VIPRA – EuroVis Workshop on Visual Process Analytics (2024)
A. Arleo, L. Pufahl, J. Rehse, F. Zerbato, S. van den Elzen, and T. von Landesberger (Organizers)

# Review of visual encodings in common process mining tools

S. Knoblich[1] and J. Mendling[1], H. Jambor[2]

[1]Humboldt Universität zu Berlin, Institute of Computer Science, Germany
[2]Centre for Data Analysis, Visualisation and Simulation, University of Applied Sciences of the Grisons, Chur, Switzerland

**Abstract**

*Process mining tools empower process analysts to scrutinize business processes by leveraging algorithmic techniques and event log datasets. To support the analysis of inefficiencies of business processes, different types of visualization techniques have been introduced for process mining. These techniques enhance process models by incorporating performance data, for instance to highlight activity duration by using gradational color palettes, and by mapping statistical parameters as text notes directly into the model. So far, tool vendors have designed a diverse spectrum of visual features for enhancing models, but research has not systematically provided insights into their mutual effectiveness. In this paper, we review the visualizations of six common business process mining tools. To account for the variability in the visual display, we expanded existing taxonomies for evaluating event sequences with marks and channels as well as accessibility dimensions, each important for end-user comprehension. Then, we performed an expert survey to assess the legibility of the visualizations to test the validity of our expanded taxonomy. In this way, we demonstrate the potential for improving process mining visualizations to expand its value in today's process mining tools.*

**CCS Concepts**

• ***Human-centered computing*** → *Visual analytics; Visual analytics;*

## 1. Introduction

Over the past two decades, a variety of techniques and methods for visualizing business processes extracted from event-log data has emerged [ACD*18]. Today, these methods have evolved into the distinct research field of process mining [vdA16]. Process mining advancements are aimed to enhance analysts' ability to make informed, quick decisions [vdA16]. Process mining includes the discovery, conformance checking, and exploration of improvements of processes [PWS*15]. Visualizations help audiences in understanding problems, processes, and probabilities [SPS11]. Recent visualization research has revealed how information is extracted from visual displays. [FPS*21]. Thus, it is not surprising that visualizations are increasingly fuelling process mining applications and tools.The effectiveness of a visual display in aiding audiences must be determined experimentally [FPS*21]. This research is still lagging for process mining models. While existing taxonomies for event sequence visualizations categorize the information displayed for numerous examples from the literature, they do not yet include the aspect of the visual design, arguably a key aspect for the tool's effectiveness in the work environment. Moreover, at present, most research of process mining focused on development of improved technology [vBJM*21], while research on its visual representation's legibility and effectiveness is lagging. In this paper, we surveyed process mining tool visual displays with a taxonomy designed for event sequence visualizations. While this indicated comparability, the displays however differed significantly in their visual appearances. To account for these differences, we therefore extended the framework to include layout, annotation, marks and channels, and accessibility. We next evaluated the applicability of our expanded taxonomy with a questionnaire with expert reviewers. This revealed dimensions that are well-designed as well as areas for improvements in current visualizations in process mining tools.

This paper is structured as follows. Section 2 describes existing work that compared visual analytic tools for event sequences in process mining. Section 3 presents and applies the existing and our expanded taxonomy to six common process mining tools. We then put the expanded taxonomy to test, and describe the study design (4) and results of an expert survey (5). In section 6, we discuss our results in the context of existing work, including limitations and opportunities for future work intersecting visual analytics and process mining. Section 7 offers concluding remarks.

## 2. Background:Event sequence visual displays

Process mining takes event log data as input and generate visual diagrams to show real-world business processes. Common visualizations are event sequence graphs [GMFJ*19] that explain the link between two activities and the path in between. Here, the visual display represents the observed sequence of events. The data contains e.g., the name and timestamp or events with additional attributes and can further be subcategorizes into event enumeration,



DOI: 10.2312/vipra.20241104

case-event enumeration, and case-state enumeration [YM]. Model-based visualisation display abstracted rules to user with which sequences can be generated and its characteristics, rather than actual sequences. These include directly-follows graphs, Petri nets, Declare constraints, and process trees [vdA16]. In directly-follows graphs, nodes show a type of event and the links/arcs their directly-follows relationships.

Despite different data inputs, visualizations in process mining share an overall organization. Attributes captured and visualized may include the timing, frequency, or changes of events (timestamp, duration, category, identifier). These events are depicted by nodes (also referred to as points) and the event sequence is delineated by links (also referred to as arcs), as well as usually by a start and an end point. The arcs/links provide additional information on the frequencies of instances following these event sequences. Arc/links can encode this information with variable line marks (color, shape, size, weight) or are textually annotated. Thus, the design space of such visualizations is defined by different ways of showing nodes, links/arcs with different color codes but also the relative arrangement, layout and orientation can carry information.

Yet, while having similarities in their overall visual display, different process mining tools vary in their precise visual realizations, which can affect interpretation. Prior work has compared visualization of process maps from the information theory and data perspective [GGJ*22] [vdLdFvdEV] [YM24]. These surveys identified coarse-granular visualization options for event sequence visualizations. For instance different displays may be compared based on the scale of the events, which data is compared, the data size and dimension, and also the visual display type and interaction mode. These categories, and in particular the visual display and interaction, must be designed with the end-user and their tasks in mind. A recent work, the Event Sequence Visualization Framework (ESeVis), comprehensively compares the implementations of several event sequences data analysis settings and in particular reviews their visual displays [YM24]. The ESeVis compares event sequence data visualizations in process mining and information visualizations research, a field that has dealt with event sequences from various domains and previously systematized the various visual analytics (VA) approaches used. Guo et al. characterized VA event sequence based on analytical tasks and applications [GGJ*22] and defined four dimensions critical in implementations: the data scale, automated sequence analysis covering the mining and modeling techniques, visual representation describing the visual display, and the interaction technique. These dimensions were expanded by van der Linden et al. into a taxonomy of five dimensions that also include the 'comparison type' task and also covers data attributes (as 'data dimension') and data size (as 'size dimension') [vdLdFvdEV].

## 3. Tool comparison

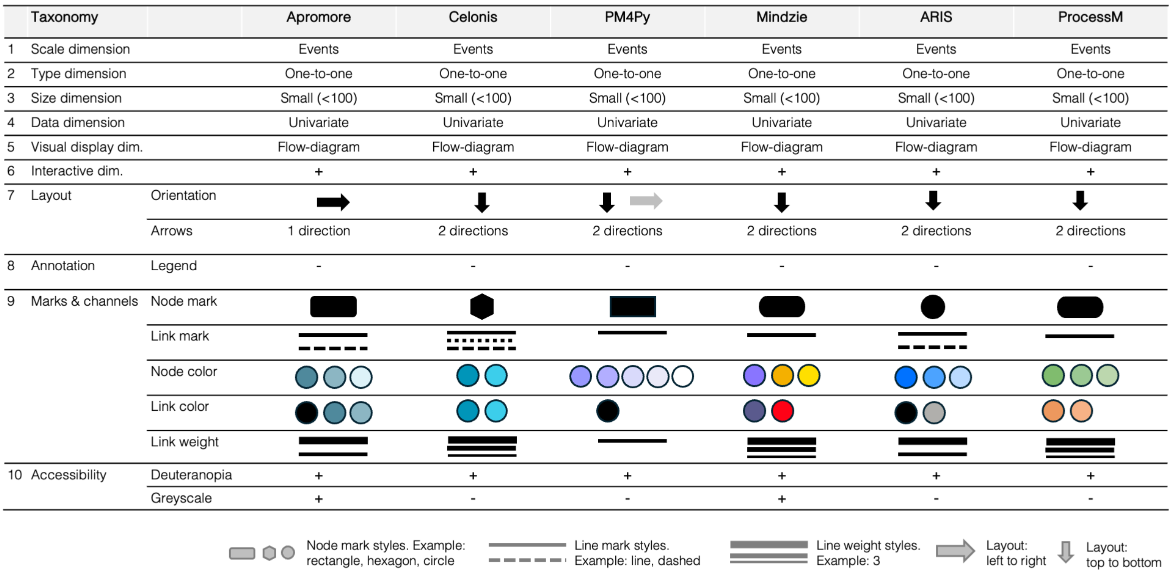
Only visual displays that have a comprehensible layout, recognizable display type, annotated and distinguishable marks and channels can fulfill the information-seeking mantra of "Overview first, zoom and filter, then details-on-demand" to empower users to "relate, history, and extract" [Shn]. We therefore first, summarize the classification taxonomy by van der Linden (3.1), second, compared the visualizations of six common tools in process mining (3.2), and third, expanded the comparison dimensions (3.3).

### 3.1. Classification

To compare visualizations of six common tools in process mining (Supplementary Figure: `https://doi.org/10.6084/m9.figshare.25665411.v2`), we applied the existing taxonomy introduced by van der Linden, as it provides fine-granular analysis criteria. A number of tools are used business process mining [VSM20]. We chose four commonly used tools [KSC21], namely Celonis, Apromore, ARIS, Mindzie, the Python library PM4Py, which is gaining traction in data-driven algorithms, and ProcessM, an add-on tool of Microsoft PowerBI. Based on the description by van der Linden, we then classified the tools. The taxonomy classes by van der Linden [vdLdFvdEV] are: Scale dimension (which data type is compared): Events, sequences, and cohorts. Type dimension (granularity and positioning of comparison needed for task): One-to-one or directly-follows graphs, one-to-many, or many-to-many—determined. Positioning refers to the method of supporting comparisons in visualizations, classified into juxtaposition, superposition, and explicit encodings. Size dimension (number of events, sequences or cohorts, number of their respective attributes; property of the input data): Size is classified as small (less than 100 sequences or events, less than 20 attributes), medium (100 to 1,000 sequences or events, 20 to 100 attributes), or large (over 1,000 sequences or events, more than 100 attributes). Data dimension (how complex is data): Raw (attributes present in the raw/original data) or derived data (attributes are computed by running an algorithm or calculating extra data based on the raw data). Visualization dimension (display type used for the data): Detailed (non summarizes, raw) or aggregated (summarized, derived) data, e.g. timeline, hierarchy-based visualizations, flow-based visualizations, treemaps. Aggregated visualizations generally capture higher-level information through data attribute aggregation. Interaction dimension: How end-users analyze data and adjust the display, are common interactions techniques [GGJ*22] are enabled.

### 3.2. Tool comparison

We initially utilized Van der Linden et al.'s taxonomy to assess the six business process mining tools. Our findings, illustrated in Figure 1 (rows 1-6), indicate high comparability among the visual displays across the five taxonomy dimensions. However, this highlights a limitation in the existing taxonomy for distinguishing process discovery visualizations in process mining tools. In all tools the 'scale dimension' is comparable, in that all tools visualize events for a wide set of processes including classic Order-to-Cash, Source-to-Pay and incident creation [vBJM*21]. Likewise, all tools have a granularity of one-to-one in the 'comparison type dimension', in that all are following one process across time. While some tools offer a one-to-many solution (object-centric process mining) [vdA23] for process mining we focused in this paper on this basic granularity. All examples used in this study share the size dimension 'small', i.e. the visual displays show usually below 100 events with below 20 attributes, and the 'data dimension', being univariate counts and frequencies of event sequences. Last, the 'visual display and interaction dimension' for all cases was a flow-



| | Taxonomy | | Apromore | Celonis | PM4Py | Mindzie | ARIS | ProcessM |
|---|---|---|---|---|---|---|---|---|
| 1 | Scale dimension | | Events | Events | Events | Events | Events | Events |
| 2 | Type dimension | | One-to-one | One-to-one | One-to-one | One-to-one | One-to-one | One-to-one |
| 3 | Size dimension | | Small (<100) | Small (<100) | Small (<100) | Small (<100) | Small (<100) | Small (<100) |
| 4 | Data dimension | | Univariate | Univariate | Univariate | Univariate | Univariate | Univariate |
| 5 | Visual display dim. | | Flow-diagram | Flow-diagram | Flow-diagram | Flow-diagram | Flow-diagram | Flow-diagram |
| 6 | Interactive dim. | | + | + | + | + | + | + |
| 7 | Layout | Orientation | | | | | | |
| | | Arrows | 1 direction | 2 directions | 2 directions | 2 directions | 2 directions | 2 directions |
| 8 | Annotation | Legend | - | - | - | - | - | - |
| 9 | Marks & channels | Node mark | | | | | | |
| | | Link mark | | | | | | |
| | | Node color | | | | | | |
| | | Link color | | | | | | |
| | | Link weight | | | | | | |
| 10 | Accessibility | Deuteranopia | + | + | + | + | + | + |
| | | Greyscale | + | - | - | + | - | - |



**Figure 1:** *Extended tool comparison*

based diagram for showing the aggregated number of transitions between events in the visualization. This display is also referred to as Sankey-based representation, node-link diagram [YM24], or directly-follows graphs [LPW19]. In each case, one attribute is visualized and no additional relations beyond the existing nodes are presented. All tools compared were in their implementation interactive allowing users to interrogate data further and tweak data to their needs.

### 3.3. Expanded Taxonomy

Although the visual displays of the business process model tools were classified as equivalent, there are obvious differences in the visual representation that are not captured with the taxonomy van der Linden. Indeed, the Nested Model for Visualization Design also considers the marks and channels used to encode data [Mun] [BM]. Marks are geometric elements (points, lines, areas, or even 3D objects) that represent information or links, while channels control the appearance of marks, with e.g., color, pattern or shape. For process visualizations, it is also important to decide if the employed marks guide the user through the visual display, and if they also encode data. For example, the color or size of a node could encode their function, hierarchy in a process, while the color of a link could encode the number of processes along this path. All information to understand the overall visual display, and all marks and channels should be available to the user, e.g. with text annotation or legends. For each visualization, several design implementations and layouts are possible, and the underlying global topography, with start and end point, must be recognizable to users. Common reading directions in displays are left to right or top to bottom [HB18] and these are often supported with arcs/links and arrows [HT06]. We therefore expanded the visual display category of Van der Linden's taxonomy with the following dimensions and example questions for each:

1. Layout dimension:
   E.g., which reading direction is used? E.g., what kind of arrows are present to support the reading direction?
2. Annotation dimension:
   E.g., are legends used to explain the visual display, the marks and the channels?
3. Mark dimension:
   E.g. which marks are used for links? E.g. which marks are used for nodes?
4. Channels dimension:
   E.g., which color(s) are used for marks? E.g., which line weights are used for marks (lines)?
5. Accessibility dimension:
   E.g., are channels accessible to color-blind readers (e.g., distinguishable to Deuteranopia vision users), or to readers with poor color vision (i.e. distinguishable in greyscale)

When applying our expanded taxonomy to the surveyed tools, differences became apparent and could be classified (Figure 1, from row 7). In 5 of 6 cases the reading direction of the event sequences was organised from top to bottom, while one tool (Apromore) presented data from left-to-right. For PM4Py the default reading direction was from top to bottom, however it is adaptable to left-to-right orientation. All tools encoded the arcs with arrows, which further support the reading direction. 5 of 6 tools employed both forward and backward arrows, and only one tool (Apromore) restricting the arrows to forward orientation. None of the tools employed text in the form or a title/subtitle or legend, meaning that all annotations are restricted to the direct labels of the nodes and links. Next, the marks used for denoting the nodes and link in the visual display were varied, nodes were shown as circle (n=1), hexagon (n=1) or variations of rectangles (n=4). The line channels ranged from solid to dashed lines, and several tools additionally varied the line widths, showing up to 3 or 4 different stroke weights. The color schemes of node and links ranged from 1-3 colors (links) to 2-5 colors (nodes). Most tools varied the saturation/lightness of the node hue. In 4/6 tools (Apromore, Celonis, ARIS, PM4Py) this was a form of blue, blue-turquoise, or blue-purple, while ProcessM used green. Only Mindzie varied the hue, combining purple, orange, and yellow nodes. Most tools varied not only the node color and also the link color, with 5/6 tools in total using five or more color channels. Despite most using a number of hues, all tools are accessible to readers with common color deficiencies, i.e. red/green colorblind safe [JB24]. However, a greyscale rendering showed that most hues used side-by side are not distinguishable based on their lightness values, having low ration in contrast ratio, meaning that color accessibility is restricted [JB24]. Thus, our expanded taxonomy was able to classify the nuanced differences in the visual display of the surveyed business process mining tools. Only a visual display that has a comprehensible layout, recognizable display type, annotated and distinguishable marks and channels can fulfill the information-seeking mantra of "Overview first, zoom and filter, then details-on-demand" to empower users to "relate, history, and extract", which have become known as the eight golden rules for user-interface design [Shn].

## 4. User study design

We next applied the expanded taxonomy in the form of an expert review to assess if no known guidelines were violated in the process model displays [TM]. We based our review questions on our expanded taxonomy for assessing the visualizations of process mining tools and applied these to the six selected tools. All participants provided informed consent and no personal data was collected. In total we interviewed eight experts from process mining and/or visualization research. This likely exceeds the number of required expert study participants, where three to five evaluators were shown to suffice for identifying usability problems present study [ZSN*]. The experts were recruited from both process mining (n=4) and visualization (n=3) fields, or both (n=1). The experience in their respective fields ranged from three to 10+ years of experience.

We next defined a hierarchical set of heuristics, covering a range of taxonomic dimensions. We then applied all heuristics to each interface item in a set of in total 17 closed-ended questions (Figure 2 'question'), each linked to one category of the taxonomy 'Visual Display,' 'Layout,' 'Annotations,' and 'Marks and Channels' to measure the effectiveness of each tool. We designed the questions to encompass both perceptual cognitive as well as the visual [ZSN*] information-seeking mantra [Shn]. Despite all tools being interactive, we surveyed the expert opinions with a static image to focus on the visual display design rather than interactive features. Presenting static/still images is also the advised strategy for validation in the foundational 'nested model for visualization [Mun] design' [BM]. Answers were collected using a dichotomous scale, with experts indicating whether they agree/agree. To calculate the final score for each question and tool, we tallied the responses. A score of 0 indicated none of the participants agreed, a score of 1.0 indicated unanimous agreement, whereas a score of 0.5 indicated parsimony. The final score thus provides a quantified measure of consensus or divergence of opinions within the expert group. No open questions and free text feedback were recorded.

## 5. User study results

Analyzing the provided data, it is evident that there are significant variations in the visual representation of the selected process mining tools. Starting with 'Visual Display', the overall score is high, indicating that most tools effectively show the basic visual representation of process mining data, and allow most experts to easily recognize nodes, arcs/links, and arc/link weights. The visual display of Celonis and ProcessM was rated slightly lower, and PM4PY achieved the lowest rating. We next assessed the overall layout of the visual display. Most experts were readily able to orient to start and end point, with the lowest raging for PM4Py, which did not explicity annotate these points. When asking about more complex tasks, such as navigating along the longest or shortest path, the scores decrease. Using only the static image, the advised starting point for reviewing design strategies, experts particularly struggled to navigate along event sequences with PM4Py, again as the visualisation for this study used a model that had no dedicated start and end symbol. As this is an optional feature in the tool itself it

| Taxonomy | Question | Apromore | ARIS | Celonis | Mindzie | PM4Py | ProcessM | Total |
|---|---|---|---|---|---|---|---|---|
| Visual Display | Recognise event sequence display? | 1.00 | 1.00 | 0.88 | 1.00 | 0.50 | 0.75 | 0.85 |
| | Visually recognise nodes? | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.88 | 0.98 |
| | Visually recognise links? | 1.00 | 1.00 | 1.00 | 1.00 | 0.88 | 0.88 | 0.96 |
| | Visually recognise link weights? | 1.00 | 0.88 | 1.00 | 0.88 | 0.57 | 0.88 | 0.87 |
| Layout | Orient to start point? | 1.00 | 1.00 | 1.00 | 1.00 | 0.25 | 0.88 | 0.85 |
| | Orient to end point? | 1.00 | 1.00 | 1.00 | 1.00 | 0.13 | 0.63 | 0.79 |
| | Navigate along a longest path? | 0.75 | 0.88 | 0.63 | 0.50 | 0.13 | 0.38 | 0.54 |
| | Navigate along a shortest path? | 0.63 | 0.75 | 0.63 | 0.63 | 0.13 | 0.38 | 0.52 |
| | Identify the busiest node? | 0.75 | 0.57 | 0.88 | 0.43 | 0.63 | 0.38 | 0.61 |
| Annotations | Understand what visual display is about? | 0.63 | 0.63 | 0.50 | 0.50 | 0.00 | 0.50 | 0.46 |
| | Are annotations legible to you? | 0.75 | 0.43 | 0.63 | 0.43 | 0.57 | 0.50 | 0.56 |
| Marks and Channels | Able to understand marks and channels based on annotation/legend? | 0.50 | 0.38 | 0.67 | 0.40 | 0.83 | 0.50 | 0.54 |
| | Are line styles understandle/decodable? (if applicable) | 0.57 | 0.43 | 0.57 | 0.20 | 0.50 | 0.29 | 0.43 |
| | Are text/number boldings understandle/decodable? (if applicable) | 0.50 | 0.67 | 0.60 | 0.40 | 0.80 | 0.50 | 0.57 |
| | Are node colors understandle/decodable? | 0.38 | 0.50 | 0.57 | 0.29 | 0.67 | 0.43 | 0.46 |
| | Are link colors understandle/decodable? | 0.50 | 0.60 | 0.50 | 0.14 | 0.40 | 0.29 | 0.39 |
| | Are colors visually distinguishable? | 0.63 | 0.71 | 0.71 | 0.75 | 0.75 | 0.50 | 0.67 |

**Figure 2:** *Heatmap of response scores tallied from all expert reviewers. Each expert was asked to rate each tool with the 17 questions representing the expanded taxonomy. Category ordered by score.*

maybe adjusted, which should lead to higher scores in this section also for PM4Py. The 'Annotations' taxonomy assessed if the tool helps its user with title and annotations and reveals that many tools insufficiently explained the data displayed and furthermore employed what the experts rated as illegible texts (small/low legible fonts, colors of text with low visibility on background). Thus, while the tools may effectively display the data, conveying the meaning through legible annotations is an aspect that has room for improvement. Finally, 'Marks and Channels' criteria, which include understanding and decoding of marks, channels, and colors, overall scored lowest across all questions. The ability to understand the marks and channels in use, e.g., typically achieved with annotations/legends, scored low across the tested tools (0-0.5, Apromore scoring highest with 0.63/0.75). Arc/line styles and boldness of text/numbers are fairly well understood (often directly annotated and/or inferrable), while the comprehension of node and link colors had very mixed scores, ranging in agreement of 0.14-0.67. A consistent issue across most tools is distinctiveness of colors, which scored from 0.5 to 0.75. Being able to distinguish colors is crucial for users to effectively differentiate and interpret process visualizations, and often not explained e.g., by a legend - furthermore, even when rating colors as distinguishable, we know that many experts underestimated the number of different colors in use and thus could not objectively distinguish all hues. Overall, our scores indicate that while some tools excel in certain areas, there is room for improvement across all tools, especially in making annotations more legible and improving users' understanding of marks and channels. These insights could guide developers to enhance their process mining tools, making them more user-friendly and effective for analyzing complex data.

## 6. Discussion

We contributed to the field of visual analytics for process mining by expanding the taxonomy to categorize the visual display of process mining visualizations. We also put the expanded taxonomy to test with our expert questionnaire, which compared the visualizations of six process mining tools. This work is foundational for next designing a controlled, randomized survey to systematically compare design choices and comprehensibility of process mining visual displays. Here, we highlight three main implications and the limitations of our study. Using our expanded taxonomy to survey process mining visualizations, we revealed that indeed across tools expert users were able to faithfully identify the broad category of the visual displays as being a type of flow-/event sequence visualization. Furthermore, these visual displays are composed of nodes/points and arcs/lines and the first step of a user, before gaining insights, is to identify nodes and links, which was unanimously possible for our expert reviewers with all tools tested, except one. Using our finely-grained questions for layout revealed that most tools effectively are able to communicate start/end point. However several tools presented as challenging when following paths, and those tools, with e.g., bi-directional arrows, many arrows with crossings, scored lower in the expert reviews. Many tools scored low in questions concerning annotations and of marks and channels, revealing that our expanded taxonomy can also capture weaknesses in the visualization of process mining tools. None of the tools included captions and/or legends explaining the marks and channels in use. When experts were able to understand what the process is about, they derived this information from the node labels, rather than a dedicated caption. The lack of explanation for marks and channels in use, e.g., arc/line width and style (dash, non-dash), and colors of nodes and arc/lines is particularly concerning, as these encode important information in forms that are often not accessible to all users. Whenever designing a visualization, it should be accessible also to color blind users but more generally also consider possible limitations of visually impaired audiences and the diversity in visual perception of visually able readers [JB24] [KJRK21]. A standard in creating accessible visual display is to include text-based explanations of all elements, for process mining visualizations this would be the arc/line and node marks and channels in use. In particular these aspects would benefit from attention by tool developers and/or implementations of the software. A more comprehensive assessment of accessibility could even ask if screen-reader software may extract the information?

One limitation of the expanded taxonomy is its so far limited practical user-testing. While visualization research [Mun] suggests that marks and channels, layout and accessibility are likely important for end-users, this needs further quantitative study for process mining visualizations. Another limitation is that the example visualizations are not entirely comparable. We used default settings and publicly available images, limiting direct tool-to-tool comparisons. However, we intentionally avoided scoring each tool and left out comprehension questions due to dataset discrepancies, focusing on the legibility of the display instead. Next, as software tools are rapidly changing or becoming outdated, reviews thereof are limited in insight. However, our focus is less on the specific software tested, but rather on defining criteria to review the respective user interfaces for process discovery with process mining tools. Last, we acknowledge that our initial studies have been conducted exclusively with male participants without verifying their comprehension levels in depth.

Our work highlights opportunities for further analysis and enhancement of PM tools' visual interfaces. Our initial survey offers insights, but lacks quantitative data due to design limitations. Our next step therefore is a more systematic survey with robust statistical design. This survey will gauge the effectiveness of encoding and interaction idioms using consistent datasets across tool implementations and will incorporate important previous work on conformance checking visualizations that defined a framework for assessing the content and comprehension levels of visual interfaces [RPGK22]. This future research will also explore the applicability of existing conceptual model understanding work to process mining solutions, which offer diverse visual encoding options [MSGGLR12] [MS08]. Despite limitations, our work extends existing visualization frameworks and taxonomies for process mining [YM24] [GGJ*22] [vdLdFvdEV] by incorporating aspects of accessibility and legibility.

## 7. Conclusion

A picture says more than a thousand words - this phrase is only true if the visual is understandable to the target audiences. In process mining, a 'picture' can significantly impact business decisions. We expanded the review-taxonomy for event sequence visualizations to also address legibility to the end-users. Our expert survey validated this taxonomy, pinpointing areas for improving current process mining models. This highlights the ability of visual analytics research for having a positive impact on process mining. Our survey confirmed the usefulness of our expanded taxonomy in designing user-friendly tools. Thus, while a poorly designed visual display may spark a thousand questions, a well-designed picture or dashboard indeed may fulfil the promise of visualizations.

## References


[ACD*18] Augusto A., Conforti R., Dumas M., La Rosa M., Maggi F. M., Marrella A., Mecella M., Soo A.: Automated discovery of process models from event logs: Review and benchmark. *arXiv preprint arXiv:1705.02288v3* (2018). URL: https://arxiv.org/abs/1705.02288. 1

[BM] Brehmer M., Munzner T.: A multi-level typology of abstract visualization tasks. 2376–2385. Conference Name: IEEE Transactions on Visualization and Computer Graphics. URL: https://ieeexplore.ieee.org/document/6634168, doi:10.1109/TVCG.2013.124. 3, 4

[FPS*21] Franconeri S. L., Padilla L. M., Shah P., Zacks J. M., Hullman J.: The science of visual data communication: What works. *Psychological Science in the public interest 22*, 3 (2021), 110–161. Publisher: SAGE Publications Sage CA: Los Angeles, CA. 1

[GGJ*22] Guo Y., Guo S., Jin Z., Kaul S., Gotz D., Cao N.: Survey on visual analysis of event sequence data. *IEEE Transactions on Visualization and Computer Graphics 28*, 12 (2022), 5091–5112. doi:10.1109/TVCG.2021.3100413. 2, 5

[GMFJ*19] Garcia C. d. S., Meincheim A., Faria Junior E. R., Dallagassa M. R., Sato D. M. V., Carvalho D. R., Santos E. A. P., Scalabrin E. E.: Process mining techniques and applications – A systematic mapping study. *Expert Systems with Applications 133* (Nov. 2019), 260–295. URL: https://www.sciencedirect.com/science/article/pii/S0957417419303161, doi:10.1016/j.eswa.2019.05.003. 1

[HB18] Hullman J., Bach B.: Picturing Science: Design Patterns in Graphical Abstracts. In *Diagrammatic Representation and Inference* (Cham, 2018), Chapman P., Stapleton G., Moktefi A., Perez-Kriz S., Bellucci F., (Eds.), Lecture Notes in Computer Science, Springer International Publishing, pp. 183–200. doi:10.1007/978-3-319-91376-6_19. 3

[HT06] Heiser J., Tversky B.: Arrows in comprehending and producing mechanical diagrams. *Cognitive Science 30* (2006), 581–592. URL: https://onlinelibrary.wiley.com/doi/abs/10.1207/s15516709cog0000_70, doi:10.1207/s15516709cog0000_70. 3

[JB24] Jambor H. K., Bornhäuser M.: Ten simple rules for designing graphical abstracts. *PLOS Computational Biology 20*, 2 (Feb. 2024), e1011789. Publisher: Public Library of Science. URL: https://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.1011789, doi:10.1371/journal.pcbi.1011789. 4, 5

[KJRK21] Kim N. W., Joyner S. C., Riegelhuth A., Kim Y.: Accessible Visualization: Design Space, Opportunities, and Challenges. *Computer Graphics Forum 40*, 3 (2021), 173–188. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/cgf.14298. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/cgf.14298, doi:10.1111/cgf.14298. 5

[KSC21] Kerremans M., Srivastava T., Choudhary F.: Gartner market guide for process mining, 2021. Research Note G00737056. Available online: www.gartner.com (accessed on 1 December 2023). 2

[LPW19] Leemans S. J. J., Poppe E., Wynn M. T.: Directly follows-based process mining: Exploration & a case study. In *International Conference on Process Mining (ICPM)* (2019), IEEE, pp. 25–32. doi:insertDOIhereifavailable. 3

[MS08] Mendling J., Strembeck M.: Influence factors of understanding business process models. In *Lecture Notes in Business Information Processing* (2008). doi:10.1007/978-3-540-79396-0_13. 5

[MSGGLR12] Mendling J., Sánchez-González L., García F., La Rosa M.: Thresholds for error probability measures of business process models. *The Journal of Systems and Software 85* (2012), 1188–1197. URL: https://www.sciencedirect.com/science/article/pii/S0164121212000017, doi:10.1016/j.jss.2012.01.017. 5

[Mun] Munzner T.: A nested model for visualization design and validation. 921–928. Conference Name: IEEE Transactions on Visualization and Computer Graphics. URL: https://ieeexplore.ieee.org/document/5290695, doi:10.1109/TVCG.2009.111. 3, 4, 5

[PWS*15] Partington A., Wynn M., Suriadi S., Ouyang C., Karnon J.: Process mining for clinical processes: A comparative analysis of four australian hospitals. *ACM Transactions on Management Information Systems 5*, 4 (2015). URL: http://dx.doi.org/10.1145/2629446, doi:10.1145/2629446. 1

[RPGK22] Rehse J.-R., Pufahl L., Grohs M., Klein L.-M.: Process mining meets visual analytics: The case of conformance checking, 2022. arXiv:2209.09712. 5

[Shn] Shneiderman B.: The eyes have it: a task by data type taxonomy for information visualizations. In *Proceedings 1996 IEEE Symposium on Visual Languages*, pp. 336–343. ISSN: 1049-2615. URL: https://ieeexplore.ieee.org/document/545307, doi:10.1109/VL.1996.545307. 2, 4

[SPS11] Spiegelhalter D., Pearson M., Short I.: Visualizing uncertainty about the future. *science 333*, 6048 (2011), 1393–1400. Publisher: American Association for the Advancement of Science. 1

[TM] Tory M., Moller T.: Evaluating visualizations: do expert reviews work? 8–11. doi:10.1109/MCG.2005.102. 4

[vBJM*21] vom Brocke J., Jans M., Mendling J., et al.: A five-level framework for research on process mining. *Business Information Systems Engineering 63* (2021), 483–490. URL: https://doi.org/10.1007/s12599-021-00718-8, doi:10.1007/s12599-021-00718-8. 1, 2

[vdA16] van der Aalst W. M. P.: *Process Mining - Data Science in Action, Second Edition*. Springer, 2016. doi:10.1007/978-3-662-49851-4. 1, 2

[vdA23] van der Aalst W. M. P.: Object-centric process mining: Unraveling the fabric of operational processes. *Mathematics 11* (2023), 2691. URL: https://www.mdpi.com/2227-7390/11/12/2691, doi:10.3390/math11122691. 2

[vdLdFvdEV] van der Linden S., de Fouw E., van den Elzen S., Vilanova A.: A survey of visualization techniques for comparing event sequences. 522–542. URL: https://www.sciencedirect.com/science/article/pii/S0097849323000717, doi:10.1016/j.cag.2023.05.016. 2, 5

[VSM20] Viner D., Stierle M., Matzner M.: A process mining software comparison, 2020. Preprint submitted to the International Conference on Process Mining (ICPM) 2020. Available at arXiv:2007.14038v1 [cs.SE]. URL: https://arxiv.org/abs/2007.14038. 2

[YM] Yeshchenko A., Mendling J.: A survey of approaches for event sequence analysis and visualization using the ESeVis framework. URL: http://arxiv.org/abs/2202.07941, arXiv:2202.07941[cs], doi:10.48550/arXiv.2202.07941. 2

[YM24] Yeshchenko A., Mendling J.: A survey of approaches for event sequence analysis and visualization. *Information Systems 120* (2024), 102283. doi:10.1016/j.is.2023.102283. 2, 3, 5

[ZSN*] Zuk T., Schlesier L., Neumann P., Hancock M. S., Carpendale S.: Heuristics for information visualization evaluation. In *Proceedings of the 2006 AVI workshop on BEyond time and errors: novel evaluation methods for information visualization*, BELIV '06, Association for Computing Machinery, pp. 1–6. URL: https://dl.acm.org/doi/10.1145/1168149.1168162, doi:10.1145/1168149.1168162. 4