Using Event logs and Rapid Ethnographic Data to Mine Clinical Pathways

by

Aditya Deotale

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Graduate Supervisory Committee:

Huan Liu, Co-Chair
M. Adela Grando, Co-Chair
Lydia Manikonda

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ABSTRACT

Background: Process mining (PM) using event log files is gaining popularity in healthcare to investigate clinical pathways. But it has many unique challenges. Clinical Pathways (CPs) are often complex and unstructured which results in spaghetti-like models. Moreover, the log files collected from the electronic health record (EHR) often contain noisy and incomplete data. Objective: Based on the traditional process mining technique of using event logs generated by an EHR, observational video data from rapid ethnography (RE) were combined to model, interpret, simplify and validate the perioperative (PeriOp) CPs. Method: The data collection and analysis pipeline consisted of the following steps: (1) Obtain RE data, (2) Obtain EHR event logs, (3) Generate CP from RE data, (4) Identify EHR interfaces and functionalities, (5) Analyze EHR functionalities to identify missing events, (6) Clean and preprocess event logs to remove noise, (7) Use PM to compute CP time metrics, (8) Further remove noise by removing outliers, (9) Mine CP from event logs and (10) Compare CPs resulting from RE and PM. Results: Four provider interviews and 1,917,059 event logs and 877 minutes of video ethnography recording EHRs interaction were collected. When mapping event logs to EHR functionalities, the intraoperative (IntraOp) event logs were more complete (45%) when compared with preoperative (35%) and postoperative (21.5%) event logs. After removing the noise (496 outliers) and calculating the duration of the PeriOp CP, the median was 189 minutes and the standard deviation was 291 minutes. Finally, RE data were analyzed to help identify most clinically relevant event logs and simplify spaghetti-like CPs resulting from PM. Conclusion: The study demonstrated the use of RE to help overcome challenges of automatic discovery of CPs. It also demonstrated that RE data could be used to identify relevant clinical tasks and incomplete data, remove noise (outliers), simplify CPs and validate mined CPs.

Keywords: Electronic Medical Records, Event logs, Rapid Ethnography, Process mining

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I dedicate this dissertation to my parents – Dr. Vijay Deotale and Dr. Asawari Deotale for their love and blessings.

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CHAPTER 1: Background and Significance

An event log can be seen as a collection of cases and a case can be seen as a trace/sequence of events(Z. Huang et al., n.d.). The number of events that are recorded in an event log in a hospital setting has been growing rapidly. PM can be used to gain valuable insights and extract knowledge from these event logs. PM is the discipline focusing on techniques, tools and methods to discover, monitor and improve real processes by extracting knowledge from event logs commonly available in today's information systems(W.M.P. van der Aalst 2011). PM techniques can be categorized into: i) discovery, ii) conformance and iii) enhancement(M. Ghasemi and D. Amyot, n.d.). In process discovery, the goal is to create a process model or clinical pathway (CP) with the help of event logs using PM algorithms. The term CP does not have a single widely accepted definition(L. De Bleser et al., n.d.). For this study, CP is defined as a set of therapy and treatment activities that represent the steps required to achieve a specific treatment objective in a patient careflow(Z. Huang et al., n.d.). It provides standardization of clinical practices and determines compliance with clinical guidelines to enhance patient care. It helps with the visualization of patient trajectories in a hospital setting which can pave the way for analyzing anomalous pathways. CPs often involve several underlying patterns of treatment activities from admission to discharge, possibly over different time scales and for varying time intervals(Z. Huang et al., n.d.). Understanding CPs could help to improve the quality of care, reduce risks, increase resource efficiency and enhance patient satisfaction(M. Ghasemi and D. Amyot, n.d.). Studies conducted on the use of CPs in surgery showed a positive impact on cost-saving and nursing activities(M. K. Müller, n.d.). Implementation of CP has resulted in a reduction in length of stay of patients which translated into lower healthcare costs(M. K. Müller, n.d.). It has also been found that CPs can have a positive impact on the providers by increasing their satisfaction and reducing working hours(M. K. Müller, n.d.; J. Schuld, n.d.). CPs can help in determining clinical guideline compliance and detecting anomalous care pathways on time, which can have an impact on the survival of the patient(Z. Huang, X.Lu, and H. Duan, n.d.). CP discovery comes with its own set of challenges. CPs are unstructured, complex and dynamic in nature. One problem encountered in PM is noisy data which could be the result of incorrect or incomplete logged data(M. Ghasemi and D. Amyot, n.d.; A. Tiwari and C.J. Turner, n.d.; W.M.P. van der Aalst, n.d.). For example, an event is not recorded or recorded at a time different than the actual time. PM algorithms operate with the assumption that the event log is noise free because causal relations should not be based on a single noisy observation(W.M.P. van der Aalst, n.d.). As a result, the noise from the event logs increases the complexity of CPs discovered using PM(M. Ghasemi and D. Amyot, n.d.). To address those challenges, CPs mined from event logs have been validated by clinicians or through comparison with standardized clinical guidelines or procedure guidelines set by the hospital(I. Litchfield and C. Hoye, n.d.; F. Mannhardt and D. Blinde, n.d.). As a method of data collection, rapid ethnography entails examining the behavior of the participants in a certain specific social situation and also understanding their interpretation of such behavior(D. R. Millen, n.d.). The use of rapid ethnographic data (observations, video ethnography, clinician interviews, etc.) to validate CPs discovered from event logs is relatively new(A. Renedo, n.d.; S. Vougiokalou, n.d.). The

Mayo Clinic has undergone an enterprise-wide, large-scale EHR conversion. Before the conversion, the ROOT (Registry of Operations and Tasks) project was launched in 2016 to document and harmonize EHR-mediated workflows and health information technologies interactions. ROOT focusses on understanding variations across different systems and sites by using a broad range of methods including video ethnography, interviews, observations, shadowing and event logs analysis. We have triangulated rapid ethnographic methods and PM of event logs generated by the EHR to discover and visualize workflows and CPs(M. A. Grando et al., n.d.; B. Doebbeling et al., n.d.; S. K. Furniss et al., n.d.; D. R. Kaufman et al., n.d.; R. Helmers et al., n.d.). The perioperative (PeriOp) setting has been the primary setting for most of our work in the ROOT project. PeriOp is defined as the period extending from when the patient goes into the hospital, clinic or doctor's office for surgery until the time the patient leaves the postoperative area(F. Mannhardt and D. Blinde, n.d.; D. R. Millen, n.d.; A. Renedo, n.d.; S. Vougiokalou, n.d.; M. A. Grando et al., n.d.). The PeriOp setting is comprised of three different settings: i) PreOp: the patient is prepared for the surgery following admission, ii) IntraOp: the patient is in the Operating Room (OR) undergoing the surgery, iii) PostOp: the patient is recovering from surgery and anesthesia and getting ready to be discharged home or to transferred to the inpatient area. PeriOp is an extremely complex and high cost setting, contributing to a significant number of patient safety-related adverse events(P. J. St. Jacques and M. N. Minear, n.d.).

CHAPTER 2: Objectives

Apply PM and rapid ethnography to discover, validate and analyze CPs from EHR interactions of clinical personnel at Mayo Clinic PeriOp setting.

CHAPTER 3: Methods

The study was deemed exempt by the Mayo Clinic Institutional Review Board (IRB). The Arizona State University IRB also approved the study based on the Mayo Clinic's review. This study took place after an enterprise-wide conversion to a new EHR. This research involved the PeriOp setting at the Eau Claire facility (Wisconsin). This is a tertiary care centre with cardiac surgery, neurosurgery and advanced medical oncology. It has 21 operating rooms and 200 beds. The site has a full complement of medical students, residents, and fellows. The methodological approach followed for this study is described in Figure 1. Below we provide more details on the steps followed.

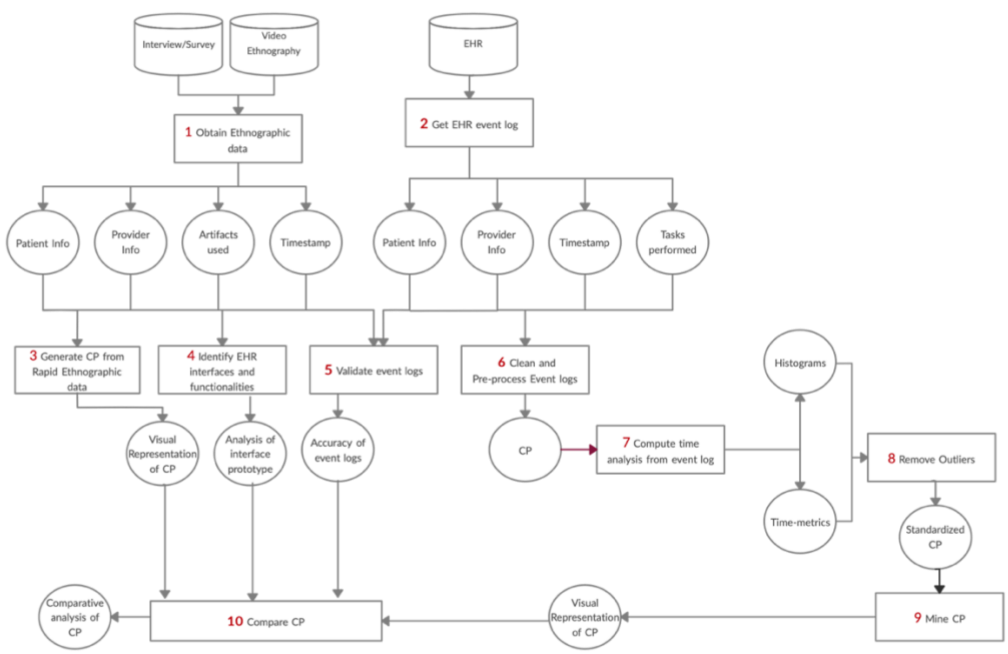

Figure 1. Schematic representation of the methodology used, including steps (squares) and their corresponding inputs and outputs (ovals)

3.1. Obtain Rapid Ethnographic Data:

Video ethnography, observations and interviews were used for this research. Providers with different roles were observed and tracked while they were performing tasks during their day to day work. They were also interviewed on the tasks they perform from the moment patient enter the hospital until they are discharged. They were asked to describe the challenges they face with the EHR use while going through their duties. Video ethnography involved capturing EHR interactions with a handheld video camera and with the Morae software(Techsmith, n.d.). Via the use of webcam, we also video recorded participants' hands, desk space and paper-based artifacts that were used during interactions with the EHR. The webcam also recorded the audio of participants, verbalizing their thoughts and conversations in the immediate vicinity.

3.2. Get Event Logs:

The other kind of data used in this research was event logs that were generated by the EHR. We received event logs for the same days when rapid ethnographic data was collected. Event logs were shared as Excel files. Event logs recorded the tasks being performed in the EHR by providers at a setting on patients at a certain time and day (see Table 1).

Table 1. Example of the event logs retrieved from the EHR, where two providers interact with the EHR to provide care to a patient in the PreOp and IntraOp settings

Timestamp	Patient ID	Provider ID	Setting: Activity
01/22/18 11:45	123	567	PreOp:Medications reviewed
01/22/18 11:52	123	567	PreOp:Consents form viewed
01/22/18 11:54	123	890	IntraOp:Consents form signed

3.3. Generate CP from rapid ethnographic data:

Ethnographic data consisting of interviews and video ethnography were used to generate CPs. Interviews helped to understand providers' roles, daily work and patient interactions. This information, along with video ethnography, was used to construct CPs for patient admission to discharge.

3.4. Identify EHR Interfaces and their Functionalities from Rapid Ethnographic Data:

Different provider roles interact with the EHR in order to perform PeriOp tasks. The EHR interface that the providers interact with can influence the order in which tasks are performed. The goal was to study the EHR interfaces and understand if the interface design played any role in providers' decision making and the order of task execution. This information was collected by observing videos that showed providers performing EHR tasks.

3.5. Identify Missing Events Using Rapid Ethnographic Data:

The event logs for a particular patient were matched with the tasks performed by PeriOp providers, as captured with video ethnography. Attributes like timestamp, patient identifier, provider identifier and the activity performed were used in the mapping, to assess how frequently clinical tasks supported by the EHR were also captured in the event logs. The goal was to identify incomplete data that may later impact the accuracy of the CPs discovered with PM.

3.6 Clean and Pre-process Event Logs:

Event logs may contain EHR interactions recorded day/s before (e.g. tasks required in the process of scheduling a surgery) or after surgery (e.g. scheduling follow up appointments). We wrote Python programs to automatically remove provider EHR interactions that did not occur on the day of the patient surgery.

3.7 Compute Time Analysis from Event Logs:

An automatic time metric analysis was performed. The event logs were used to estimate how much time a patient spends in the PeriOp setting. Python programs were written to analyze the timestamps in the event logs and compute means, standard deviations and median times of the discovered CPs. Finally, a histogram was created using Excel to visualize the distribution of time spent by patients in the PeriOp.

3.8 Remove Outliers Using Time Metrics:

Python programs were written to automatically create histograms and to remove CPs that have significantly shorter or longer duration. We assumed that outliers may result from incomplete or noisy data.

3.9 Model Clinical Pathways:

The event logs resulting from removing the outliers were input into the Disco software to automatically mine and visualize CPs(Fluxicon, n.d.). CP generated using PM consists of tasks (visually represented as squares), task transitions (arrows) and time metrics, including frequency of task enactment and task transitions.

3.10 Compare Clinical Pathways Discovered Through Rapid Ethnography and Process Mining:

To determine the accuracy of the PreOp, IntraOp and PostOp CPs discovered through PM techniques, the outcomes from steps 3 and 9 were manually compared and validated with rapid ethnographic data. Outcomes from steps 4 and 5 guided the analysis to capture high-frequency tasks and task transitions discovered through PM that were confirmed as relevant tasks by the rapid ethnographic data. Infrequent or non-relevant tasks were disregarded to simplify the resulting CP.

CHAPTER 4: Results

4.1 Rapid Ethnographic Data:

We collected rapid ethnographic data from January 15th to 26th of 2018. Data included three ethnographic videos for the PreOp phase capturing 499 minutes. We also collected three IntraOp and one PostOp video corresponding to 207 minutes and 171 minutes respectively. We also interviewed four different providers covering roles ranging from PostOp Registered Nurse (RN), PreOp Health Unit Coordinator (HUC), PreOp RN and PreOp registration clerk (?). We shadowed a Patient Care Aid (PCA) and a HUC.

4.2 Event Logs:

Event logs were collected for the same dates when rapid ethnographic data was collected. The number of event logs was 1,917,059. They captured interactions between 100 providers and 1,386 patients.

4.3 CP Obtained from Rapid Ethnographic Data:

Figure 2 represents the CP discovered from ethnographic data. The Lead RN starts the PreOp process by checking the PeriOp schedule a day before the patient arrives. The essential responsibilities of the Lead RN include checking the patient and dividing the patients among the nurses available on the following day. On the day the patient arrives, it starts with a volunteer escorting the patient to the waiting area. The HUC then checks the patient with the master schedule, prepares the chart and puts the patient sticker on the clipboard for the RN. The RN then picks up the clipboard and assigns the patient to the PreOp room. The patient is prepared, and vitals are conducted. This is usually done by the PCA. The RN then uses the EHR to perform tasks like verifying the patient, releasing any signed orders, signing the consent forms, assigning devices, changing medication status, etc. After the operation room (OR) report is created, the patient is ready to be transferred to the OR. There are two RNs in the OR. One RN, called Scrub RN, assists the surgeons with sterilizing the table and the patient. The other RN, called Circulatory RN, prepares the instruments or medicines needed during the surgery. The Circulatory RN is also responsible for interacting with the EHR and performing charting during the IntraOp phase. After the procedure, the patient is transferred to recovery. The Perianesthesia Care Unit (PACU) RN then receives the report from the OR RN. The PACU RN then performs a series of assessments and monitors vital signs. The PACU RN performs assessments periodically and makes sure that the patient is recovering well. Once the patient is fit to be transferred to phase 2 recovery, the PACU RN informs the lead RN that the patient can be moved to a different room. At this stage, the patient is ready to leave the perioperative area.

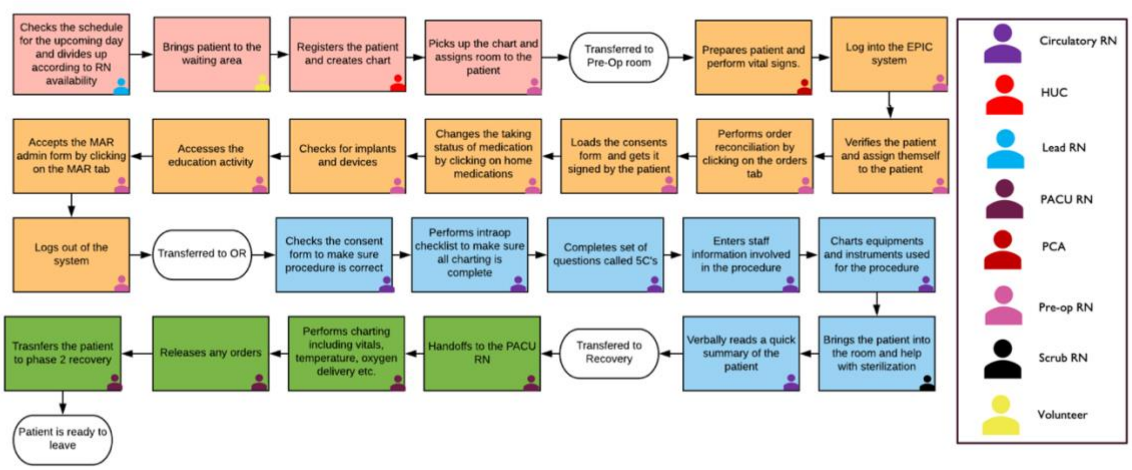

Figure 2. CP discovered from rapid ethnographic data

4.4 EHR interfaces and functionality:

We wanted to examine if the EHR interface had any impact on the way providers complete clinical tasks. We observed EHR interfaces in Preop, IntraOp and PostOp settings. For all settings, the EHR interface can be classified into a main interface and an intermediate interface. For all settings, the main interface consists of tabs called Orders, Flowsheets, MAR, Chart review, Care everywhere, etc. (see Figure 3 for the full list of tabs) The main interface also contains a tab corresponding to the setting. For instance, the PreOp setting contains a tab called PreOp which reveals the primary interface where providers spend most of the time. The ordering of the tabs in the main interface differs across different settings. The ordering of the tabs within the same setting can also be different based on the provider's role. In the intermediate interface (Figure 3), the tabs are arranged such that providers can perform them from top to bottom order. For instance, in the PreOp setting, the order of the tabs is Pre-incision, Specimen/Copaths, Procedures and Closing. As a result, providers often perform tasks following the order of the tabs. However, even though the interface tabs are organized to help providers perform tasks from top to bottom, it was observed that providers differ in their behavior patterns. For instance, one provider in the IntraOp setting preferred to check off tasks at the bottom of the interface before performing tasks at the top. This could be based on the patient case or providers' personal style.

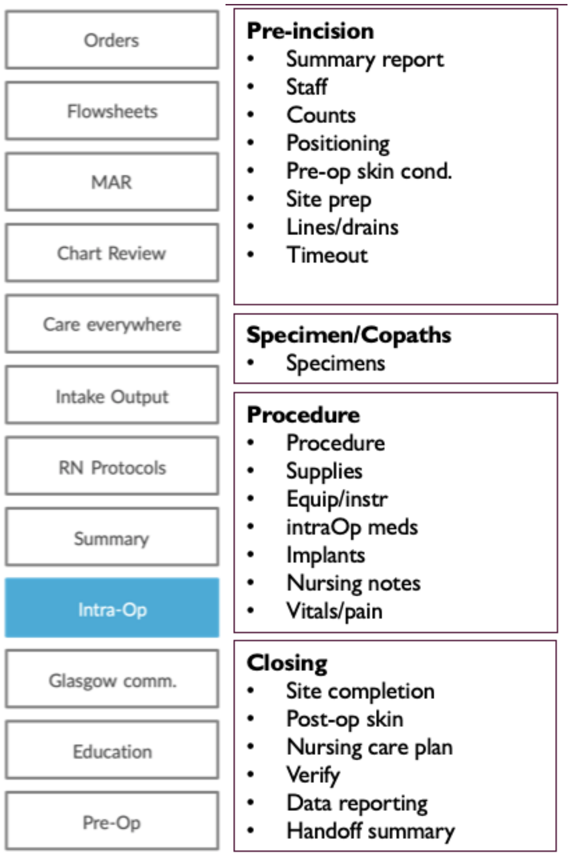

Figure 3. Main PreOp EHR interface (left) and intermediate interface (right). The intermediate interface is accessed after clicking the IntraOp tab in the main interface.

4.5 Missing Events Identified by Analyzing EHR Interfaces:

We mapped the tasks supported by the EHR interface, as captured by video ethnography, with the tasks recorded in the event logs (Table 3). We found that the highest mapping (45%) was in the IntraOp setting.

Table 2. Mapping of EHR-mediated tasks as captured by video ethnography and event logs.

Setting	Tasks supported by the EHR	Tasks captured by the event logs	% mapping
PreOp	28	10	35%
IntraOp	22	10	45%
PostOp, PACU	22	4	18%
PostOp, Discharge	36	9	25%

4.6 Event Logs Cleaned and Pre-processed:

The number of event logs and patient cases was reduced to 9,53,792 and 1,236 respectively after automatic pre-processing and data cleaning.

4.7 Time Analysis:

Time metric analysis was performed on the discovered CPs. Disco was used to compute the median=189 minutes, mean= 279 minutes and standard deviation (SD)=291 minutes.

4.8 Outlier Removal:

Patients who spent more than median + 2*SD= 189 + 2* 291 = 771 minutes were considered outliers and removed. After looking at the histogram (Figure 4) generated during the time metric analysis, there was a peak at the 20 minutes mark. It was decided that all CPs that lasted less than 20 minutes were most probably not reflective of the full trajectory of patients in the PeriOp setting, and therefore removed. Four hundred fifty nice CPs were removed when it was found that they were significantly shorter or longer.

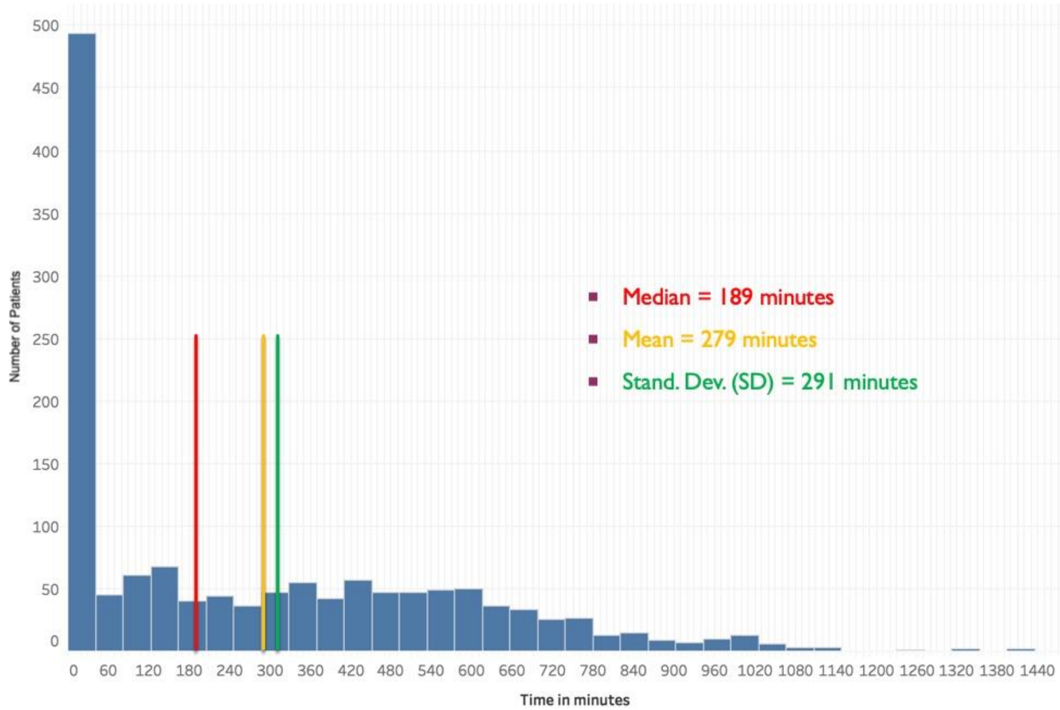

Figure 4. Histogram showing the distribution of the total time (in minutes) spent by a patient in a hospital setting, as captured by event logs

4.9 Mined CP:

Figure 5 depicts the discovered "spaghetti-like" CP. Figure 6 depicts a simplified CP derived from the complex CP showed in Figure 5. The CP describes series of tasks that are performed by the provider on the patient throughout the PeriOp environment while interacting with the EHR. The number of tasks in the PreOp and IntraOp setting are twice as much as the number of tasks in the PostOp setting. This could be explained by the higher event log mapping in the PreOp and IntraOp setting and lower event log mapping in the PostOp setting (Table 3).

The resulting simplified CP starts with the provider logging into the system and initiating a log entry for patient. The PreOp RN starts performing tasks like associating a device to a patient, performing medication reconciliation, changing status of medications, accessing line, drain and airway (LDA) properties, retrieving patient education activity and reviewing the implants. These are some of the most essential tasks performed in the PreOp setting, as seen in Figure 3. The PreOp tasks are completed when the PreOp RN views the OR report and the patient is transferred to the IntraOp setting. The Circulatory RN then performs preprocedural tasks like entering staff information, assessing the skin condition, filling the positioning form and entering the surgeon and procedure information. Some of these tasks are also recorded in the CP generated using RE in Figure 3. The Circulatory RN then proceeds with entering information related to supplies, equipment and medications. The IntraOp tasks conclude with the Circulatory RN entering postprocedural information, like reporting on post-surgery skin condition and completing the case summary. It can be noted that tasks performed by the Scrub RN are not recorded in the CP (Figure 7) because the Scrub RN performs tasks away from the computer. As a result, in the IntraOp setting, we only see tasks performed by the Circulatory RN. The patient is moved to the PostOp setting where the PostOp RN performs tasks like modifying the LDA properties which was initialized in PreOp, accessing patient device data, modifying patient education activity and performing chart review. This is the end of the PeriOp setting and depending on the procedure and the patient, the patient is either discharged home or transferred to inpatient care.

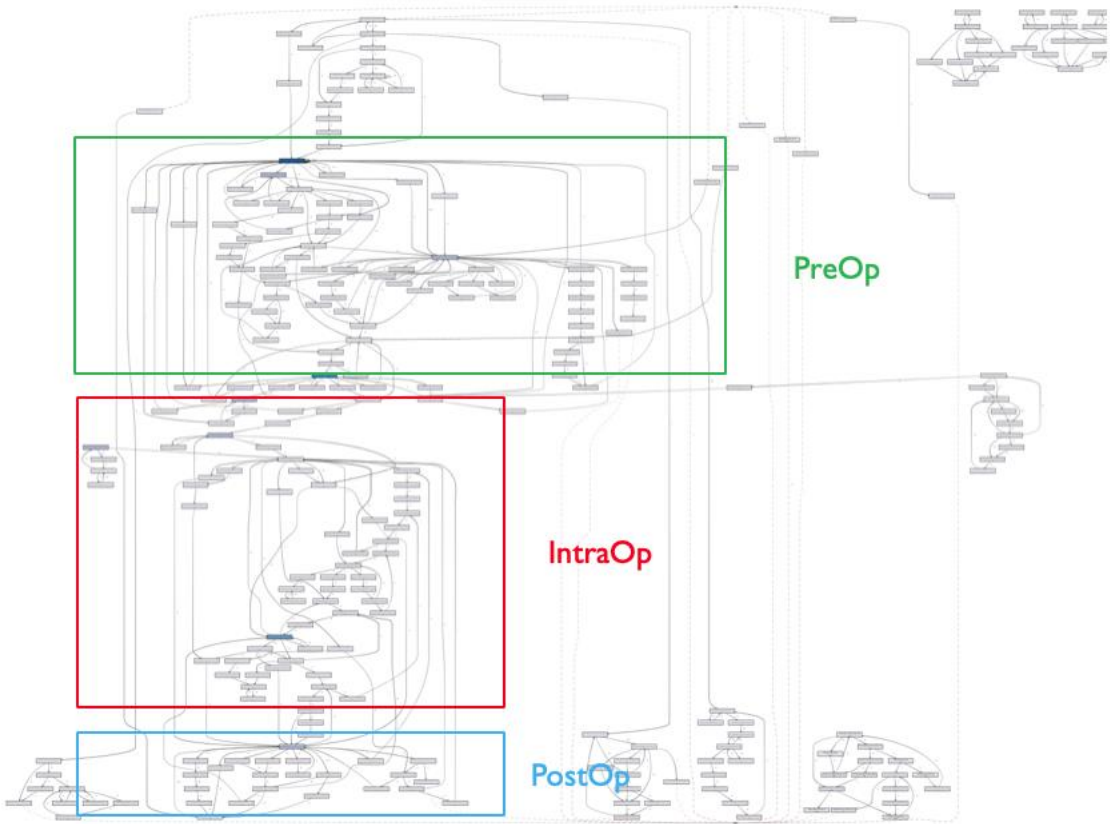

Figure 5. CP generated after applying PM on the event logs, differentiating between PreOP, IntraOP and PostOp clinical tasks. Squares represent clinical tasks and arrows sequential transitions between tasks.

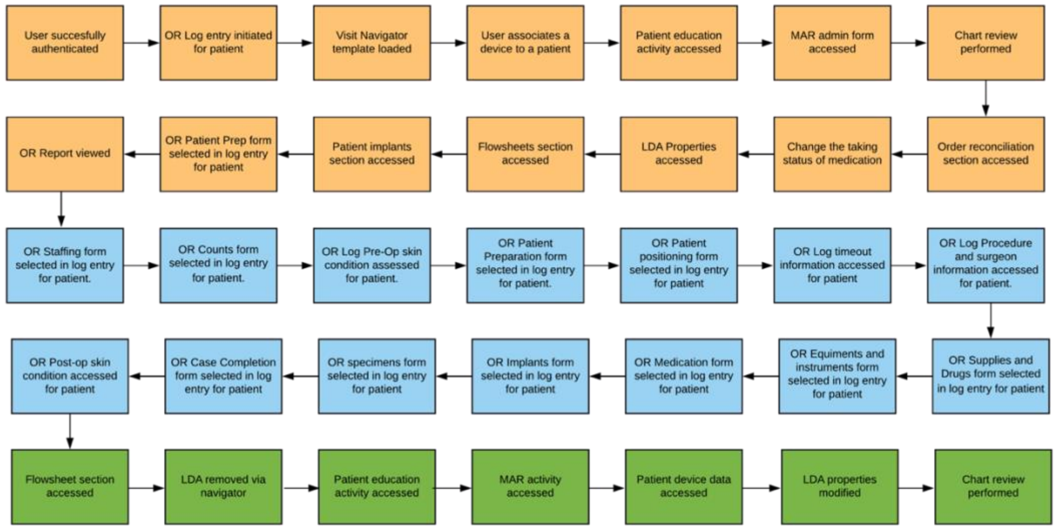

Figure 6. Simplified CP generated after analyzing spaghetti-like CP from Figure 5, differentiating between PreOP (orange), IntraOP (blue) and PostOp (green) clinical tasks. Squares represent clinical tasks and arrows sequential transitions between tasks.

4.10 CP Comparison:

Figures 7, 8 and 9 depict side by side comparisons of the CPs generated from rapid ethnographic data and process mining in the PreOp, IntraOp and PostOp settings respectively. As expected, similar tasks were identified across CPs. For instance, in Figure 7, 'Log into the EPIC system' and 'User successfully authenticated' represent similar tasks.

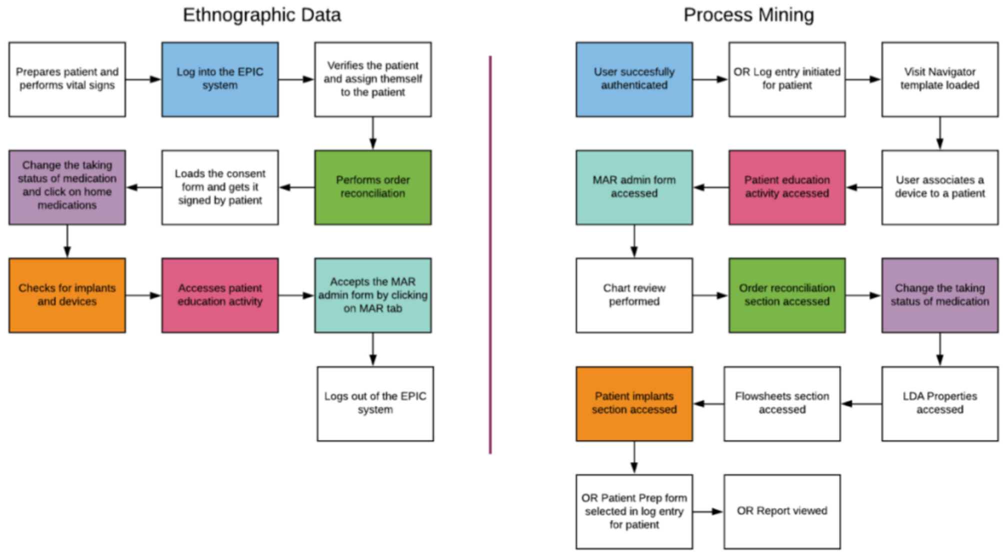

Figure 7. Side by side comparison of the CP generated using rapid ethnographic data (left) and the CP generated using PM (right) in the PreOp setting. Similar tasks across both the CPs are represented with the same color.

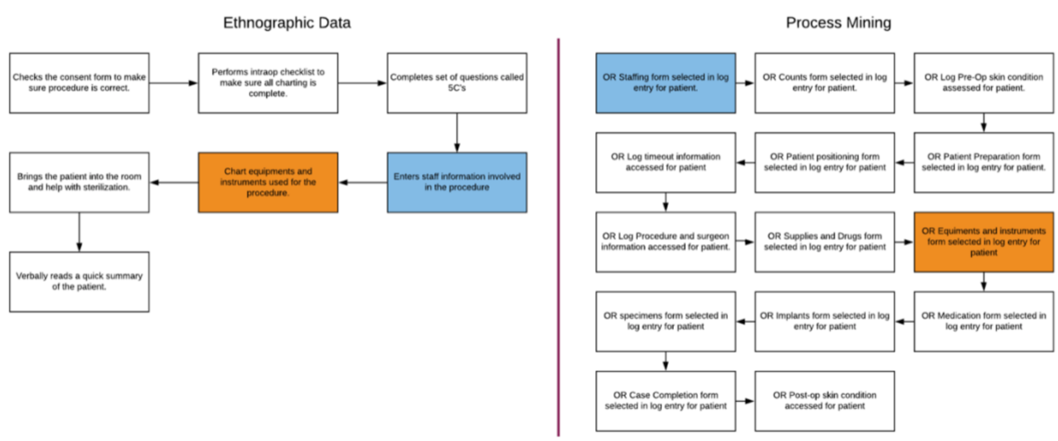

Figure 8. Side by side comparison of the CP generated using rapid ethnographic data (left) and the CP generated using PM (right) in the IntraOp setting. Similar tasks across both the CPs are represented with the same color.

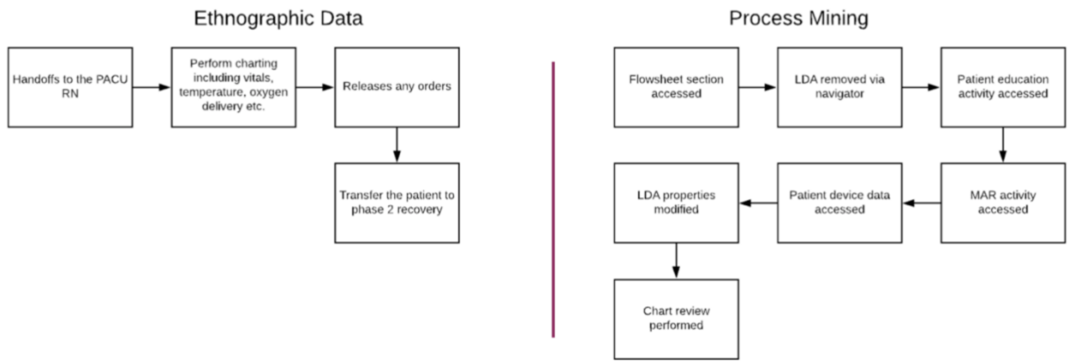

Figure 9. Side by side comparison of the CP generated using rapid ethnographic data (left) and the CP generated using PM (right) in the PostOp setting. Similar tasks across both the CPs are represented with the same color.

Higher task similarity was found in the PreOp setting (Figure 7), followed by the IntraOp setting (Figure 8). No task similarity was found in the PostOp setting (Figure 9). Though the mapping of event logs and EHR-mediated tasks in the IntraOp setting (Table 3) was higher than in the PreOp setting, higher task similarity may be explained by rapid ethnographic findings. A higher number of PreOp tasks are documented in the EHR, while a higher number of IntraOP tasks are performed outside the EHR. No task similarity between PostOp CPs (Figure 9) could be explained by the lower mapping of event logs and EHR-mediated tasks across the PostOp setting (Table 3). The order of the EHR-mediated tasks in the PreOp CPs is different. This discrepancy may be explained by differences in the order that providers perform EHR-mediated tasks (see findings from section 4.4).

CHAPTER 5: Discussion

PM in healthcare has many unique challenges. Hospitals cannot be treated as factories and patients cannot be cured on a conveyor belt(R. Gatta, n.d.). Medical processes are often complex and unstructured which results in spaghetti-like models(Z. Huang et al., n.d.; M. Ghasemi and D. Amyot, n.d.; Z. Huang, X.Lu, and H. Duan, n.d.; I. Litchfield and C. Hoye, n.d.). Some of the other challenges faced in mining CP pattern is noisy and incomplete data3. Research has been done to automatically simplify spaghetti-like models discovered from PM, including using clustering techniques(E. Batista, n.d.; G. M. Veiga and D. R. Ferreira, n.d.; M. Song, n.d.). Clustering techniques allow to adjust the degree of clustering to group event logs or process models together and visualize simplified clustered models. A main challenge associated with clustering techniques is determining the number of clusters, as a high number of clusters can result in oversimplified process model while a lower number of clusters may not simplify the complex process model well enough. An additional challenge of clustering techniques is that the simplification of the process models does not necessarily consider the clinical significance or relevance of an event and therefore can lead to incomplete or difficult to interpret CPs. In this study, the analysis of EHR interfaces helped to identify the most frequent transitions of clinical activities (see Section 4.4). The mapping of event logs and EHR-mediated tasks helped to identify functionalities supported by the EHR but not captured by the event logs that may impact the completeness of the mined CP (see Section 4.5). In addition, rapid ethnographic data was used in combination with time metrics calculated with PM techniques to automatically remove noise. In our case, noise corresponded to events that were outside of the surgery days (see Section 4.6) or CPs that were too long or too short to represent cases of PreOp care delivery (see Section 4.7). Mixed method approaches like the one we used here can be time and resource-intensive. It requires access to health care environments to support the in-situ collection of ethnographic data and collaboration of an interdisciplinary research team with expertise in both computational and ethnographic methods to analyze, triangulate and validate collected data. On the other hand, mixed methods can help build on the strengths of rapid ethnographic data and temporal data mining techniques by integrating the two to overcome the biases inherent in either type of method alone. The limitations of small rapid ethnographic samples could be overcome by the incorporation of big event log samples. In our case, we found some discrepancies in most frequent clinical task sequencing when comparing the CP captured from rapid ethnographic samples and the CP mined from event log samples (Figures 7 and 8). On the other hand, rapid ethnographic data helped to guide the process of interpreting, simplifying and validating mined CPs. The types of research questions that can be answered with PM methods depend on the quantity and quality of the event logs used. In our study, we were not able to choose the information coded in the event logs. As reported in Section 4.6, some EHR functionalities were not captured by the event logs, limiting the accuracy of the mined CPs. Our analysis could help identify the type of information that should be coded in the event logs to help guide the automatic discovery of more complete CPs. Previous studies have demonstrated the impact of CP analysis on quality of care, patient safety and guideline compliance(M. Ghasemi and D. Amyot, n.d.; M. K. Müller, n.d.; W. Mater and

R. Ibrahim, n.d.; S. Marchisio and M. Vanetti, n.d.). The study of CPs in hospital settings can help reduce the healthcare cost for patients by identifying bottlenecks, discovering anomalies and shortening the length of stay(M. K. Müller, n.d.). Another potential future area of research will be utilizing time metrics generated from PM techniques to find out if there are bottlenecks in the CPs that can lead to workflow optimization recommendations.

CHAPTER 6: Conclusion

Our study demonstrated the benefits of using rapid ethnographic data to help overcome challenges of automatic discovery of CPs, including assessing the completeness of event logs, removing noisy data, identifying clinically relevant tasks to simplify spaghetti-like CPS, and validating mined CPs. As future work, we plan on expanding our study to different Mayo Clinic facilities to identify bottlenecks in CPs to help optimize PreOp care delivery and compare CPs to assess standardization of care after the transition to the same EHR.

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