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Understanding the behavior of process mining analysts: a catalogue of exploratory process mining behaviors

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Abstract

Most research on the process of process mining has focused on exploratory process mining, which is defined as a first exploration of process data to find interesting insights and develop hypotheses. Within this research topic, the focus has been so far on better understanding the behavior of the process mining analysts. However, a comprehensive overview of exhibited behaviors has yet to be established. Such an overview enables a direct comparison of empirical findings and serves as a tool for documenting exploratory process mining behavior. Drawing from (human) ethology, the study of behavior, this paper introduces a catalog of behaviors for exploratory process mining, better known as an ethogram. Through a systematic analysis of published process mining case studies, we identified a first list of behaviors performed during exploratory process mining. This first list was validated and updated using 15 interviews with experienced process mining analysts. The final ethogram consists of 31 behaviors, including “Inspect graphic”, “Check assumption”, and “Define question”. This ethogram provides a vocabulary to describe exploratory process mining behavior in a structured way, contributing to a more comprehensive understanding of the role of a process mining analyst.

Keywords Process mining behavior, Exploratory process mining, Ethogram, Process of process mining, Human behavior

Introduction

Process mining is a data-driven discipline focusing on extracting valuable insights from process data consisting of process execution data captured by business information systems. Process mining analysts analyze process data, to gain insights into how the process actually works, which enables them to spot inefficiencies (Van Der Aalst and Van der Aalst 2016). The way the process data is analyzed and insights are gained is better known as the process of process mining. The focus of this research topic is on the human aspect of process mining, investigating the behavior of process mining analysts. Within this research topic, the focus has been mainly on exploratory process mining, a practice focused on gaining an initial understanding of the data, identifying patterns, and

generating hypotheses. Exploratory process mining aligns closely with the five principles of exploratory data analysis, defined by Tukey (1977). 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 (Tukey 1977).

To conduct exploratory process mining, an analyst needs to possess a certain set of skills and domain knowledge. As exploratory process mining heavily relies on human interpretation and decision-making, the quality of an analysis is strongly influenced by the expertise of the analyst (Zerbato et al. 2021). Consequently, it is vital that process mining analysts receive adequate support and training to ensure the reliability and effectiveness of process mining outcomes. To provide meaningful support and guidance, it is important to understand how process mining analysts approach their work: how they explore data, interpret results, and make decisions, as this behavioral insight can inform the design of targeted training programs, tool improvements, and analysis frameworks. In the field of process of process mining, research has been performed to gain insights into behavior by, for example, discovering different analysis strategies (Zerbato et al. 2022b). However, a comprehensive overview of exhibited behaviors has yet to be established. A structured list of behaviors would provide a common vocabulary and framework for describing process mining analyst behavior, which in turn would enable consistent coding and comparison of empirical findings across studies. Additionally, such a list would serve as a reference point for systematically documenting exploratory process mining behavior in both research and practice. This list, known as an ethogram, systematically catalogs the various behaviors exhibited by process mining analysts (Immelmann and Beer 1989). Ethograms are traditionally used in behavioral sciences, where they serve as standardized inventories of behaviors. An ethogram can be used as a data collection and analysis tool by recording behavioral observations in a quantitative manner (Lehner 1998).

In this paper, an exploratory process mining ethogram is proposed, i.e., a catalog of behaviors performed during exploratory process mining. This paper is an extension of Van Suetendael et al. (2025b), where a first version of the ethogram was already developed through systematically analyzing published process mining case studies. Van Suetendael et al. (2025b) is extended in this paper by proposing an adapted version of the first ethogram and validating and updating it using 15 interviews with experienced process mining analysts. The final ethogram consists of 31 behaviors, including “Inspect graphic”, “Check assumption”, and “Define question”. This catalog provides researchers with a common vocabulary by systematically describing and categorizing the behaviors exhibited during exploratory process mining. By capturing these behaviors, it enables researchers to consistently label and interpret behaviors across studies. Which, in turn, aids in building a clearer understanding of the task of process mining analysts. Furthermore, the ethogram can be used to analyze fine-grained behavioral data, which describes each small action undertaken by the process mining analyst. The ethogram can be used to transform these fine-grained actions into more coarse grained behaviors which are more easily interpretable.

The remainder of this paper is structured as follows. “[Background and related work](#)” section discusses related work on the process of process mining, ethology, and exploratory data analysis. “[Methodology](#)” section details the methodology followed to

construct and validate the ethogram. “[Results](#)” section presents the developed ethogram of exploratory process mining behavior. “[Discussion](#)” section discusses the ethogram, and the paper ends with a conclusion in “[Conclusion](#)” section.

Background and related work

Process of process mining

The process of process mining is a research area focusing on the human aspects of process mining, specifically investigating the behavior of process mining analysts (Zerbato et al. [2021](#), [2022b](#)). As process mining has a highly interactive nature, the way analysts handle process data and interpret process-related insights plays a crucial role in the effectiveness of the analysis. By better understanding process mining behavior, improvements in tools and practices can be developed to better support process mining analysts (Sorokina et al. [2023](#)). There are several key areas within this field that have already been explored, such as discovering analysis strategies by examining how process mining analysts navigate and interact with process data (Zerbato et al. [2021](#)). Analysis strategies are here defined as overarching approaches used by analysts to achieve a specific task. These strategies consist of a sequence of multiple behaviors. Question development was also investigated to gain a better understanding of how process mining analysts formulate and refine questions and how it guides their analysis (Zerbato et al. [2022a](#)). In another study, common difficulties experienced by analysts when using process mining were identified, such as data quality issues and cognitive overload (Zimmermann et al. [2022](#)). To investigate the above-mentioned topics, a range of qualitative and quantitative data-gathering techniques were employed. These methods help capture both the cognitive and behavioral aspects of process mining analyses. Some of the commonly used techniques include interviews (Zerbato et al. [2022b, a](#)), think-aloud (Zerbato et al. [2021](#)), and digital trace data (Sorokina et al. [2023](#)).

Within the field of the process of process mining, a cognitive process model called PEM4PPM has been developed to describe how process mining behavior can be analyzed in a theory-guided manner (Sorokina et al. [2023](#)). This model provides a structured framework for understanding how process mining analysts cognitively engage with process mining tasks, breaking down the process of process mining into a series of cognitive steps. Each of these steps is linked to a step from the Prediction Error Minimization Theory. In this theory, the brain functions as a prediction machine: it continuously generates predictions about sensory input and tries to minimize the difference between these predictions and actual sensory information, which is called the prediction error (de Bruin and Michael [2021](#)). This is translated to process mining in the sense that based on the exploration of process data, hypotheses are generated (predictions) and tested (calculate prediction error).

Other research directions focused on discovering process mining operations (Capitán-Agudo et al. [2022](#)) and work practices (Klinkmüller et al. [2019](#)). In the work of Capitán-Agudo et al. ([2022](#)) they analyzed and coded answers found in literature and discovered 55 different operations that were performed to answer time-performance related questions. These 55 operations were divided into 6 groups according to their purpose, such as operations to manipulate the data and operations to calculate statistics. Klinkmüller et al. ([2019](#)) also investigated process mining reports, but for a different purpose. They were interested in gaining insights into work practices and information needs in process

mining projects. The goal of this paper was to show the current state of practice within process mining projects, with a specific focus on visualization techniques. They for example discovered that problems are largely explored by not using process mining specific visualization techniques.

Our paper complements existing work on the process of process mining by developing a list of behaviors specifically focused on a part of process mining, namely exploratory process mining. Furthermore, adopting an inductive approach, as seen in Capitán-Agudo et al. (2022); Klinkmüller et al. (2019), in the development of our ethogram enables the identification of previously unrecognized behaviors.

Ethology and ethograms

The process of process mining can be related to ethology, a scientific field dedicated to the study of animal behavior. Ethology follows a systematic approach to observing, documenting, and analyzing behaviors to uncover patterns, motivations, and cognitive processes of animals (Immelmann and Beer 1989). A well-established methodology in ethology is the ethological approach developed by Lehner (1998). This approach emphasizes the importance of a holistic behavioral analysis, which integrates observational, experimental, and theoretical perspectives to gain a better understanding of behavior. While our work primarily adopts the observational component of this approach, focusing on the systematic description of behavior, it lays the groundwork for future studies that could incorporate experimental validation and theoretical modeling.

A fundamental component of Lehner (1998)'s ethological approach is the development of an ethogram, which serves as a catalogue of behaviors. The primary purpose of an ethogram is to provide a structured framework for describing and analyzing behavior, enabling researchers to gain a deeper understanding of behavior and behavioral patterns. The ethogram plays an important role in ethological research as it allows an objective classification and quantification of behavior, making it possible to conduct comparative analyses. Traditionally, ethograms are developed through observational studies, where all visible actions and behaviors of the species under investigation are systematically recorded (Immelmann and Beer 1989). These observational records are typically organized in a table format, which includes: the name, a description, and, optionally, a drawing of the behavior (Lehner 1998). Besides observations, approaches to developing an ethogram using texts describing behavior have also been proposed. For instance, Stanton et al. (2015) used literature describing behaviors to make a standardized ethogram for the Felidae. Instead of relying on observational studies, their methodology synthesized information from multiple sources, creating a comprehensive catalog of behaviors. The methodology used in our paper is based on this direction of ethogram building.

Exploratory data analysis

In this paper, we aim to construct an ethogram describing the behaviors of process mining analysts during exploratory process mining. Exploratory process mining does not have a clear-cut definition within the process mining community. Therefore, it is important to clearly define how we, the authors, define this concept. In this paper, the definition of exploratory process mining finds its roots in one of the earliest definitions of exploratory data analysis defined by Tukey (1977).

Exploratory data analysis is an iterative process, starting with initial questions and evolving them as new insights emerge. Exploratory process mining behavior follows this idea and is defined according to the characteristics of exploratory data analysis defined by Tukey (1977), which are the following:

- The focus of the analysis lies in getting a better understanding of the data and understanding what the data describes.
- During the analysis, graphical representations play an important role in better understanding the data and what it describes. Visualisations reveal patterns, trends and outliers that might not be obvious from a numerical perspective.
- The focus lies on generating hypotheses and model-building directly from the data. Data exploration without any preconceived notions allows analysts to discover unexpected patterns and relationships that contribute to model and hypothesis generation.
- Robust measures, subset analysis, and reexpression are used during analysis. Robust measures are defined as measures that are resistant to outliers and skewed distributions. Subset analyses involve clustering the data into subsets to uncover patterns. Reexpression refers to making the data more interpretable by applying transformations.
- Flexibility and adaptability are necessary conditions. There should not be any strict rules or procedures that have to be followed to conduct the analysis. Using various techniques and tools is highly encouraged, along with the possibility of adapting your strategy as new information is uncovered.

According to Tukey (1977); Milo and Somech (2020), exploratory data analysis is an iterative process involving multiple iterations of analysis as analysts refine their understanding of the data through repeated re-examination.

Methodology

The methodology of this paper is situated within the Design Science Research (DSR) paradigm, which focuses on creating and evaluating purposeful artifacts to address real-world problems. As framed by Hevner (2007), DSR involves three interconnected cycles: the Relevance Cycle (ensuring practical utility), the Rigor Cycle (grounding in existing knowledge), and the Design Cycle (iterative development and refinement of the artifact). The central artifact in this study is our ethogram, a structured tool for systematically observing and categorizing the behavior of process mining analysts. It is both descriptive and instrumental, enabling comparison of behavioral patterns. The artifact is grounded in domain-specific knowledge and behavioral science principles, fulfilling both the relevance and rigor criteria of DSR.

This journal paper extends our earlier conference contribution (Van Suetendael et al. 2025b), which reported on the first design cycle: the creation of a Literature-based Ethogram (v1) developed through open coding of process mining case studies. That version was evaluated through expert feedback, which resulted in the Altered Ethogram (v2) in the second design cycle. This version was then evaluated through semi-structured expert interviews. Based on those insights, the third design cycle produced the Validated Ethogram (v3). As illustrated in Fig. 1, these three iterative design cycles reflect how the artifact matured through evaluation and refinement, fulfilling the design criteria of DSR.

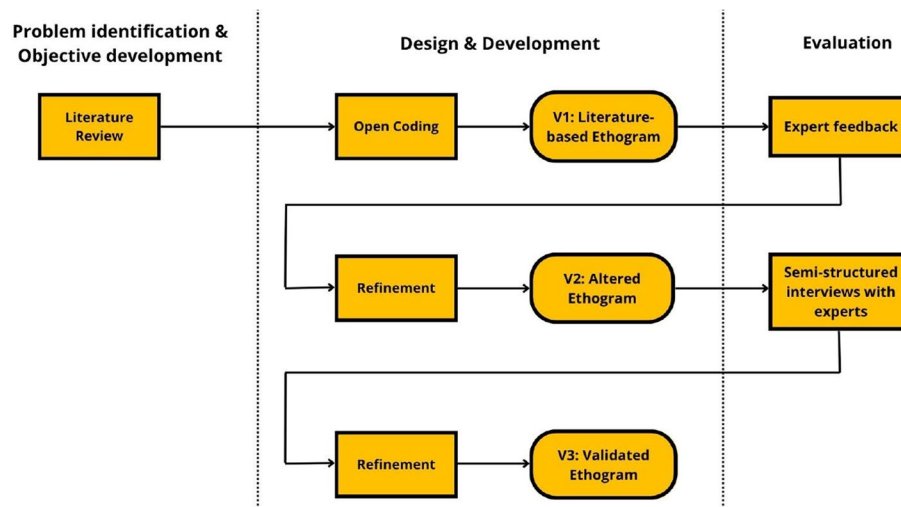


Fig. 1 Iterative Ethogram Development Aligned with DSR Principles

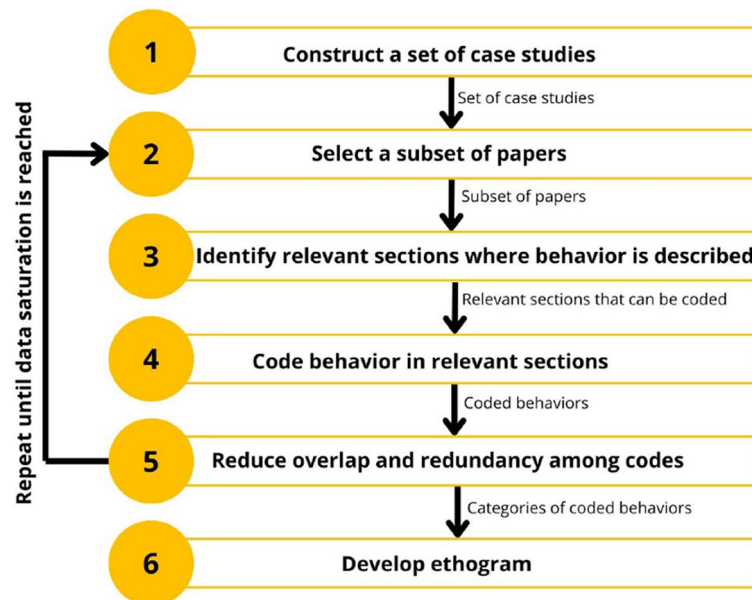


Fig. 2 Procedure that is followed in this study to construct an ethogram

Construction of literature-based ethogram

To develop our literature-based ethogram, inductive coding will be applied. Inductive coding was chosen over deductive coding since it allows for the discovery of previously unrecognized behaviors (Thomas 2006) and due to the fact that no list of behaviors exists that could be used as a coding scheme. To perform inductive coding and discover exploratory process mining behaviors, the coding procedure of Thomas (2006), visualized in Fig. 2, will be followed. Relevant papers are selected and coded first to find behaviors; whereafter an ethogram is constructed. The remainder of this section describes the procedure in more detail.

Step 1: construct a set of case studies

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

- 45 publicly available case studies on the IEEE Task Force on Process Mining website;
- 36 BPI Challenge reports by professionals and academics. The reports made by students are excluded as their quality cannot be assured. An overview of the number of identified reports per edition of the challenge can be found in Table 1.
- 92 case study papers collected by three recent systematic literature reviews on process mining case studies (Corallo et al. 2020; Dakic et al. 2018; Thiede et al. 2018), containing 18, 36 and 38 case studies, respectively;
- 12 case studies discussed in the textbook “Process mining in Action” by Reinkemeyer (2020).

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

- INCLUSION: A paper containing a process mining case study.
- EXCLUSION: A paper not written in English.
- EXCLUSION: A paper without an online record.
- EXCLUSION: A paper that does not describe exploratory process mining behavior.

The inclusion criterion requires the papers to include a process mining case study. The focus on papers containing case studies is deliberate as our study requires a description of actual process mining analysts’ behavior. The first two exclusion criteria require the paper to be written in English and to be available online. The last exclusion requirement is about the content of the paper. The paper has to describe exploratory process mining behavior. Exploratory process mining behavior is defined according to the criteria of exploratory data analysis defined by Tukey (1977). Examples of process mining practices that fit these criteria are listed below:

A process mining practice that can be classified as exploratory process mining is process discovery. The focus of process discovery is on discovering the underlying process from the process data and thereby better understanding the process and its underlying data, which satisfies the first, second, and third characteristics of Tukey (1977). It satisfies the first characteristic due to the fact that the focus lies on understanding the data. By focusing on building models and graphical representation through the discovery of a process model, the second and third characteristics are satisfied. The fourth characteristic, the use of robust measures, is satisfied due to the use of performance metrics in process discovery. The fifth and final characteristic is satisfied because a multitude of process discovery algorithms exist, which creates flexibility regarding the methodology used. Conformance checking, on the other hand, is not seen as exploratory process mining as its focus is not on model building or generating hypotheses but on comparing

Table 1 Overview of BPI challenge reports

BPI challenge	Count	BPI challenge	Count
BPI 2015	9	BPI 2018	3
BPI 2016	5	BPI 2019	9
BPI 2017	9	BPI 2020	1

a log with a model or hypothesis. This essentially translates to testing the hypothesis, which contradicts the third characteristic. As a final example, predictive process mining can also not be classified as exploratory process mining as it contradicts the first characteristic. Predictive process mining focuses on predicting outcomes or parts of the process instead of focusing on better understanding the process.

Step 2-6: open coding

The following steps (steps 2 to 6) aim at coding the literature to discover exploratory process mining behaviors and are performed in multiple iterations. The coding procedure is repeated until no new codes are found and data saturation is reached. The coding was performed by one coder.

Steps 3 to 6 of the procedure align closely with the steps of open coding described in Thomas (2006). His methodology consists of five major steps, which are listed below. These five major steps are conferred into four steps in our procedure:

- Perform an initial reading of the text (related to step 3)
- In the text, identify specific segments that are related to your objective (related to step 3)
- Code the selected segments (related to step 4)
- Reduce overlap and redundancy among the labels by creating categories (related to step 5)
- Create a model with the most important categories (related to step 6)

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 In step 3, relevant sections that describe exploratory process mining behavior within each paper are selected. These sections are used in the following steps for coding behavior (Thomas 2006). The purpose of this step is to separate the relevant from the non-relevant sections in the paper. Not all sections in the paper describe exploratory process mining behavior; those sections are deemed irrelevant and are not coded. The input of this step is the subset of 16 papers, and the output is all the identified relevant sections within these 16 papers.

Step 4: Code Behavior in Relevant Sections Before the coding can start, the level of abstraction needs to be defined at three different levels. Firstly, the *coding unit* defines how small a portion of the text can be to be coded. Secondly, the *context unit* determines the largest portion of text that can be coded into a category. Lastly, the *recording unit* determines which text parts can be coded (Mayring 2014). In this paper, the coding unit is a word, while the context and recording units are paragraphs. These decisions are made with the mindset of not constricting the coding process. The coding unit is chosen as small as possible, while the context unit is chosen as large as possible to ensure the behavior is thoroughly described. The recording unit was also chosen rather large to ensure we could code all the described behaviors.

In this fourth step, all relevant sections are coded according to the principles of open coding. This entails coding without a predefined set of codes (Saldaña 2021). The purpose of this step is to find behaviors in the text and code them. The input is all sections in the case studies deemed relevant in the previous step. The output is a set of codes.

An example of the coding process performed in the fourth step can be found in Fig. 3. In this figure, a segment of Van den Spiegel and Blevi (2015) is coded. In this paragraph of text, six different codes are identified. Each code is assigned to a sentence or a part of a sentence. Certain keywords are sought to code behavior in sentences that describe the displayed behavior. For example, two keywords are identified in the first sentence: “suggest” and “not long ago”. The first keyword indicates that a hypothesis of some sort was made. They make the hypothesis, or they predict that the move occurred not long ago. The second keyword indicates that a time aspect is involved. Combining the two together forms the code “Make a hypothesis about time”. A similar thought process is used for the second sentence. The keywords in this sentence are “assumed” and “six months ago”. The first keyword indicates that an assumption is made, while the second keyword indicates that it is time-related. Combining the two forms the code “Make time-related assumption”. The third sentence is split into two parts. The first part of the sentence refers to the action of filtering, and the second part refers to actions performed after applying the filter. Therefore, the parts are coded independently. The first part is coded as “Filter time” as a timeframe filter is applied. The second part is coded “Compare process flows” as a comparison is made of process flows. The fourth and final sentence of the paragraph is also divided into two parts. The first part describes the timeframe selection, while the second part describes interpretations of the process flows. The first part of the sentence is coded as “Select timeframe” due to the keywords “selecting” and “timeframe”. The last part does not have very specific keywords that can be used to code the behavior. The sentence’s meaning is used to make a code, namely “Interpret process flow”. The example in Fig. 3 illustrates the chosen level of abstraction. The coding unit selected is a word; none of the marked text is smaller than a word, and none of the marked text exceeds a paragraph, which is the context unit. The recording unit is a paragraph, and the example is a paragraph.

Step 5: Reduce Overlap and Redundancy among Codes After coding all the 16 selected papers, the codes are revised and combined into categories. The list of codes found in Step 4 will be long and contain overlap and redundancy. To remove both, the list is reviewed and similar behaviors are combined into one category. The goal of this step is

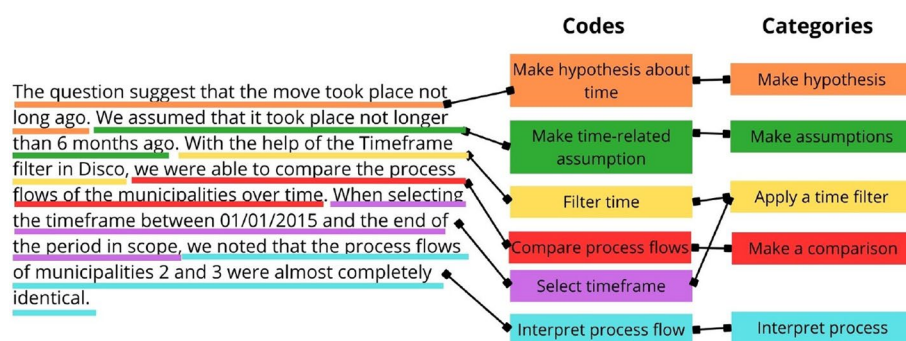


Fig. 3 Example of coding

to refine the list from Step 4, and create a shorter aggregated list of categories, which will be the output of this step.

The example displayed in Fig. 3 also demonstrates the execution of step 5, where codes are combined into categories. In the previous step, six codes are identified. These codes need to be reviewed to reduce overlap and redundancy. The codes “Filter time” and “Select timeframe” are combined into the category “Apply a time filter”. Both codes describe the same action: filtering data based on a time aspect. Therefore, they are combined into one category. The other four codes are put into more general categories to reduce the number of codes describing the same behavior action. For instance, the code “Make hypothesis about time” is transformed into “Make hypothesis” to combine all the codes that describe making a hypothesis about a certain aspect. The same logic is followed for the code “Make time-related assumption”. Lastly, the code “Interpret process flow” is changed into the category “Interpret process” to make it more generic. Grouping the fine-grained codes into categories enables generating a usable ethogram consisting of a manageable number of exploratory process mining behaviors.

Step 6: Develop Ethogram The input of this last step is the revised coding list containing the categories. This list is transformed into a systematic framework consisting of behaviors. Therefore, the categories from the coding list have to be transformed into behaviors. This entails combining categories with the same purpose into one behavior. For example, the categories such as “Calculate frequency”, “Calculate mean”, and “Calculate wait times” are all combined into the behavior “Calculate metric”. Another example can be found in Fig. 3. The category “Apply a time filter” is combined with other kinds of filters to the behavior “Apply a filter” in the ethogram. Each behavior included in the ethogram is accompanied by a clear and concise definition (Lehner 1998). Once the list of behaviors is completed, the different behaviors are divided into phases to make the ethogram more comprehensible.

Step 6 aims to translate the found categories into actual behaviors. The input of this step is the list of categories formed in the previous step, and the output is an ethogram describing exploratory process mining behavior.

The literature-based ethogram

The literature-based ethogram was constructed after 3 literature review/coding iterations, i.e. after inspecting case studies in 3 iterations to find exploratory process mining behavior. After 3 iterations, data saturation was reached, and 80 coding categories were identified (75, 5, and 0 in three consecutive iterations). The 80 coding categories were grouped into 26 behaviors. An overview and description of the behaviors discovered can be found in Van Suetendael et al. (2025b).

Construction of altered version of literature-based ethogram

Based on the literature-based ethogram, constructed in Van Suetendael et al. (2025b), an altered version was constructed as a starting base for the validation through interviews. This altered version was constructed after discussion among the others, where the feedback received about (Van Suetendael et al. 2025b) was used as a starting base for discussion. The altered ethogram can be found in Appendix Table 5. The exact changes are listed below.

The main difference between the literature-based ethogram and the altered ethogram is that the intent of the behaviors was omitted, since the ethogram would become too complex for use if intent was included. Furthermore, four kinds of changes were applied to the literature-based ethogram: adding, omitting, altering behaviors, and name changes. One behavior was added to Phase 2 (Analysis) of the ethogram: “Take notes” since this is an often-performed behavior but was not yet a part of our ethogram. One behavior, “Categorize data”, was also omitted because it was deemed too specific at the time and could be classified under other behaviors such as “Transform data”. The behavior “Create figure/table” was split up into two behaviors: “Inspect graphics” and “Inspect tabular” to make the distinction between the two more prominent. Furthermore, the behavior “Discover process model” was removed since it can be classified under the new behavior “Inspect graphics” and the behavior “Calculate metric” was also removed since it can be classified under the new behavior “Inspect tabular”. The last kind of alterations were name changes with the intention to make the names more understandable. Firstly, “Profile data” was changed into “Inspect raw data”. Secondly, “Analyze different perspectives” was changed into “Choose a specific perspective”. Thirdly, “Discuss with stakeholders” was changed into “Check assumptions”. The content of this behavior did not change, but since assumptions can be checked in multiple ways (not only with stakeholders). The behavior received a more general neutral name. Lastly, “Consult with stakeholders” was changed to “Evaluate with stakeholders”.

The behaviors in the altered ethogram are still divided into five phases (Phase 0 to 4): Preparation, Pre-processing, Analysis, Interpretation, and Conclusion. Phase 0 involves preparatory actions to support exploratory process mining analysis and to gain a clearer understanding of the analysis context. In Phase 1, the data is pre-processed and prepared for analysis. Phase 2 focuses on analyzing the prepared data to discover patterns and generate insights. In Phase 3, the results of the analysis are interpreted. Finally, Phase 4 consists of synthesizing the interpretations and drawing overall conclusions. 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.

Validation of ethogram

The literature-based approach to composing the ethogram has a key limitation. The ethogram is purely based on behaviors described in published case studies. This implies that some behaviors might be missing because they are not being explicitly or implicitly reported in the case studies.

To validate the ethogram and address this limitation, semi-structured interviews were conducted with experienced process mining analysts. The interviews serve as a way to validate the literature-based ethogram with real-life experiences from process mining analysts. In this way, the risk of not identifying all behaviors because they were not explicitly or implicitly reported in the case studies is reduced.

Participant selection

We use purposive sampling to identify participants who meet our criteria. Purposive sampling is a non-probability sampling technique in which participants are selected

based on specific characteristics or qualities (Etikan et al. 2016). The specific type of purposive sampling chosen for this study is maximum variation sampling. This type aims to capture a broad range of perspectives by including participants with diverse characteristics, which ensures heterogeneity (Etikan et al. 2016). In our case, we focus on individuals who can perform process mining analyses independently and have recent experience with exploratory process mining. To be as diverse as possible, we target different ages, experience levels, tools, and companies. Furthermore, we aim to have a mix of participants from academia and industry in our study. To reach potential participants, the professional networks and industry associations of the authors are used.

Data was collected from a total of 15 interviews, from which 3 pilot interviews during which the interview methodology was tested. Since the methodology proved to work as expected and was not changed after the pilot interviews, the pilot interviews are included in the analysis. Each participant had recent experience with analyzing process data, which was checked with the question “How many projects have you performed in the last two years where you had to analyze third-party process data?”. The number of projects ranged from 2 to 15, with a mean of 5. The participants consisted of a mix of practitioners and academics from 10 different companies and 2 universities. The ages of the participants ranged from 28 to 50 years, with a mean value of 36 years of age. Their years of experience with analyzing both data and process data ranged from 1,5 to 25 years, as can be observed in Fig. 4 (left part). In the right part of Fig. 4 the different tools used by the participants are displayed. Celonis was the most used tool, closely followed by BupaR. Disco and PM4PY were less used and, most of the time, in combination with another process mining tool.

Development of interview guideline

To conduct semi-structured interviews, we followed (Mason 2002) overview to plan and prepare for qualitative interviews. This overview consists of seven major steps, including two cross-reference steps.

The first step of developing an interview guideline is to define the big research questions that need to be answered. In our case, we define two major questions: (A) “Does the ethogram contain all the behaviors performed during exploratory process mining?” and (B) “Is the ethogram structured in a comprehensible way?”.

The second step is to develop the so-called mini research questions, which divide the big research questions into smaller segments. The first research question (A) is divided into four mini-research questions: (A1) “Which behaviors do you perform during exploratory process mining?”, (A2) “Does the ethogram contain behaviors that you performed during exploratory process mining?”, (A3) “Does the ethogram contain behaviors that are not performed during exploratory process mining?”, and (A4) “Are there exploratory process mining behaviors missing in the ethogram?”. And the second research question (B) is divided into two mini-research questions: (B1) “Do the phases make sense? Or are they unnecessary?” and (B2) “Are the behaviors correctly divided among the phases?”.

The interview topics and questions are developed in the third step based on the large and small research questions. We define three main topics with their corresponding research questions: exploratory process mining (A1), behaviors described in the ethogram (A2, A3, A4), and structure of the ethogram (B1, B2). After creating the topics, a

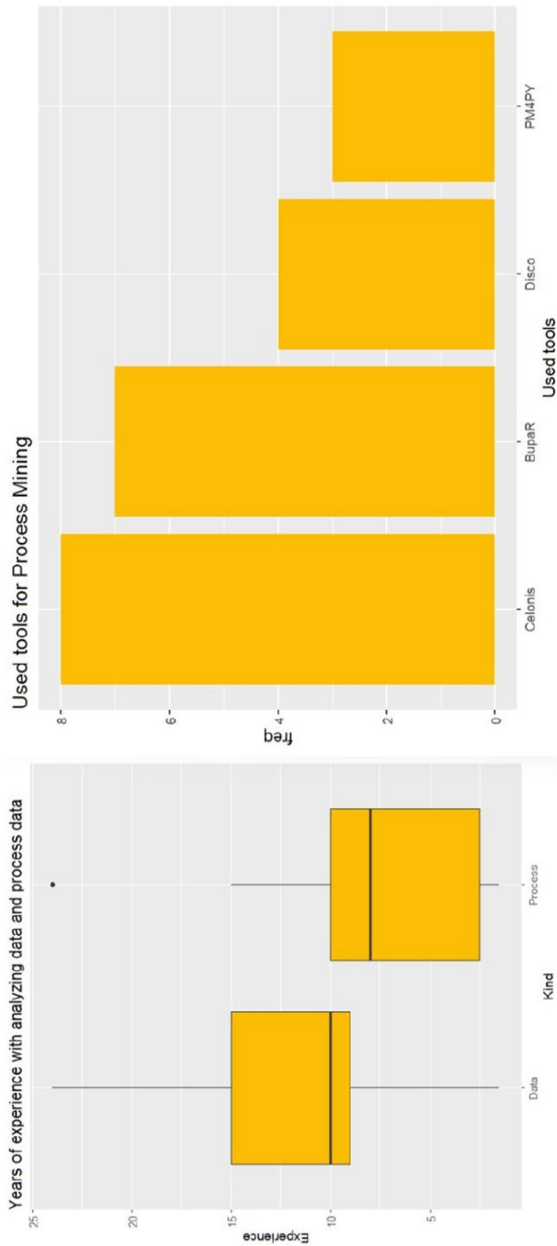


Fig. 4 Data and process experience and tool use of participants

cross-reference check is conducted in the fourth step. This step is performed to ensure all research questions are linked to a specific research topic.

In the fifth step, the interview structure is decided. The interview is structured into four main parts. Firstly, a short introduction is given. In this introduction, the goal of the interview is repeated, and an overview is given of how the interview will be conducted. Secondly, a few demographic questions are asked. These questions include name, age, experience and used tools. Thirdly, past process mining experiences are discussed (A1). Lastly, the ethogram is discussed in three stages: the behaviors (A2, A3, A4), the phases (B1), and the behaviors together with the phases (B2).

Standardized sections and questions are determined in step 6. These sections and questions are parts of the interview that will be the same for each participant. The first two sections of the interview, described in the fifth step, are standardized. The explanation and questions are the same for each participant. The questions from the other sections heavily depended on the input given by the participant, but the main questions of these sections still are addressed. In the last step, step 7, another cross-check is done to ensure everything is covered in the interview.

All the interviews are fully transcribed and coded. For the coding, the literature-based version of the ethogram is used as a starting point. However, new behaviors are added whenever they appear during the coding sessions. After coding the interviews, the insights gained are used to develop a new version of the ethogram.

Results

In this section, the results from the interviews will be discussed together with the validated ethogram. The validated ethogram is an update of the altered ethogram, where the improvements are based on the insights gained from the interviews.

Results from interviews

The interview started with asking the participant to recount past exploratory process mining experiences (A1). After which they were question about three different aspects of the ethogram: the behaviors (A2-A4), the phases (B1), and the placement of the behaviors in the phases (B2).

A1: Which behaviors do you perform during exploratory process mining? During the interview, the participants were first asked to recount past exploratory process mining experiences. These stories were coded using the altered ethogram. During this coding process, new behaviors were discovered due to them not fitting into any existing defined behaviors. The newly discovered behaviors are listen in Table 2 together with new behaviors mentioned explicitly by the participants.

A2: Does the ethogram contain behaviors that you performed during exploratory process mining? After recounting their past exploratory process mining experiences, the participants were shown the altered ethogram (Appendix Table 5). They were then asked which behaviors of the ethogram they have performed. Sixty percent of participants claimed to have performed all the behaviors described in the altered ethogram. Of the six participants who did not perform all the behaviors from the altered ethogram,

Table 2 Newly identified behaviors by participants and by coding

A walk along the process	Data quality issues	Report findings
Add data	Data validation	Retain information from third sources
Categorization/clustering	Define activities	Tool selection
Combine data	Enrich the data	Upload data
Create data model	Intermediate evaluations	Validate analysis
Create event log	Make report	Validation
Create mapping between technical and practical language	Manage expectations of client	Verify results
Curiosity	Reflection	

Table 3 Not performed behaviors of the literature-based ethogram

Behavior	Amount	Behavior	Amount
Apply a filter	1	Extract raw data	2
Choose a specific perspective	1	Generate a hypothesis	1
Define analysis strategy	1	Make assumptions	1
Define metrics	1	Make recommendations	2
Define scope	1	Remove data	1
Evaluate with experts/stakeholders	1	Revise hypothesis	1

three only omitted one behavior. The remaining three participants omitted a total of 2, 4, and 5 behaviors, respectively.

A3: Does the ethogram contain behaviors that are not performed during exploratory process mining For each behavior, no more than 2 participants indicated to have never performed this behavior during exploratory process mining. A list of behaviors, including the number of times it was claimed to not be performed, can be found in Table 3.

A4: Are there exploratory process mining behaviors missing in the ethogram? Besides discussing the already-defined behaviors, new behaviors were also discussed. Eighty-six percent of the participants suggested new behaviors to be added to the ethogram. Either directly by stating they missed a behavior, or a new behavior was discovered during the coding of their interview transcripts. The proposed new behaviors are shown in Table 2. The behaviors that were added to the ethogram are marked in yellow. The other behaviors were omitted for several reasons. For example, the behaviors “Combine data”, “Create event log”, and “Upload data” can all be classified under the already existing behavior “Transform data”. Just as the behaviors “verify results”, “Validate analysis”, “Data validation”, and “Intermediate evaluations” can be classified under the newly created behavior “Validate Findings”. The suggestion “curiosity” was not included because this is more a state of mind than an actual behavior. All the not mentioned behaviors that are not marked yellow were also omitted because they can be linked to either an already existing behavior or a newly discovered behavior in the ethogram.

B1: Do the phases make sense? Or are they unnecessary? All participants recognized the 5 phases as relevant and accurate. They also all agreed that there is some kind of iteration between the different phases. However, 5 participants (1/3) indicated that they missed a validation phase. They described the validation phase as a moment where they validated their findings or assumptions with experts or stakeholders of the process under analysis.

B2: Are the behaviors correctly divided among the phases? Besides questioning whether the right phases were discovered in the right order, the behaviors placed in the phases were also scrutinized. Eighty percent of the participants had at least one change they wanted to implement. In total 30 changes were suggested for 15 out of 25 behaviors defined in the altered ethogram. Most changes were only mentioned by one person. The changes mentioned by at least three people are briefly described below. Three participants asked for the behavior “Revise hypothesis” to be placed in phase 3 instead of phase 4. However, there were also 3 cases where participants asked to place the behavior in phase 2. Another behavior that was discussed by three participants was “Take notes”. The behavior did not fit any phase in their opinion, they saw take notes as a behavior that occurred everywhere. All the suggested movements of behaviors were taken into account when developing our validated ethogram.

Final version of ethogram

Changes to altered ethogram

After the interviews were conducted, the ethogram was updated based on the insights gained from these interviews. In total, 7 new behaviors were added, and one behavior was excluded from the list. The new ethogram consists of 31 behaviors. The new behaviors are: “Create data model”, “Identify data quality issue”, “Cluster data”, “Enrich data”, “Reflect on analysis strategy”, “Validate finding”, and “Report finding”. The behavior “Evaluate with experts/stakeholders” was removed since this behavior is part of the behavior “Validate finding”. Besides changing the behaviors, the phases in which the behaviors were placed were also updated. A new phase, “Phase 4: Validation,” was added.

The validated ethogram

The ethogram containing the different behaviors, their description, and a toy example can be found in Table 4. The behaviors are listed in the phase in which they fit most. Behaviors can occur in multiple phases, but to keep the ethogram clear and concise, each behavior is only listed once and placed in the most corresponding phase. A short overview of all the phases and the behaviors connected to these phases is described below. Each behavior is indicated in the text with a bold font.

Phase 0: Preparation Phase 0, Preparation, involves the initial steps an analyst takes to set the stage for an exploratory process mining analysis. This phase typically begins with specifying the problem statement and defining the scope of the analysis to ensure a targeted approach. Furthermore, the analyst also formulates questions that will guide the investigation and determines the analysis strategy. Finally, this phase also includes examining the context in which the process operates. These preparatory behaviors may be carried out independently by the analyst or collaboratively with the process owner, depending on the setting. The goal is to establish a clear understanding of the process and to align the analysis with its intended purpose.

Phase 1: Pre-processing After developing a clearer understanding of the process, the data representing that process is closely examined during the pre-processing phase. Based on insights from extraction and inspection of the raw data, process mining analysts can create a data model. In addition, data quality issues may be identified, prompting the data to be transformed or removed as needed to address these issues and prepare it for the next phase: the analysis phase.

Table 4 Validated Ethogram

Behavior	Description	Example
Phase 0: Preparation		
Define analysis strategy	Decide on or refine the approach that will be taken to solve the predefined questions or achieve the predefined goal. This approach can be predetermined or decided along the way. This also includes choosing which tools and metrics will be used.	To analyze the process, you developed a four-step approach, where you first focus on finding bottlenecks in the process...
Define problem statement	Define the problem that will be scrutinized or the goal of the analysis.	The process owners want to know which resources are involved at what stages of the process and what kind of interactions occur between the resources.
Define question	Define the questions that need to be answered after the analysis. This can be done beforehand or during the analysis.	With analysis of the data, an answer will be formulated to the following two questions: "What is the cheapest way to get the product to the customer?" and "Which resources are vital to our process?"
Define scope	Establish the boundaries and focus of the analysis by identifying relevant data, tools, and constraints.	The analysis will only focus on the first part of the process until activity E. All activities happening after activity E will not be analyzed.
Examine context	Gain a better understanding of the context of the data/process without analyzing the data. This involves reading the documentation that was given to you and/or consulting experts or stakeholders.	Company B specializes in the delivery of tape. The process of interest is B2B transactions, performed by the financial department.
Phase 1: Pre-processing		
Create data model	Create a data model by structuring event data, defining cases, activities, and timestamps while integrating relevant attributes for the analysis.	The events followed through the process are tickets made in a customer support process which is defined by the attribute Ticket ID. The activities are defined by their Activity ID and include: "Make a ticket", "Review ticket", "Ask for help", "Resolve ticket"...
Extract raw data	Retrieve data from information systems or databases for analysis.	Retrieve the process data from the information system for the years 2020 to 2024.
Identify data quality issue	Identify inconsistencies, missing values, noise, or other flaws in the data that could impact analysis reliability.	Some events are missing timestamps and there are duplicate events.
Inspect raw data	Have a look at the data to get an idea of the structure and content of the data. This involves identifying the variables and some summary statistics, such as the columns of the dataset, the number of cases, events, activities, etc.	The dataset contains 1,654,128 events across 562,123 cases. There are 50 activities. The process ends in three different ways, starting from a single activity.
Remove data	Remove variables, instances, or data points from the raw data permanently. Reasons for removing include data quality issues and scoping.	Remove the instances in the data where the case is not identified.
Transform data	Apply transformations such as splitting, renaming, and restructuring the data. This also includes solving data quality issues by transforming the data.	Converting a date column in a dataset from the format YYYY/MM/DD (e.g., 2024/11/18) to DD-MM-YYYY (e.g., 18-11-2024).
Phase 2: Analysis		
Apply filter	Focus on a specific part of the data/process by excluding instances, cases, or variants. This behavior also includes removing a filter.	Filter the data such that only the activities performed by Resource 1 are visible.
Choose specific perspective	Choose a specific perspective to analyze the process, a metric, figure, or table such as the performance or resource perspective.	You choose to look at the performance perspective and therefore look at durations, waiting times, throughput times, etc.

Table 4 (continued)

Behavior	Description	Example
Cluster data	Group or degroup events, cases, or attributes into categories or clusters based on predefined criteria or discovered patterns.	The data contains different types of activities in an order fulfillment process, such as "Receive Order," "Check Inventory," "Pack Order," and "Ship Order". Categorizing data involves grouping these activities into higher-level categories like "Order Processing," "Packaging," and "Shipping".
Define metric	Define measurable criteria to evaluate a phenomenon quantitatively. These metrics provide a basis for quantitative analysis and comparison.	To evaluate process efficiency, you use the average throughput time, which is defined as the sum of all case durations divided by the total number of cases.
Enrich data	Enhance the data by adding information to improve its completeness or relevance for analysis. This can include adding new attributes or combining data.	The data only contains timestamps for each activity, but no information about working hours. You can enrich the data by adding a new attribute that marks whether an event occurred during business hours or outside of them.
Generate hypothesis	Formulate predictions/expectations about patterns, relationships, or behaviors in the data. These hypotheses guide further analysis to gain deeper insights into the process.	You hypothesize that ordering a product in the store will take longer to be delivered than when the product is ordered online.
Identify element of interest	Make an observation based on a figure, process, table, or metric. This observation may lead to further analysis or making assumptions or hypotheses.	One of the activities in the process only occurred 5 times.
Inspect graphics	Analyze (and create) visual representations of the data, such as charts or process models, to identify patterns, trends, or anomalies.	A process map is created from the event log to show the process flow.
Inspect tabular	Examine (and create) structured data in a tabular format to identify patterns, inconsistencies, or anomalies.	A table displaying the case and absolute frequency for each case from the event log is created and studied.
Make comparison	Compare two or more metrics, figures, process models, etc. with one another.	Compare the process flows followed by male and female customers in the sales process.
Phase 3: Interpretation		
Interpret found result	Give meaning to the things you observed. This behavior is a step towards formulating answers to the questions.	Our analysis reveals that only two resources are involved in the entire process.
Make assumption	State an assumption about the process or data without immediate empirical validation. Assumptions guide the analysis and can later be tested or refined based on findings.	The assumption was made that each discharge event in the event log corresponds to a single patient and does not represent aggregated discharges.
Revise hypothesis	Revise a previously made hypothesis based on the insights gained during the analysis.	Based on insights into the process, you learned that resource planning is probably not the cause for the bottleneck. You revise your hypothesis as follows: "The bottlenecks occur due to a shortage of equipment".
Phase 4: Validation		
Check assumption	Check predefined assumptions about the (intermediate) results of the analysis by consulting the data and/or stakeholders.	The assumption that all orders are closed in the process is checked by checking the event log for cases that do not end with "Close Order".

Table 4 (continued)

Behavior	Description	Example
Reflect on analysis approach	Evaluate the chosen approach, methods, and metrics used in the analysis to assess their effectiveness, relevance and correctness.	After conducting an analysis of the customer support process, you reflect on your analysis strategy by evaluating whether the chosen metrics (e.g., time to resolving ticket, time until ticket is first handled) provided meaningful insights.
Validate finding	Validate findings of the analysis such as results, data quality issues, the data model, etc. by consulting the data and/or stakeholders.	After discovering a process model for an order-to-cash process, you evaluated it with stakeholders by asking: "Does the identified bottleneck in invoice generation align with your experience?"
Phase 5: Conclusion		
Answer question	Formulate an answer to the defined questions using the analysis results and their interpretations.	The answer to the question "Why are some orders taking significantly longer to ship?" is: "Analysis of the event log shows that delays are primarily caused by a rework loop in the order validation activity, which occurs in 35% of cases probably due to incomplete customer information".
Make recommendation	Recommend actions or improvements based on the analysis findings to enhance process performance or decision-making.	Recommend adding resources to activity A, because this activity is a bottleneck at the moment.
Report finding	Report the findings of your analysis in written or oral format. This involves sharing the found hypotheses, insights, answers and recommendations.	You report that you have found that for 5% of the cases are not resolved within 72 hours, in the customer support ticket process, and your hypothesis for this finding is that these tickets were placed on a backburner and were forgotten.
Phase 0-5: All phases		
Take notes	Make notes about interpretations, assumptions, analyses steps, meetings...	Notes are taken about the main paths in the process map: The process map reveals two main paths after "Approve PO". The first path goes directly to "Send to Supplier" and the second path has a loop back to "Create PO" before going to "Send to Supplier".

Phase 2: Analysis Phase 2, Analysis, encompasses the core activities in which analysts engage directly with the process data to uncover patterns, generate insights, and explore relationships. This phase is characterized by a dynamic and iterative interaction with both visual and tabular representations of the data. Analysts inspect graphics, such as process models or performance charts, as well as tabular data. They make comparisons across different cases, time periods, or process variants to identify meaningful differences. To deepen their understanding, analysts may enrich the data with additional attributes or derive new variables. They often generate hypotheses based on observed trends, and identify specific elements of interest, such as bottlenecks, frequent paths, or outliers. Defining metrics helps quantify these observations, while clustering techniques can reveal subgroups or patterns. Filters are applied to focus the analysis on particular segments, and different perspectives (case, activity, resource) are chosen depending on the analytical goal.

Phase 3: Interpretation The third phase, Interpretation, focuses on making sense of the results obtained during the analysis phase. In this phase, analysts interpret findings identified earlier, considering their implications in light of the original analysis goals and the broader process context. Assumptions may be made to explain observed behaviors

or deviations, drawing on domain knowledge or prior expectations. Analysts also revise earlier hypotheses based on new insights, adjusting their understanding of the process accordingly.

Phase 4: Validation The validation phase focuses on assessing the credibility and robustness of the findings generated during the analysis. In this phase, process mining analysts check earlier made assumptions and verify them either by consulting third parties, such as domain experts or process owners, or by cross-checking them against the data. Similarly, the findings are validated to ensure they hold under different perspectives or data segments. In addition, the analysis strategy is reviewed to confirm that the chosen approach appropriately supports the conclusions drawn. This phase plays a critical role in reinforcing the trustworthiness of the results and supporting well-founded interpretations and recommendations.

Phase 5: Conclusion The last phase of the ethogram is the conclusion phase, where all the insights gained from the previous phases are used to make recommendations, answer questions, and ultimately report all the findings of the analysis.

Phase 0-5: All phases One of the behaviors could not be classified into one specific phase, since this behavior is performed across all phases. In the preparatory phase, notes are taken about the problem definition, the context of the process, or the initial analysis plan. During the pre-processing phase, analysts may document decisions related to data cleaning, filtering, or transformations. In the analysis phase, notes often capture emerging insights, hypotheses, or intermediate findings. In the interpretation phase, these notes help structure reflections on what the observed patterns mean in light of the analysis goals. In the validation phase, notes can support the tracking of feedback from stakeholders, the rationale behind adjustments made to the analysis, or discussions around the credibility of findings. Finally, during the conclusion phase, notes may be used to summarize key findings, highlight open questions, or record recommendations.

Discussion

In the discussion section, three topics will be discussed. First, an overview of the different implications of the developed ethogram will be discussed. Second, a comparison will be made with the PEM4PPM model from Sorokina et al. (2023) and our validated ethogram. Thirdly, a short overview of the limitations of this paper will be discussed.

Implications

Ethograms, traditionally used in behavioral sciences, serve as a list or inventory of behaviors performed by a specific species. With this list, researchers can quantitatively record observations of behavior (Lehner 1998). In the context of process mining, an ethogram can be used to identify and classify analysts' behaviors. Beyond serving as a descriptive tool, the ethogram can also function as a data collection and analysis tool.

By recording observations in a quantitative manner, it becomes easier to identify patterns and compare behaviors from different process mining analysts. However, behavioral data often takes the form of fine-grained observational data, such as digital trace data. 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. For instance, actions like 'select rows' and 'delete rows' can be combined into the behavior "Remove data". This shift in granularity allows for a more meaningful analysis of process mining behavior. 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. This not only enables us to better understand the individual behavior of process mining analysts but also allows us to analyze the impact of different process mining strategies or tools on analysts' behavior. Such insights can inform the development of training programs, user interfaces, and decision-support systems that enhance the analytical capabilities of process mining analysts.

While the ethogram is primarily intended as a research tool to systematically capture and analyze the behavior of process mining analysts, we believe that the insights gained from such analysis can be translated into practical guidance. Rather than functioning as a step-by-step guide, the ethogram enables the identification of behavioral patterns and strategies commonly used during exploratory process mining analysis. These insights can inform the development of training materials and tool features to support process mining analysts in navigating process data more effectively. Ultimately, by advancing our understanding of how process mining analysts explore process data, we can bridge the gap between human expertise and computational analytics. This knowledge not only enhances the effectiveness of exploratory process mining but also contributes to the broader goal of making process mining tools more accessible, intuitive, and actionable for process mining analysts at all levels of expertise.

Comparison with PEM4PPM model

The PEM4PPM model, developed by Sorokina et al. (2023), aims describe process mining behavior, which is similar to our validated ethogram. However, there are key differences. First the construction of both models is different. PEM4PPM is constructed based on theory and adapted according to findings in real-time observations. The ethogram on the other hand is constructed based on literature and interviews. Secondly, the ethogram defines more specific behaviors, while PEM4PPM remains at a higher level. Thirdly, PEM4PPM is process-structured, where the different steps occur in a certain order, whereas the ethogram categorizes behaviors into six phases, where the phases occur in a certain order, but the behaviors have no particular order. Lastly, the ethogram focuses on exploratory process mining, while PEM4PPM describes theory-guided process mining. Despite their differences, the PEM4PPM model and our ethogram share similarities. Nine out of ten cognitive steps of the PEM4PPM model align with various behaviors from the ethogram, however PEM4PPM lacks coverage of dataset preparation and certain detailed behaviors like data modeling and note-taking. The only step from PEM4PPM that could not be linked was the step "Test Hypotheses" due to ethogram's exploratory focus. Figure 5 illustrates the connections between PEM4PPM and the validated ethogram.

The first cognitive step of the PEM4PPM model, “Task understanding”, links to 2 behaviors defined in Phase 0 (Preparation). The step is described as understanding the problem or task and the data, which corresponds to the behaviors “Define questions”, and “Examine context”. The “Set/Refine goal” step from PEM4PPM links to the other 3 behaviors from the ethogram in Phase 0: “Define analysis strategy”, “Define problem statement”, and “Define scope”. The focus of this step from PEM4PPM lies in formulating a goal, deciding how this goal can be achieved, and deciding the scope of solving this goal. The “Focus” step of PEM4PPM corresponds to the behavior “Apply filter” as both aim to focus on a specific part of the process. The “Explore” step from PEM4PPM aligns with all the behaviors from Phase 2 (Analysis) besides “Generate hypothesis” and “Apply filter”, demonstrating PEM4PPM’s higher-level definition compared to the ethogram. It also aligns with “Inspect raw data” from Phase 1 (Pre-processing) as the data is also explored in this behavior. The behaviors “Interpret results” and “Make assumptions” from the ethogram can be linked to the step “Interpret data” in PEM4PPM, which is defined as the process of explaining insights from the analysis/exploration. The step “Assess results” from PEM4PPM, which aims to evaluate insights from the analysis/exploration can be linked to the behaviors of Phase 4 (Validation). “Generate hypotheses” is defined as both a step in PEM4PPM and as a behavior in the ethogram. Besides the behavior “Generate hypotheses”, the behavior “Revise hypotheses” is also linked to the step “Generate hypotheses” from PEM4PPM. The “Create artifact” step from PEM4PPM involves goal-driven object creation. This step can be linked to the same behaviors as the step “Explore”, as long as the focus lies on exploratory analysis. Finally, the “Conclude” step from PEM4PPM corresponds to behaviors “Answer question”, “Make recommendations”, and “Report findings”, focusing on addressing predefined questions with answers, findings or recommendations.

The step “Test hypotheses” from PEM4PPM could not be linked to the ethogram as it does not align with our definition of exploratory process mining. In exploratory process mining the focus is on building hypotheses, testing them is more considered to be confirmatory analyses in the opinion of the authors. Additionally, PEM4PPM lacks coverage of dataset preparation and omits behaviors such as “Create data model”, “Extract raw data”, “Identify data quality issue”, “Remove data”, and “Transform data”. Furthermore, the behavior “Take notes” also does not have a counterpart.

We compare our ethogram with the PEM4PPM framework because both aim to conceptualize analyst behavior in the context of process mining. PEM4PPM provides a high-level, phase-based model of behavior, whereas our ethogram captures behavior at a more granular level, focusing on concrete, observable behaviors. The comparison illustrates that our ethogram aligns with PEM4PPM but offers a more detailed view.

Limitations

Despite the carefully designed research methodology, we acknowledge 4 key limitations to this study. First, the analysis was based on a selected set of published case studies, which may not reflect the full range of behaviors exhibited during exploratory process mining. Consequently, some behaviors might remain unidentified. Second, as the ethogram was developed using secondary data, there is a risk of reporter bias, where certain process mining analyst behaviors may not have been explicitly or implicitly documented by the original authors and therefore could not be included. Third, although

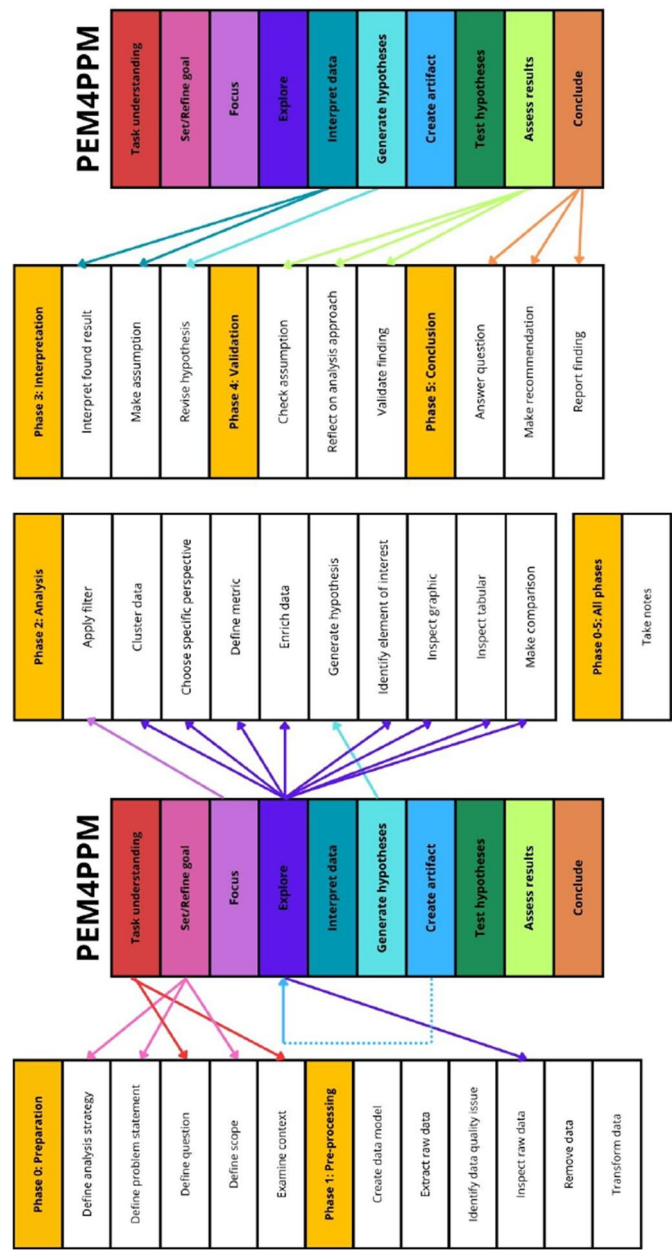


Fig. 5 Comparison between Ethnogram and PEM4PPM

the ethogram was validated through expert interviews, the possibility remains that not all relevant behaviors were captured due to memory bias. Fourth, the behavioral coding was carried out by a single researcher, which introduces the possibility of subjective interpretation. However, this risk was mitigated by validating the initial coding through expert interviews, which provided an external check and helped refine and supplement the identified behaviors.

Conclusion

Analyzing exploratory process mining behavior is not always straightforward since exploratory process mining requires navigating complex process data, selecting appropriate analysis techniques, and interpreting results, making it highly dependent on the process mining analyst's expertise. Therefore, this paper aims to help in this endeavor by developing an ethogram describing exploratory process mining behavior. First, a literature-based ethogram was developed by investigating and coding 48 case studies. After this, the ethogram was updated based on insights gained from interviewing 15 experienced process mining analysts, resulting in the validated ethogram. This ethogram consists of 31 different behaviors such as "Identify data quality issue", "Inspect tabular", and "Validate finding". These 31 behaviors were categorized into 6 different phases: Preparation, Pre-Processing, Analysis, Interpretation, Validation, and Conclusion. This ethogram not only provides a clear overview of the different behaviors of exploratory process mining, but it also provides a vocabulary that can be used to analyze exploratory process mining behavior.

Future research directions include using the ethogram during observations of exploratory process mining behavior, to uncover patterns in behaviors. Another possible future research direction is the application of the ethogram to make fine-grained digital trace data more comprehensible for analysis purposes by linking the fine-grained actions to the behaviors of the ethogram. Additionally, future research could focus on further validating and refining the ethogram to ensure that all relevant behaviors in exploratory process mining are captured. While the ethogram has been validated through interviews, there remains a risk that certain behaviors were overlooked due to reporter bias in its development and memory bias during validation. Addressing these limitations through alternative validation methods, such as real-time observational studies or think-aloud protocols, could enhance the ethogram's completeness and reliability. Lastly, new ethograms can be developed describing other phases of process mining, such as predictive process mining. The ethogram developed in this study is specifically tailored to exploratory process mining and might, therefore, not enable an accurate description of behaviors occurring when performing other kinds of process mining.

Appendix A Ethogram used during interviews

Table 5 Ethogram used during interviews

Behavior	Description
Phase 0: Preparation	
Define analysis strategy	Decide or refine the approach that will be taken to solve the predefined questions. This approach can be predetermined or decided along the way. This also includes choosing which tools and metrics will be used.
Define problem statement	Define the problem that will be scrutinized or the goal of the analysis. What do you want to achieve?
Define questions	Define the questions that need to be answered after the analysis.
Define scope	Define the scope of the analysis.
Examine context	Gain a better understanding of the context of the data and/or the process without analyzing the data. This involves reading the documentation that was given to you and consulting experts or stakeholders.
Extract raw data	Select and collect raw data for the analysis.
Phase 1: Pre-processing	
Inspect raw data	Identify the variables, such as the number of cases, events, activities, etc.
Remove data	Remove variables, instances, or data points from the raw data permanently. Reasons for removing include data quality issues and scoping.
Transform data	Apply transformations such as splitting, renaming, and restructuring the data.
Phase 2: Analysis	
Apply a filter	Focus on a specific part of the data/process by excluding instances, cases, or variants. This behavior also includes removing a filter.
Choose a specific perspective	Choose a specific perspective to analyze the process, a metric, figure, or table such as performance or resource perspective.
Define metrics	Define a metric to measure or describe phenomena quantitatively.
Generate a hypothesis	Make a hypothesis about expected outcomes.
Identify an element of interest	Make an observation based on a figure, process, table, or metric. This observation may lead to further analysis or making assumptions or hypotheses.
Inspect graphics	Create and observe a graphic such as a process model or figure.
Inspect tabular	Create and observe a metric or a table.
Make a comparison	Compare two or more metrics, figures, or process models with one another.
Take notes	Making notes during the analysis, to make space in the working memory.
Phase 3: Interpretation	
Interpret found results	Give meaning to the things you have observed. This behavior is a step towards formulating answers to the predefined questions.
Make assumptions	Make an assumption about the data/process.
Phase 4: Conclusion	
Answer questions	Formulate an answer for the main questions using the analysis results and their interpretations.
Check assumptions	Check predefined assumptions with the (intermediate) results of the analysis.
Evaluate with experts/stakeholders	Validate previously made assumptions and discuss results that were found.
Make recommendations	Make recommendations based on the results of the analysis.
Revise hypothesis	Revise a previously made hypothesis based on the insights gained during the analysis.

Acknowledgements

This work is an extended version of the paper “Towards an Ethogram of Exploratory Process Mining Behavior” (Van Suetendael et al. 2025b), originally presented at the Empirical Research in Process Mining (ERPM) workshop during the 6th International Conference on Process Mining (ICPM 2024).

Authors' contributions

Jessica Van Suetendael: Conceptualization, Methodology, Formal analysis, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization Benoît Depaire: Conceptualization, Methodology, Writing - Review & Editing, Supervision Mieke Jans: Conceptualization, Methodology, Writing - Review & Editing, Supervision Niels Martin: Conceptualization, Methodology, Writing - Review & Editing, Supervision.

Funding

This study was supported by Research Foundation– Flanders (FWO) under Grant No. 11A2225N and the Special Research Fund (Bijzonder Onderzoeksfonds, BOF) of Hasselt University under Grant No. BOF24TT02.

Data availability

The codings for the literature-based ethogram, the interview protocol, and transcripts are uploaded to Zenodo: <https://doi.org/10.5281/zenodo.15845469>. Van Suetendael et al. (2025a).

Code availability

Not applicable.

Declarations

Ethics approval and consent to participate

Participation in our user study was entirely voluntary. Participants could withdraw at any time without providing a reason. All identifying information was anonymized during data collection. Our research was approved by the Social and Societal Ethics Committee (SMEC) at Hasselt University.

Consent for publication

The intent of publishing the study's findings was made transparent by mentioning the connection to the research project and the research team at the beginning of the user study. Participants could opt-out at any stage, in which case their data was excluded from analysis and not used further.

Competing interests

The authors declare no competing interests.

Received: 31 March 2025 / Accepted: 16 July 2025

Published online: 15 August 2025

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