Towards an Ethogram of Exploratory Process Mining Behavior

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Abstract. Exploratory process mining aims to better understand event logs. However, this is not a clear-cut procedure and relies heavily on the analyst's cognitive skills. Research has been conducted to better understand the analyst's behavior, yet an overview of exhibited behaviors during exploratory process mining is lacking. Such an overview would not only facilitate the direct comparison of empirical findings but would also serve as a recording tool for such process mining behavior. Drawing inspiration from the field of (human) ethology, which studies behavior, this paper presents an ethogram of exploratory process mining behavior, i.e., a catalog of behaviors. Via a systematic analysis of published process mining case studies, we developed an ethogram, consisting of 26 distinct behaviors such as "Discover process model", "Define questions", and "Explore data". This ethogram provides insights into analysts' actions, contributing to a more comprehensive understanding of their role.

Keywords: Process of Process Mining · Ethogram · Exploratory Process Mining · Human Behavior

1 Introduction

Process mining (PM) aims to extract valuable insights from event logs originating from business information systems. Most endeavors of PM start with an exploratory analysis [9]. Exploratory PM is defined according to Tukey's [13] five characteristics of exploratory data analysis. These five characteristics entail a focus on understanding the data, as well as model and hypothesis building through the use of robust measures. Furthermore, graphical representations and flexibility regarding the methods used are important.

Performing exploratory PM requires a certain set of skills and knowledge, and the quality of the work depends heavily on the analyst [16]; therefore, it is vital that PM analysts receive the proper guidance and support. A better understanding of PM analysts' behavior is vital to aid them in their endeavors.

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This can be achieved by developing an ethogram, a catalog of behaviors exhibited by PM analysts [4]. Furthermore, the ethogram can also be used as a data collection and analysis tool by recording behavioral observations in a quantitative manner [6].

In this paper, an exploratory PM ethogram will be developed by systematically analyzing published PM case studies. The ethogram consists of 26 behaviors, including, "Discover process model", "Explore data", and "Define questions". This overview provides researchers with a common vocabulary of exploratory PM behavior and will aid in better understanding the task of exploratory PM. Furthermore, the ethogram can be used to analyze fine-grained behavioral data capturing exploratory PM.

The remainder of this paper is structured as follows. Section 2 discusses related work on the Process of Process Mining and human ethology. Section 3 details the methodology followed to construct the ethogram. Section 4 presents the developed ethogram of exploratory PM behavior. Section 5 discusses the ethogram, and the paper ends with a conclusion in Sect. 6.

2 Related Work

2.1 Process of Process Mining

Process of Process Mining focuses on the human aspect of PM and studies the behavior of PM analysts [16,17]. By better understanding PM behavior, improvements can be developed to better support PM analysts [9]. Areas that have already been researched include exploratory analysis [16], question development [18], and challenges that PM analysts face [19]. This research discipline employs a variety of qualitative and quantitative data-gathering techniques, such as interviews [17,18], think-aloud [16] and digital trace data [9]. Within this field, a cognitive process model (PEM4PPM) has been developed to describe how PM behavior can be analyzed in a theory-guided manner. This model can be related to our ethogram is the sense that both describe a kind of behavior. However, unlike our ethogram, the activities from this model were identified in a deductive way, which restricts unique discoveries of behaviors. Furthermore, the focus on both models is different since our ethogram is focused on exploratory PM.

While the work of Sorokina et al. [9] leans into the concept of an ethogram, the work of Capitan et al. [1] and Klinkmüller et al. [5] use a similar methodology as ours to investigate the cognitive aspect of PM. Both papers code PM case studies to find either PM operations [1] or information needs [5]. Furthermore, the work of Capitan et al. [1] identified 55 PM operations to answer performance-related questions. These operations are defined at a different granularity level than our ethogram and are focused on performance-related analysis instead of exploratory PM. In sum, no catalog of behaviors (an ethogram) exists that could support understanding exploratory PM behavior.

2.2 Human Ethology and Ethograms

Process of Process Mining can be related to human ethology, a field focused on human behavior. Like ethology, human ethology studies behavior by documenting and analyzing it to discover patterns [4]. A commonly used method is the ethological approach developed by Lehner [6], which provides a way to gain a holistic understanding of behavior by integrating observations with experimental and theoretical perspectives.

A part of Lehner's [6] ethological approach is the development of an ethogram, a catalog of behaviors, intending to develop a better understanding of behavior displayed by a certain species. In the later stages of the approach, the ethogram is used to record qualitative data in a quantitative manner [6]. Traditionally, ethograms are developed through an observational study where all the actions of the behavior of the species in question are recorded table-wise [4]. The table consists of the name of the behavior, a description of the behavior, and, optionally, a drawing of the behavior [6]. However, ethogram development has taken a new direction, where ethograms are developed using texts describing behavior. For instance, Stanton et al. [10] used literature describing behaviors to make a standardized ethogram for the Felidae. The methodology used in this paper is based on this new direction of ethogram building.

3 Methodology[1]

Based on the coding process of Thomas [12], a six-step procedure, visualized in Fig. 1, is followed to develop our ethogram. First, relevant papers are selected and coded to find behaviors; whereafter, an ethogram is constructed. The remainder of this section describes the procedure in more detail. Further details about the methodology can be consulted in [15].

3.1 Step 1: Construct a Set of Case Studies

In the first step of the procedure, a set of published PM case studies is composed to extract behavior from. The following four different literature sources are identified to extract case studies from:

- 45 publicly available case studies on the IEEE Task Force of PM website.
- 36 BPI Challenge reports by professionals and academics. The reports made by students are excluded as their quality cannot be assured.
- 3 of the most recent systematic literature reviews about PM case studies [2, 3, 11], containing 18, 36 and 38 case studies, respectively.
- 12 case studies discussed in the book "Process mining in Action" [7].

To qualify whether the papers from the sources are relevant, the following exclusion and inclusion criteria are established:

[1] Given the limited space, a separate document is provided with more detailed information [15].

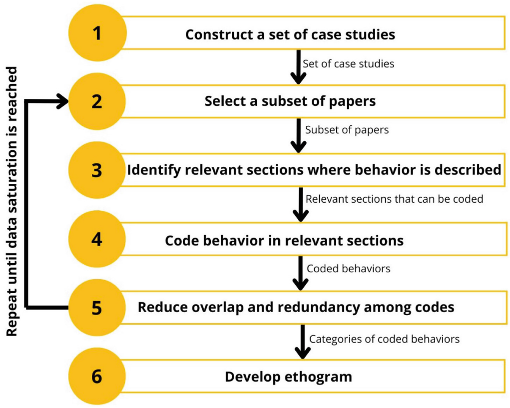

Fig. 1. Procedure that is followed in this study to construct an ethogram

- INCLUSION: A paper containing a PM case study.
- EXCLUSION: A paper not written in English.
- EXCLUSION: A paper with no online record.
- EXCLUSION: A paper that does not describe exploratory PM behavior.

The inclusion criterion requires the papers to include a PM case study. The focus on papers containing case studies is deliberate, as our study requires a description of actual PM analysts' behavior. The exclusion criteria are self-explanatory.

Exploratory analysis is iterative, starting with initial questions and evolving them as new insights emerge. Exploratory PM behavior follows this idea and is defined according to the characteristics of exploratory data analysis defined by Tukey [13], which are the following:

- a focus on understanding the data, and discovering what is going on
- graphical representations are important
- emphasis on model building and generating hypotheses
- use of robust measures, subset analysis, and reexpression
- flexibility regarding which methods are applied

Process mining practices are categorized as exploratory PM whenever the practices correspond with one of the characteristics of Tukey [13] and do not contradict any of the five characteristics. For example, process discovery is classified as exploratory because it emphasizes data understanding, uses graphical models, and applies robust measures like fitness and precision. In contrast, conformance checking is not considered exploratory, as it primarily compares logs with models rather than building new models or hypotheses.

Behavior is defined as high-level actions with specific intent. Similar behaviors are not merged if their intents differ. For instance, "Consult with experts/stakeholders" aims to extract hidden information, while "Discuss with experts/stakeholders" seeks to validate conclusions through discussion.

Applying these definitions to our inclusion and exclusion criteria, we identify 103 of 185 papers as relevant. Most papers are excluded based on a lack of describing exploratory PM behavior.

3.2 Step 2-5: Open Coding

The following steps (step 2 to 5) are performed in multiple iterations. The coding procedure is repeated until no new codes are found and data saturation is reached. Steps 3 to 5 (and 6) align closely with the steps of open coding described in [12].

Step 2: Select a Subset of Papers. For each iteration, a subset of 16 papers is selected, where four papers are selected randomly from each of the four sources. Once one of the sources is depleted, more papers are chosen from the other sources to keep the total of 16 papers per iteration constant.

Step 3: Identify Relevant Sections Where Behavior is Described. After selecting the papers for the coding iteration, relevant sections are identified within each paper. A section is deemed relevant when it describes exploratory PM behavior. These sections are used in the following steps for coding behavior.

Step 4: Code Behavior in Relevant Sections. In open coding, behaviors are labeled by examining the text line by line and marking segments where the behaviors are described. Coding involves using words or brief phrases that encapsulate the essence of each concept [8]. One person codes all the papers in Atlas.ti. Each behavior is coded independently, without the need to fit it into predefined categories. An example of this coding process applied to a segment of [14] can be found in Fig. 2. In this paragraph, six different codes are identified. Each code is assigned to a sentence or a part of a sentence. For example, the sentence "We assumed that it took place not longer than 6 months ago" is coded as an assumption due to the fact that they state "we assume".

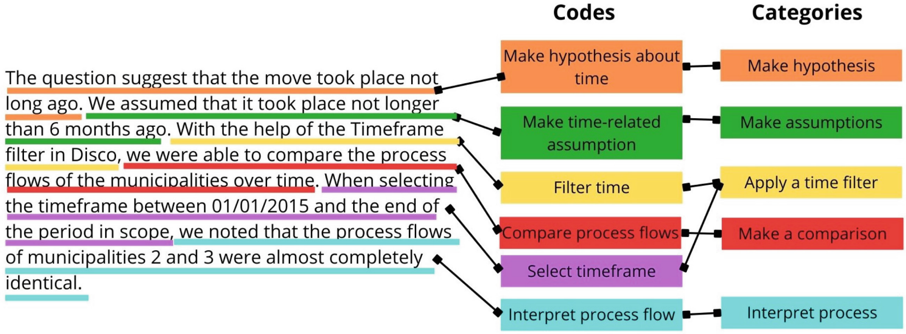

Fig. 2. Example of coding

Step 5: Reduce Overlap and Redundancy Among Codes. After all the papers are coded, the found codes are revised and combined into categories. In Fig. 2, the codes "Filter time" and "Select timeframe" are combined into one category named "Apply a time filter". The code "Compare process flows" is put into the category "Make a comparison" to make the code more general.

After step 5, a check is performed to assess whether data saturation is reached. Steps 2 to 5 are repeated until no new categories are identified.

3.3 Step 6: Develop Ethogram

To construct the ethogram, the coded categories are transformed into behaviors by grouping similar categories together, ensuring the ethogram's structure and comprehensibility. Each behavior included in the ethogram is accompanied by a clear and concise definition [6].

4 Results

This section describes the ethogram, which can be found in Table 1, which was constructed after a total of 3 iterations. After 3 iterations, data saturation was reached, and 79 coding categories were identified (75, 5, and 0 in three consecutive iterations). The 79 coding categories were grouped into 26 behaviors. The behaviors are divided into five phases: Preparation, Pre-processing, Analysis, Interpretation, and Conclusion. Note that these phases are merely introduced as a structuring element to present the ethogram in a more comprehensible way. The behaviors per phase are listed alphabetically; their order does not portray the order in which they are executed. In turn, the phases are in order of execution, although it is possible to return to a particular phase when necessary.

4.1 Phase 0: Preparation

In this phase, preparatory actions are taken for exploratory PM analysis to gain a better understanding of the context of the analysis.

Consult with Experts/Stakeholders: Consult experts/stakeholders to retrieve information that is not (easily) deductible from the data in combination with more context about the data. Furthermore, learn the expectations of the experts/stakeholders.

Define Problem Statement: Define the problem to be scrutinized with the intent of guiding what has to be analyzed and aiding the questions, scope, and strategy development. The problem statement describes the problem and the related challenges. The problem statement is often already defined.

Define Questions: Define the leading questions of the analysis to stimulate creative thinking about the application of the scope and solving the problem statement. Predefined questions are always present in exploratory process mining, even as simple as "What is going on in the data?".

Define Scope: Define the analysis scope, to set boundaries and align the analysis with its objectives. The scope determines what will be investigated and what will not. The scope should align with the problem statement and questions.

Define Strategy: Define the analysis strategy, which includes the used metrics and tools. The strategy heavily depends on the problem statement, scope, and questions. This behavior aims to provide a guide for conducting the analysis. It differs from "Define problem statement" since the focus is not on what has to be analyzed but on how to analyze it.

Examine Context: Gain a better understanding of the context of the data, which includes information about the goal of the process, the organization linked to the process, etc.

Extract Raw Data: Select and collect raw data for the analysis to create a first collection of data. This data should describe a process utilizing events. Transforming this raw data into an event log is done is the next phase (Phase 1: Pre-processing).

4.2 Phase 1: Pre-processing

The first phase entails pre-processing the data and preparing it for analysis.

Profile Data: Profile the raw data to get familiar with its content and structure. This could include calculating summary statistics or identifying data quality issues.

Remove Data: Remove data points, instances, or variables from the raw data to improve its quality. Reasons to remove data include incorrect or irrelevant data.

Transform Data: Transform the data to make it more approachable for analysis. This involves splitting, renaming, and restructuring the data. At the end, an event log should be constructed.

4.3 Phase 2: Analysis

In the second phase, the data is analyzed to discover patterns and insights.

Analyze Perspectives: Analyze the data from a specific process to gain a comprehensive understanding. Commonly used perspectives are control-flow, organizational, or time perspectives.

Apply a Filter: Focus on specific information by excluding parts of the data. A commonly applied filter is a path filter, which filters out infrequent paths. A filter will not erase data; it only temporarily excludes data.

Calculate a Metric: Calculate a previously defined metric based on the data to quantify a certain aspect of the data.

Categorize the Data: Organize the data into categories to find patterns within or across categories. These categories can be predefined or self-made by the analyst. For example, categories can be based on who executes the activity.

Create a Figure/Table: Create a figure or table to visualize patterns in the data. Examples include dotted charts and frequency tables. Process discovery is not included in this behavior since it has a different intent, namely discovering/visualizing the process instead of visualizing patterns.

Define a Metric: Define a metric to measure or describe phenomena quantitatively. This can be a more known metric or a newly defined one.

Discover a Process Model: Discover the process with a process discovery technique. The process model can represent the control flow, social network, etc. The goal of this behavior is to visualize the dynamic between activities or entities of the process.

Generate a Hypothesis: Create a testable statement or prediction that guides further analysis.

Identify an Element of Interest: Make a first observation based on the generated figure, process, table, or metric with the intent to further analyze and interpret it. This observation is a high-level observation, something that catches your eye.

Make a Comparison: Compare two or more metrics, figures, tables, or process models with one another. The goal of this behavior is to find similarities and differences.

4.4 Phase 3: Interpretation

During the third phase, the results from the analysis phase are interpreted.

Interpret Found Results: Make interpretations about the analysis results (metrics, figures, process models, etc.) to better understand them. It involves recognizing patterns, relationships, and interesting data points.

Make Assumptions: An assumption is a belief or statement accepted as true without direct evidence. An assumption is made to reduce uncertainty and ease the process of analyzing data. There is a distinction between an assumption and a hypothesis. An assumption is a belief that someone has, while a hypothesis is a prediction you make.

4.5 Phase 4: Conclusion

The last phase involves combining the interpretations that were made and drawing conclusions from them.

Answer Questions: Formulate an answer to the predefined questions using the interpretations made in the previous phase. The goal of this behavior is to provide clarity and advance the understanding of the data.

Table 1. Ethogram describing Exploratory PM behavior

Behavior	Description	Intent
Phase 0: Preparation		
Consult with experts/stakeholders	Consult experts/stakeholders to retrieve information	Retrieve information that is not (easily) deductible from the data
Define problem statement	Define the problem that will be scrutinized	Guide the analysis and aid the scope, question, and strategy development
Define questions	Define questions that need to be answered after the analysis	Stimulate creative thinking about solving the problem statement
Define scope	Define the scope of the analysis	Set boundaries and align the analysis with its objectives
Define strategy	Define the analysis strategy, such as used metrics and tools	Guide how to solve the defined questions of the analysis
Examine context	Gain a better understanding of the context of the data	Learn about the context of the data
Extract raw data	Select and collect raw data for the analysis	Create a first collection of data which will be analyzed in the later phases
Phase 1: Pre-processing		
Profile data	Profile the raw data to get familiar with it	Get familiar with the content and structure of the data
Remove data	Remove variables, instances, or data points from the raw data	Improve the quality of the data
Transform data	Apply transformations such as splitting, and restructuring	Make the data more approachable for exploratory analysis
Phase 2: Analysis		
Analyze perspectives	Analyze the process, a metric, ... from a specific perspective	Get the full picture of the process
Apply a filter	Exclude part of the data/process	Focus on specific information
Calculate a metric	Calculate a previously defined metric based on the data	Quantify a certain aspect of the process or data
Categorize the data	Organize the data/process into categories	Organize and structure the data to find patterns
Create a figure/table	Based on the data, create a figure or table	Visualize patterns in the data
Define a metric	Define a metric to measure phenomena quantitatively	Define a measure to describe a phenomena quantitatively
Discover a process model	Discover the process flow by building a process model	Visualize the sequence of a process
Generate a hypothesis	Make a hypothesis about expected outcomes	Serve as a guiding point to further analyze a certain aspect of the data
Identify an element of interest	Make an observation based on a figure, process, table, ...	Identify an interesting element which will be further analyzed
Make a comparison	Compare two or more metrics, figures, ... with one another	Find similarities and differences
Phase 3: Interpretation		
Interpret found results	Make interpretations about the results	Gain a better understanding of what is discovered during the analysis
Make assumptions	Make an assumption about the data/process	Simplify the analysis process by accepting certain conditions
Phase 4: Conclusion		
Answer questions	Formulate an answer for the questions	Provide clarity and advance the understanding of the data
Discuss with experts/stakeholders	Validate previously made assumptions	Validate assumptions through discussion
Make recommendations	Make recommendations based on the results	Provide guidance for further actions or further analysis
Revise hypothesis	Revise a previously made hypothesis	Ensure the relevance and accuracy of the created hypothesis

Discuss with Experts/Stakeholders: Validate previously made assumptions and discuss found results by consulting with experts/stakeholders.

Make Recommendations: Make recommendations based on the interpretations made in the previous phase. It gives guidance for the next steps to improve or better understand the process under analysis.

Revise Hypothesis: Revise a previously made hypothesis to ensure the relevance and accuracy of the created hypothesis. The hypothesis is not tested, since this is not a part of exploratory PM.

5 Discussion

5.1 Implications

Fine-grained activity data, such as digital trace data, has its challenges when searching for meaningful patterns and insights about the behavior described in the data. An ethogram can be used to transform such fine-grained activity data into more comprehensible behavioral data by aggregating detailed actions into broader behaviors based on their shared intent. For instance, actions like 'filter', 'select', and 'remove' related to a variable can be combined into the behavior "Remove data." This shift in granularity allows for a more meaningful analysis of PM. However, digital trace data only reveals actions, not the intent behind them. Qualitative methods such as interviews or think-aloud practices are necessary to uncover intent. These methods help clarify why certain actions were taken, providing a fuller understanding of observed behaviors. Combining quantitative data with qualitative insights is crucial for accurately interpreting behaviors.

5.2 Comparison with PEM4PPM Model

Sorokina et al. [9] developed the PEM4PPM model to describe PM behavior, similar to our ethogram but with key differences. The ethogram defines more specific behaviors, while PEM4PPM remains at a higher level. Furthermore, PEM4PPM is process-structured, whereas the ethogram categorizes behaviors into five phases. Additionally, the ethogram focuses on exploratory PM, while PEM4PPM describes theory-guided PM. Despite their differences, the PEM4PPM model and our ethogram share similarities. Nine out of ten PEM4PPM activities align with behaviors in the ethogram based on matching actions and intents. Figure 3 illustrates these connections.

The activity "Task understanding" links to Phase 0 (Preparation) and Phase 1 (Pre-processing) behaviors. It involves understanding the problem, data, and consulting experts, corresponding to the behaviors "Examine context", "Define questions", "Explore data", and "Consult with experts/stakeholders." The "Set/Refine goal" activity links to "Define strategy", focusing on deciding how to analyze data to answer predefined questions. The "Focus" activity corresponds with "Apply a filter" since both aim to focus at a specific part of the process.

The "Explore" activity aligns with Phase 2 (Analysis) behaviors, excluding "Generate a hypothesis" and "Apply a filter", illustrating PEM4PPM's higher-level definition compared to the ethogram. "Interpret results" can be linked to both "Interpret data" and "Assess results", which aim to explain insights from the analysis phase. The difference is that checking hypothesis is included in "Assess results", which is not part of exploratory PM. "Generate hypotheses" is similarly defined in PEM4PPPM and the ethogram, focusing on generating hypotheses from data insights. The "Create artifact" activity involves goal-driven object creation, aligning with "Explore" if focused on exploratory analysis but not matching any ethogram behaviors if outside this scope. Finally, the "Conclude" activity corresponds to "Answer question", focusing on addressing predefined questions.

The activity "Test hypotheses" could not be linked to the ethogram as it does not align with exploratory PM. Additionally, PEM4PMM lacks coverage of dataset preparation and omits behaviors such as "Define problem statement", "Extract raw data", "Remove data", and "Transform data". Futhermore, the behaviors "Revise hypothesis", "Discuss with stakeholders", and "Make recommendations" also have no counterparts.

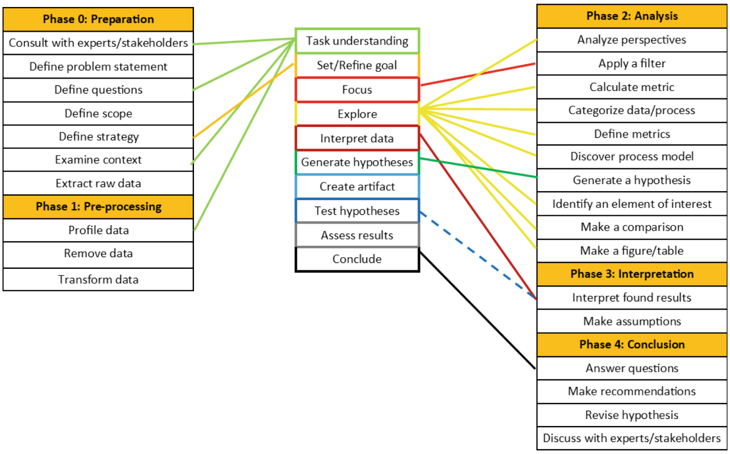

Fig. 3. Comparison between Ethogram and PEM4PPM

6 Conclusion

Analyzing exploratory PM behavior can be challenging. To aid in this endeavor, this paper developed an ethogram of 26 behaviors observed during exploratory PM, categorized into 5 phases: Preparation, Pre-processing, Analysis, Interpretation, and Conclusions. This ethogram provides a clear overview of the different behaviors and a vocabulary that can be used to analyze exploratory PM behavior. The ethogram is based purely on the behavior described in the literature; 48 case studies were investigated and coded to this end. Despite the meticulously designed research method, we acknowledge three key limitations to this research. Firstly, only selected sources of case studies have been considered. Therefore, there is a risk that not all behaviors have been identified. Secondly, as the ethogram is based on published case studies, some performed behaviors might not be explicitly or implicitly reported since some behaviors might be omitted by the authors of the case studies. Those behaviors could not be integrated as part of the ethogram. Thirdly, since coding was only performed by one person, some subjectivity is introduced into the results. Future research directions include the application of the ethogram to make fine-grained digital trace data more comprehensible for analysis purposes by linking the behaviors of the ethogram to the fine-grained actions. Another area for future research is to refine the ethogram based on interviews with PM analysts. Through interviews, the intent of the different behaviors can be further investigated. Lastly, our ethogram was tailored to exploratory PM. Ethograms describing other PM behaviors, such as predictive PM, can be developed in future research.

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