is currently executed at both a private dental practice and a dental lab in the Netherlands. For the control-flow, organizational, and performance perspectives we have obtained detailed insights. The validity of our results were confirmed by people involved in the analyzed process. Our evaluation demonstrates that process mining is a technology that is of value to discover actual process behavior, even when it involves multiple parties across organizational boundaries, as is clearly the case in the dental domain. Several innovative methodological and technical steps were taken to deal with this aspect, which has not been part of previous work on process mining.

When looking beyond the results of this paper, it is useful to reflect on the operational process that was considered. It involved one dental practice and one dental lab. We expect that due to the introduction of digital dentistry more independent dental business entities will play a role in similar processes. For example, the usage of an intra-oral scanner for making a scan of a patient’s mouth requires that an external organization is required to process the scan. Additionally, in the future a CAD tool may be used in the lab for designing the final restoration. Afterwards, the design is sent to the milling center in order to produce the final restoration. Finally, the restoration is sent to the lab.

In such a context, it is clear to us that workflow management technology will become important to provide additional support for the changing dental process. Workflow management primarily focuses on the automation and support of processes. In particular, workflow management is extremely useful when many different business entities are involved that need to be supported and guided. However, a drawback is that workflow management tools as they are



**Figure 5: Performance values of the process and its tasks are discovered.**



typically used do not meet the requirements of the dental industry yet. Two current shortcomings are:

- The need to optimize a process over many different small entities that together form the dental process. For the healthcare domain, the work of Mans et al. [16] can be seen as a starting point to deal with this issue, as it shows how process fragments and their relationships can be captured and executed.
- Workflow management researchers typically optimize on throughput time and effort. The quality of the resulting product is often not explicitly modeled. In a “paper” environment this can be sufficient. A paper form that is completed via process A or B can be considered equal. In dentistry this is not sufficient. Here, a very important aspect is “precision of fit”. This can be measured in microns and needs to be optimized over the entire process. This is exactly what is currently happening in modeling digital processes in the dental industry. An example: it is interesting for both the dentist and the patient to place the implants and the prosthetics in one visit. However, the prosthetics only allows a placement inaccuracy of 30 microns while the analogues placement of the implant is 100 microns inaccurate. An important question is now: “How can a superstructure with prosthetics be designed accurate enough so it can be manufactured before the implants are placed [25]”?

We argue that workflow management will play a significant role in making digital dentistry happen. However, modeling alternative process flows without considering and modeling precision will not be convincing for dental professionals, since it is untested on the one hand and precision does not behave linearly like time and work efforts on the other. For example, losing microns in scanning cannot be compensated later on by more precise manufacturing steps. Even worse, loss of precision early on the process typically propagates through the process and increases the inaccuracies later on. Modeling this kind of accuracy in workflow models is a relevant and interesting challenge for workflow management researchers.

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## 7. REFERENCES

- [1] W.M.P. van der Aalst. *Process Mining: Discovery, Conformance and Enhancement of Business Processes*. Springer-Verlag, Berlin, 2011.
- [2] W.M.P. van der Aalst, H.A. Reijers, and M.S. Song. Discovering Social Networks from Event Logs. *Computer Supported Cooperative Work*, 14(6):549–593, 2005.
- [3] W.M.P. van der Aalst, B.F. van Dongen, J. Herbst, L. Maruster, G. Schimm, and A.J.M.M. Weijters. Workflow Mining: A Survey of Issues and Approaches. *Data and Knowledge Engineering*, 47(2):237–267, 2003.
- [4] W.M.P. van der Aalst, A.J.M.M. Weijters, and L. Maruster. Workflow Mining: Discovering Process Models from Event Logs. *IEEE Transactions on Knowledge and Data Engineering*, 16(9):1128–1142, 2004.
- [5] R. Agrawal, D. Gunopulos, and F. Leymann. Mining Process Models from Workflow Logs. In *Sixth International Conference on Extending Database Technology*, pages 469–483, 1998.
- [6] A. Datta. Automating the Discovery of As-Is Business Process Models: Probabilistic and Algorithmic Approaches. *Information Systems Research*, 9(3):275–301, 1998.
- [7] P.C. Diniz and D.R. Ferreira. Automatic Extraction of Process Control Flow from I/O Operations. In M. Dumas, M. Reichert, and M.-C. Shan, editors, *Proceedings of the Business Process Management 6th International Conference, BPM 2008, Milan, Italy, September 2-4, 2008*, volume 5240 of *Lecture Notes in Computer Science*. Springer-Verlag, Berlin, 2008.
- [8] B.F. van Dongen and W.M.P. van der Aalst. Multi-Phase Process Mining: Building Instance Graphs. In P. Atzeni, W. Chu, H. Lu, S. Zhou, and T.W. Ling, editors, *International Conference on Conceptual Modeling (ER 2004)*, volume 3288 of *Lecture Notes in Computer Science*, pages 362–376. Springer-Verlag, Berlin, 2004.
- [9] M. Dumas, W.M.P. van der Aalst, and A.H.M. ter Hofstede. *Process-Aware Information Systems: Bridging People and Software through Process Technology*. Wiley & Sons, 2005.
- [10] J. Ghattas, M. Peleg, P. Soffer, and Y. Denekamp. Learning the Context of a Clinical Process. In S. Rinderle-Ma, S. Sadiq, and F. Leymann, editors, *BPM 2009 International Workshops, Ulm, Germany, September 7, 2009. Revised Papers*, volume 43 of *Lecture Notes in Business Information Processing*, pages 545–556. Springer-Verlag, Berlin, 2010.
- [11] J. Herbst. A Machine Learning Approach to Workflow Management. In *Proceedings 11th European Conference on Machine Learning*, volume 1810 of *Lecture Notes in Computer Science*, pages 183–194. Springer-Verlag, Berlin, 2000.
- [12] C. Li, M. Reichert, and A. Wombacher. Mining Business Process Variants: Challenges, Scenarios, Algorithms. *Data & Knowledge Engineering*, 70(5):409–434, 2011.
- [13] L. T. Ly, S. Rinderle, P. Dadam, and M. Reichert. Mining Staff Assignment Rules from Event-Based Data. In C. Bussler et al., editor, *Business Process Management 2005 Workshops*, volume 3812 of *Lecture Notes in Computer Science*, pages 177–190. Springer-Verlag, Berlin, 2006.
- [14] R.S. Mans, M.H. Schonenberg, G. Leonardi, S. Panzarasa, S. Quaglini, and W.M.P. van der Aalst. Process Mining Techniques : An Application to Stroke Care. In S.K. Andersen et al., editor, *eHealth Beyond the Horizon - Get IT There (Proceedings 21st International Congress of the European Federation for Medical Informatics, MIE 2008)*, volume 136 of *Studies in Health Technology and Informatics*, pages 573–578. IOS Press, 2008.

- [15] R.S. Mans, M.H. Schonenberg, M.S. Song, W.M.P. van der Aalst, and P.J.M. Bakker. Process Mining in Healthcare: a Case Study. In L. Azevedo and A.R. Londral, editors, *Proceedings of the First International Conference on Health Informatics (HEALTHINF 2008)*, volume 1, pages 118–125. INSTICC Press, 2008.
- [16] R.S. Mans, W.M.P. van der Aalst, N.C. Russell, P.J. Bakker, and A.J. Moleman. Lightweight Interacting Patient Treatment Processes. *Accepted for Publication in the International Journal of Knowledge-Based Organizations (IJKBO)*, 2012.
- [17] J. Poelmans, G. Dedene, G. Verheyden, H. van der Mussele, S. Viaene, and E. Peters. Combining Business Process and Data Discovery Techniques for Analyzing and Improving Integrated Care Pathways. In P. Perner, editor, *Advances in Data Mining. Applications and Theoretical Aspects 10th Industrial Conference, ICDM 2010*, volume 6171 of *Lecture Notes in Computer Science*, pages 505–517. Springer-Verlag, Berlin, 2010.
- [18] A. Rebuge and D.R. Ferreira. Business Process Analysis in Healthcare Environments: A Methodology Based on Process Mining. *Information Systems*, 2011. In Press.
- [19] W. Reisig. *Petri Nets: An Introduction*, volume 4 of *EATCS Monographs in Theoretical Computer Science*. Springer-Verlag, Berlin, 1985.
- [20] A. Rozinat, R.S. Mans, M.S. Song, and W.M.P. van der Aalst. Discovering Simulation Models. *Information Systems*, 34(3):305–327, 2009.
- [21] A. Rozinat and W.M.P. van der Aalst. Conformance Checking of Processes Based on Monitoring Real Behavior. *Information Systems*, 33:64–95, 2008.
- [22] Y. Shan, D. Jeacocke, D.W. Murray, and A. Sutinen. Mining Medical Specialist Billing Patterns for Health Service Management. In J.F. Roddick, J. Li, P. Christen, and P.J. Kennedy, editors, *Conferences in Research and Practice in Information Technology*, volume 87, pages 105–110, 2008.
- [23] M.S. Song and W.M.P. van der Aalst. Supporting Process Mining by Showing Events at a Glance. In K. Chari and A. Kumar, editors, *Proceedings of the Seventeenth Annual Workshop on Information Technologies and Systems (WITS 2007)*, pages 139–145, 2007.
- [24] M.S. Song and W.M.P. van der Aalst. Towards Comprehensive Support for Organizational Mining. *Decision Support Systems*, 46(1):300–317, 2008.
- [25] A. Tahmaseb, R. de Clerck, and D. Wismeijer. Computer Guided Implant Placement: 3D Planning Software, Fixed Intraoral Reference Points and CAD/CAM Technology. A Case Report. *The International Journal of Oral and Maxillofacial Implants*, 24(3), 2009.
- [26] J.M.E.M. van der Werf, B.F. van Dongen, C.A.J. Hurkens, and A. Serebrenik. Process Discovery using Integer Linear Programming. *Fundamenta Informaticae*, 94(3–4):387–412, 2009.
- [27] A.J.M.M. Weijters and W.M.P. van der Aalst. Rediscovering Workflow Models from Event-Based Data using Little Thumb. *Integrated Computer-Aided Engineering*, 10(2):151–162, 2003.
- [28] L. Wen, J. Wang, W.M.P. van der Aalst, B. Huang, and J. Sun. A Novel Approach for Process Mining Based on Event Types. *Journal of Intelligent Information Systems*, 32(2):163–190, 2009.
- [29] W.-S. Yang and S.-Y. Hwang. A Process-Mining Framework for the Detection of Healthcare Fraud and Abuse. *Expert Systems with Applications*, 31:56–68, 2006.