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Conformance checking visualizations: development, evaluation, and demonstration of a taxonomy

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Abstract

Organizations use conformance checking, a sub-discipline of process mining, which compares process executions with predefined process models, to identify deviations in business processes. These capabilities make conformance checking highly relevant. To make its results accessible and tailored to specific tasks, effective visualizations are essential. Although the need for such visualizations has already been identified and acknowledged by researchers in process mining, so far, the development of these visualizations has been left to tool providers, leading to visualizations that are highly different and difficult to compare. A better understanding of these existing visualizations and their components would support research to gain deeper insights and assess them more closely. To address this gap and establish a foundation for future research, this paper provides an overview of the existing breadth of characteristics of conformance checking visualizations in the form of a taxonomy. It enables to describe and assess existing visualizations in a structured manner, achieving a detailed understanding, which was not possible before. It consists of six dimensions, which systematically highlight what information is displayed and how this is visualized across academic and commercial tools. We evaluate the taxonomy through expert interviews and demonstrate its applicability through four individual exemplary visualizations and an assessment of common visualizations across tools. Our research enhances the comprehension of visual analytics in process mining, particularly for conformance checking, and highlights promising future research avenues.

Keywords Conformance checking, Process mining, Visual analytics, Taxonomy

Introduction

Process mining provides organizations with analytical techniques to gain insights into their business processes (Van Der Aalst 2022b). One important sub-discipline of process mining is conformance checking, which compares process execution data, captured in event logs, with predefined to-be processes, captured typically in process models. This makes it possible to determine whether an executed process deviates from or conforms to the to-be process (Carmona et al. 2022). It can help organizations to detect violations

of internal or external regulations or find process improvements (Emamjome et al. 2019). These analytical capabilities of conformance checking make it highly relevant for many different domains and emphasize its relevance in research.

To make conformance checking results accessible to expert and non-expert users and tailor them to the intended tasks, visualizations are essential (Keim et al. 2008; Gschwandtner 2017; Rehse et al. 2023). Effective visualizations significantly support the analysis process by allowing users to acquire new insights more quickly, draw conclusions more effectively, and make more knowledgeable decisions to solve the task in focus (Keim et al. 2008; Mendling et al. 2021). As a result, visualizations not only improve analytical effectiveness but also contribute to a more intuitive and satisfying user experience (Keim et al. 2008). This is especially important in conformance checking, where the complexity of the data can make results challenging to interpret without appropriate visual support (Carmona et al. 2022; Gschwandtner 2017).

Although the need for such visualizations has already been identified and acknowledged by researchers in process mining (Gschwandtner 2017; Rehse et al. 2023; Klinkmüller et al. 2019; Mendling et al. 2021), research on this topic, especially on conformance checking visualizations, has been limited. So far, their development has mostly been left to the process mining tool providers, who have developed their own visualizations, based on the context and goals of the respective tools (FAU 2021). Consequently, the visualizations differ highly with regard to the displayed data and their representation (Rehse et al. 2023). A better understanding of these existing visualizations and its components would support research to gain deeper insights, assess them more closely, compare their differences, and eventually improve them. Moreover, these new insights would provide a foundation for further research on process mining visualizations, which could result in new insights on the users, their preferences and the effects the different visualizations have on them (Rehse et al. 2023; Gschwandtner 2017; García-Bañuelos et al. 2017).

To create such a foundational understanding of the existing visualizations, this paper provides a detailed overview of the existing breadth of conformance checking visualizations in the form of a taxonomy, enabling a systematic assessment and description of conformance checking visualizations. A taxonomy is a multi-dimensional classification of a set of entities that allows to relate and structure them (Kerracher and Kennedy 2017). We developed this taxonomy (Kundisch et al. 2021) through a comparative analysis of academic and commercial process mining tools that include conformance checking visualizations. It consists of six dimensions and various characteristics per dimension. The taxonomy presents, in a structured manner, what information is currently contained in conformance checking visualizations and how this is visualized across the different tools. Further, we demonstrate its applicability through four exemplary visualizations and an assessment of different tools. This assessment highlights the most frequently used conformance checking visualizations and shows the current focus of the tools. Moreover, we evaluate it in eight expert interviews considering multiple evaluation goals and desirable properties, such as ease or value of use.

This paper is a revised version of our previous work (Häge and Rehse 2024), originally presented at the Empirical Research in Process Mining workshop during the 6th International Conference on Process Mining (ICPM 2024), which we have extended in three ways:

- (1) In the [Method](#) section, we adapt our method to the guidelines by Kundisch et al. (2021), which extend the development method by Nickerson et al. (2013) used in our previous work.
- (2) In the [Evaluation of the taxonomy](#) section, we evaluate the taxonomy through expert interviews, providing external validation of the taxonomy's usability.
- (3) In the [Demonstration of the taxonomy: individual exemplary visualizations](#) and [Demonstration of taxonomy: assessment across tools](#) sections, we demonstrate the applicability of the taxonomy:
 - (a) to different exemplary visualizations, thereby demonstrating the categorization of visualizations with the taxonomy.
 - (b) for an assessment of common visualizations across tools, thereby demonstrating how the taxonomy can provide an overview of the currently most used conformance checking visualizations.

The paper is structured as follows. The necessary background and related work is presented in the [Background & related work](#) section. Next, in the [Method](#) section, the method used to develop the taxonomy is outlined. Afterwards, in the [Evaluation of the taxonomy](#) section, we describe the evaluation method and results in detail, highlighting the taxonomy's value. In the [Conformance checking visualization taxonomy](#) section, we present and describe the final taxonomy. Moreover, we demonstrate the applicability of the taxonomy with four exemplary visualizations and an assessment of different tools to identify the most common conformance checking visualizations. In the [Discussion](#) section, we discuss the results, their limitations, and future implications and conclude in the [Conclusion](#) section.

Background & related work

In this paper, we investigate visualizations in conformance checking and thereby connect process mining research with the field of visual analytics. In this section, we provide the relevant background information on the two research fields and elaborate on the existing work connecting visual analytics and process mining.

Process mining

The first relevant research field is process mining, a family of techniques aimed to analyze process data from information systems, to gain data-driven insights into their processes (Van Der Aalst 2022a). The most common sub-disciplines are process discovery, conformance checking, and process enhancement (Van Der Aalst 2022b). Process mining can consider different perspectives on the process, of which the most common one is the control-flow, which represents the ordering of activities. Other perspectives may refer to time, data, or resources (Van Der Aalst 2022b).

Event logs

To conduct process mining, we require an event log, which is a collection of events captured in information systems and provides data on the real-world execution of a process. A single event contains at least a case identifier, an activity name, and a timestamp or another ordering mechanism. Events can also include additional attributes, such as resources or costs. A single trace is made of a sequence of events that describe a process

execution. If a trace contains timestamps, we can measure its throughput time, i.e., the time from start to end. Multiple traces can follow the same activities, which can be then summarized as a variant. In the end, the results are often visualized as process models (Van Der Aalst 2022a).

Business process models

These business process models capture business processes and are used by organizations to support them in communicating, analyzing, documenting, redesigning, improving, monitoring or implementing processes (Dumas et al. 2018). For this purpose, different process model notations can be used. The most common ones for process mining are DFGs (Directly-Follow-Graph), Petri Nets, and BPMNs (Business Process Model and Notation) (Van Der Aalst 2022a). Each notation has a different focus, leading to differences in their depiction. In Fig. 1, these process model notations are used to visualize the same process. All models show the allowed process executions for different cases. Each case is an individual occurrence of the process, which is shown in the model through a path going from start to end. Each path contains activities that can or must be completed (Weske 2019). To visualize single cases, a suitable alternative notation are chevron diagrams, which depict the sequence of executed activities (Reinkemeyer 2020).

Although process models provide many advantages to organizations, they also present certain challenges. Those include the reduction of the process complexity in the models, the discrepancy between reality and the process model, the maintenance, and the restrictions of the different notations (Van Der Aalst 2022a; Weske 2019; Dumas et al. 2018).

Conformance checking

In conformance checking, the sub-discipline of process mining we focus on in this paper, existing process models and event logs are compared to analyze how accurately they align. The process model usually represents the intended process, whereas the event log contains the real-world process execution. Through this comparison, deviations between them can be detected (Carmona et al. 2022). This can help organizations to identify violations of internal or external regulations or find novel opportunities for process improvement (Emamjome et al. 2019). Thus, deviations can be categorized by their impact but also by the deviation type, such as skipped or repeated, showing the pattern

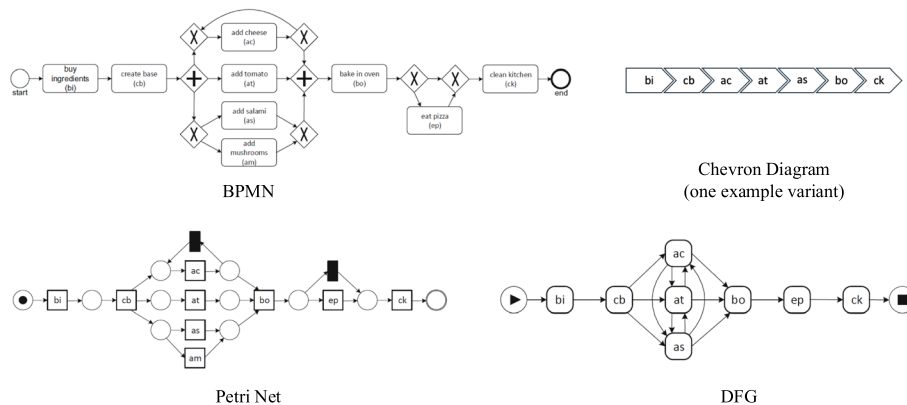


Fig. 1 Example process depicted in four process model notations (Van Der Aalst (2022b), p. 10 ff.)

the deviation follows (Grohs et al. 2024). The impact of the deviation can be assessed from multiple perspectives, such as control-flow, time, or costs.

There are three main conformance checking techniques: *token replay*, *rule checking*, and *alignments*. The latter two are the current state-of-the-art and can also be applied to other perspectives than the control-flow (Carmona et al. 2022). Whereas rule checking techniques analyze if behavioral rules defined in a model are violated by certain traces in the log, alignment-based techniques compare a trace of an event log directly with a process execution in the model and identify possible alignments, which are made out of single event-activity matches. To quantify the degree of conformance between a log and a model, a fitness measure is typically used, which indicates how well the model covers the recorded behavior in the event log (Carmona et al. 2022).

Visual analytics

Visual analytics, the second relevant research area for this paper, can be defined as the “science of analytical reasoning facilitated by interactive visual interfaces” (Thomas and Cook 2005). The aim is to improve human understanding, reasoning, and decision-making with regard to provided datasets. Compared to other fields, such as information visualization, visual analytics emphasizes the importance of including the user throughout the analysis process. The goal is to provide the user with an intuitive and useful interpretation of data rather than a cognitive or information overload when presenting only results (Cui 2019; Keim et al. 2008). Hence, the data analysis and the implemented algorithms are the focus of this research. Moreover, the task that needs to be solved with the visualizations is always the focus, ensuring that the visualization provides the desired insights (Munzner 2014; Keim et al. 2008). Through interactive capabilities, the user can see dynamics within the data, gain hidden insights, and adjust the complexity to their needs. As a consequence, they can fulfill tasks more effectively and efficiently (Gschwandtner 2017; Munzner 2014).

Munzner (2014) defines an analysis framework to systematically evaluate visualizations based on three questions: ‘Why’, ‘What’, and ‘How’ (Fig. 2). ‘Why’ analyzes the reasons for using the visualization (tool) and identifies the performed task. ‘What’ specifies the kind of data the users see in the visualization. The last question, ‘How’ describes the design of the visualization and its possible interaction options (Munzner 2014). By answering these questions, a fitting visualization for a given situation can be identified. We rely on to this framework in our work as it is a frequently-cited and well-known framework in visual analytics. Furthermore, it is simple, easily understandable,

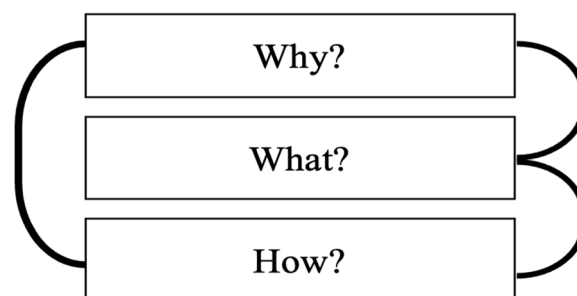


Fig. 2 Analysis framework (Munzner (2014), p. 17)

well-structured, and has already been applied in the process mining and modeling domain (Rehse et al. 2023; Dani et al. 2019).

Visual analytics in process mining

In 2011, Van Der Aalst et al. (2011) first suggested to combine process mining and visual analytics. Since then, there have been a few research initiatives in this direction. Two Dagstuhl seminars in 2023¹ and 2025² highlighted the relevance of the topic again (Di Ciccio et al. 2024), underlining that an interplay of both research fields could provide an improved understanding of the processes and an increased support of the user's analysis process (Gschwandtner 2017). Nevertheless, improving process mining through visual analytics comes with certain challenges and research gaps that still need to be tackled. According to Gschwandtner (Gschwandtner 2017), these challenges include (1) the visualization of time-oriented data, which is essential for the control-flow perspective in process mining and refers to any data considering time as an essential element, (2) the question of visualization evaluation, and (3) the issue of scalability and aggregation, among others.

To address some of these challenges, existing research on visual analytics in process mining has focused on the categorization of visualizations (Klinkmüller et al. 2019; Yeshchenko and Mendling 2024; Rehse et al. 2023; Kriglstein et al. 2016), the establishment of frameworks (Klessascheck et al. 2024; Sirgmets et al. 2018), and the assessment of visualizations (Hoogmoed et al. 2024; Knoblich et al. 2024; Kaouni et al. 2021; Gall and Rinderle-Ma 2021; Brinkman et al. 2024).

Categorization of visualizations

When categorizing visualizations, researchers group them depending on their task or other characteristics (Klinkmüller et al. 2019; Yeshchenko and Mendling 2024; Rehse et al. 2023; Kriglstein et al. 2016). Klinkmüller et al. (2019) identify the visualizations used for different process mining domain problems, as mentioned in analysis reports. These domain problems are kept very general and represent the different process mining sub-disciplines. Kriglstein et al. (2016) use visual analytics to categorize process mining techniques. These two papers provide a good foundation, but do not focus on detailed visual components or specifically on conformance checking.

Another paper by Yeshchenko and Mendling (2024) establishes a framework that categorizes possible visual representations for event-sequences, which refer to any sequences of events over time that can differ in the event granularity level. These are used in different areas of computer science but are essential in process mining. The paper focuses on event-sequences, so it does not explicitly consider conformance checking and does not analyze the individual components of the visualizations. Finally, Rehse et al. (2023) focus on conformance checking and apply the three-part analysis framework by Munzner (2014) to identify conformance checking tasks that are addressed by the currently available visualizations in academic and commercial tools. However, they do not analyze the existing visualizations in detail.

¹<https://www.dagstuhl.de/23271>

²<https://www.dagstuhl.de/25152>

Establishment of frameworks

When establishing frameworks considering visual analytics, researchers aim to provide new approaches or structures to work with visualizations (Klessascheck et al. 2024; Sirgmets et al. 2018). Klessascheck et al. (2024) develop and empirically evaluate a structural model summarizing conformance checking applications, and helping to create accessible and appropriate visualizations for concrete analyses. Sirgmets et al. (2018) assess current process mining outputs and propose a framework to support developers when designing visualization for such outputs. Both papers provide frameworks to support creating new visualizations rather than assessing existing ones.

Assessment of visualizations

When assessing visualizations, researchers aim to identify which visualizations are used and how suitable they are for process mining and the individual task (Hoogmoed et al. 2024; Knoblich et al. 2024; Kaouni et al. 2021; Gall and Rinderle-Ma 2021; Brinkman et al. 2024). They also often provide newly developed solutions. For example, Hoogmoed et al. (2024) focus on resource analysis and Kaouni et al. (2021) consider the identification of bottlenecks. Gall and Rinderle-Ma (2021) introduce a novel visualization for constraints, accompanied by an empirical study on user preferences for these visualizations. Similarly, Brinkman et al. (2024) conduct a user study on visualizations of discovered process models and identify requirements and challenges. Knoblich et al. (2024) analyze current process mining tools to identify what visual encodings are used for event sequences. However, these two papers focus on discovered process models, the latter extending a taxonomy from event sequences research (Van Der Linden et al. 2023).

Current research gap

The cited works highlight that research on process mining and visual analytics has been picking up recently and a starting point for improving process mining through visual analytics has been established. Nevertheless, visualizations have mainly been analyzed in their entirety so far. Only one paper (Knoblich et al. 2024) had a more detailed look at discovered process models, breaking visualizations down into individual components to reduce complexity and gain a deeper understanding. Moreover, research on existing conformance checking visualizations is also limited.

Therefore, a more detailed analysis, especially on conformance checking visualizations, is necessary, showing what visualizations are currently used, what information they depict, and what visualization components they are made of. This would allow to reduce the complexity of the visualizations through a systematic assessment and would help describe and assess existing visualizations in more detail.

Method

To close the research identified in the [Background & related work](#) section and provide a detailed overview of existing conformance checking visualizations and their components, we set out to develop a taxonomy for conformance checking visualizations (Keracher and Kennedy 2017; Nickerson et al. 2013). In general, a taxonomy serves to organize knowledge and uncover relationships between the underlying concepts. It provides a multi-dimensional classification of a set of entities, enabling a clearer understanding and organization of the field. A taxonomy comprises several dimensions, with

each dimension encompassing multiple characteristics. In this paper, the entities are conformance checking visualizations, for which we want to offer a structured overview to simplify their analysis and support future research.

To develop such a taxonomy, we followed the iterative development method by Kundisch et al. (2021). This method extends the one by Nickerson et al. (2013) and is therefore also based on the design science paradigm in the information systems field. The method suggests to develop a taxonomy over multiple iterations, following either an empirical-to-conceptual or a conceptual-to-empirical approach. A conceptual-to-empirical iteration derives the information from theory and literature, whereas an empirical-to-conceptual iteration uses empirical data.

According to this development method (Kundisch et al. 2021), we first need to identify the intended purpose of the taxonomy, including the target user group and the observed phenomenon. Then, we set the meta-characteristic that defines the objective of the taxonomy, the ending conditions that define the criteria for ending the development process and the evaluation goals that define the objectives of the evaluation. Afterwards, the development iterations start. In each iteration, we will collect data in either a conceptual-to-empirical or empirical-to-conceptual way, structure the collected data, identify common characteristics, and, lastly, group those characteristics into dimensions, which eventually make up the taxonomy. We will repeat this process until the ending conditions are fulfilled (Nickerson et al. 2013). Then, we will design and execute the evaluation. The taxonomy is finalized if the evaluation results show that it fulfills the set ending conditions and evaluation goals. Otherwise, we return to one of the previous steps. Once the development is finished, the finalized taxonomy is reported and communicated with the consideration of the target group, which allows to make the taxonomy accessible and usable for the specific domain (Kundisch et al. 2021). In the following, we outline how we followed these steps in our taxonomy development.

Observed phenomenon, target user groups, intended purpose

In the first step, we identify the *observed phenomenon*. In our case, this concerns the existence of numerous conformance checking visualizations and the lack of a comprehensive overview and detailed insights into the types of data they present and the ways in which this data is visualized. The *target user groups* we aim to support with our taxonomy are researchers, practitioners or tool vendors who work or interact with conformance checking visualizations and need knowledge about conformance checking and its visualization. Thus, the *intended purpose* is to provide an overview of the different dimensions of the currently existing conformance checking visualizations, which helps users to gain a more detailed understanding of the visualizations.

Meta-characteristic, ending conditions and evaluation goals

Next, we defined the *meta-characteristic*, i.e., the overall objective of our taxonomy, to be the identification of the data and visualizations that existing process mining tools currently use for conformance checking results.

As *ending conditions*, we adopted the five objective and five subjective conditions from Nickerson et al. (2013). The objective ending conditions require that (1) no new dimensions or characteristics were added in the last iteration, (2) no new dimensions or characteristics were merged or split in the last iteration, (3) every dimension is unique and

not repeated, (4) every characteristic is unique and not repeated within its dimension, and (5) each dimension consists of collectively exhaustive characteristics. Nickerson et al. (2013) also suggest the ending condition that each dimension should have mutually exclusive characteristics, meaning only one characteristic per dimension is applicable when categorizing an object within the taxonomy. We excluded this condition due to the nature of visualizations and the underlying principles, e.g., visual expressiveness, which suggests the use of multiple variables. This does not completely contradict the ending condition as each combination of the characteristics and dimensions will be mutually exclusive and, therefore, unique (Szopinski et al. 2020; Oberländer et al. 2019). In addition to these five objective ending conditions, the subjective ending conditions are that the taxonomy needs to be (1) concise, (2) robust, (3) comprehensive, (4) extendable, and (5) self-explanatory (Nickerson et al. 2013).

By defining the *evaluation goals* in the beginning, a clear scope is set (Kundisch et al. 2021). In line with our overall purpose, we selected “describing” and “classifying” as our evaluation goals. Thus, the evaluation should show that with the taxonomy the conformance checking visualizations can be adequately described and classified, providing especially research with more details on the existing visualization and its components (Kundisch et al. 2021).

Iterations

After defining all requirements in detail, we developed the taxonomy in seven iterations, outlined in Fig. 3. Before the first iteration, we selected all tools supporting conformance checking from the current tool landscape (Rehse et al. 2023). In total, we were able to get access to 11 academic and commercial tools: Appian, Apromore, ARIS, Celonis, IBM, Microsoft Power Automate, mpmX analytics, ProM ‘Replay a Log on Petri Net for Conformance Analysis’, ProM ‘Replay alignment on Performance/Conformance Checking’, ProM ‘Mine with Inductive Visual Miner’, and SAP Signavio Process Intelligence. For mpmX analytics, we only had screenshots available. To allow for a comparison between the different visualizations of these tools, we used the same dataset.³ We pre-processed it and generated a BPMN process model by applying different ProM plug-ins, enabling the application of conformance checking in all tools.

In the following, we describe the individual iterations of our development process. The identified dimensions and characteristics are described in the [The final taxonomy](#) section.

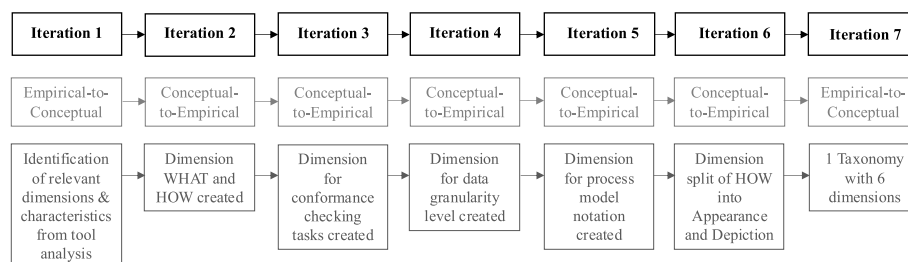


Fig. 3 Taxonomy development process

³Dataset: Road Traffic Fine Management Process

First iteration (empirical-to-conceptual)

Because academic literature on conformance checking visualizations is scarce, we could not perform the more common conceptual-to-empirical first iteration. Instead, we conducted the first iteration following an empirical-to-conceptual approach and analyzed the existing visualizations in the selected process mining tools. These visualizations⁴ had similar characteristics that could be clustered into groups, although each tool focused on different parts of conformance checking. For example, many tools used some type of process model notation, which we clustered together to a group called process models. For each of these groups, we developed fitting abstract dimensions resulting in the first version of the taxonomy that was then further specified throughout the next iterations.

Second iteration (conceptual-to-empirical)

To structure the information we gained in the first iteration appropriately, we applied the framework by Munzner (2014), shown in Fig. 2, which helps to systematically evaluate visualizations. Thus, we added the questions ‘What’ and ‘How’ as dimensions in our taxonomy. For those dimensions, fitting characteristics were derived through the examples given by Munzner (2014), which were transferred to process mining, and through the characteristics that could be identified in the different tools. For example, elements of networks were transferred to elements of process models, as they are a specific type of network used in process mining. For the ‘What’, one characteristics group we identified was everything around activities, e.g., ‘Activity Name’, as they are an important element of process models and often shown in conformance checking. For the ‘How’, identified characteristics were, for example, ‘Number’, ‘Text’, or ‘Table’.

Third iteration (conceptual-to-empirical)

Because the individual visualizations differed significantly, we divided them into high-level groups, characterizing them according to their main purpose (the ‘Why’). For the characteristics, we relied on the four conformance checking task types currently supported by process mining tools: ‘Quantify Conformance’, ‘Break Down and Compare Conformance’, ‘Localize and Show Deviation’, and ‘Explain and Diagnose Deviation’ (Rehse et al. 2023).

Fourth iteration (conceptual-to-empirical)

As the visualizations contain different levels of data, we again used a conceptual-to-empirical approach, leading to the addition of a new dimension ‘Data Granularity Level’. In particular, the insights from literature provided by Rehse et al. (2023) and others, such as De Weerd and Wynn (2022), regarding the granularity level of process mining data, were used to differentiate between the data levels used in the visualizations. This allows for a better classification. In detail, process mining data can be analyzed and visualized on log, variant, deviation, deviation category, or trace level in conformance checking (Rehse et al. 2023). We conceptualized these levels as characteristics under one dimension.

⁴Screenshots available upon request

Fifth iteration (conceptual-to-empirical)

For the task type ‘Localize and Show Deviation’, we recognized that the same visualization, a process model, was always used in the tools, but in different notations. Based on process modeling literature (Van Der Aalst 2022a), we hence added this as a dimension, with DFGs, BPMNs, Petri Nets, and chevron diagrams as characteristics to differentiate this in more detail. Chevron diagrams only show a single trace whereas the others are more expressive, but all notations create a visualization of a process. As the other tasks do not necessarily use process models, we also added the characteristic ‘No Model’.

Sixth iteration (conceptual-to-empirical)

Next, we went back to Munzner’s framework (Munzner 2014), with the goal of increasing the conciseness of the taxonomy. The framework divides the ‘How’ into two aspects (Munzner 2014): graphical elements and visual appearance. Graphical elements describe how primitive objects are depicted in a visualization and are characterized through their visual appearance. Together, they define the design space of visualizations (Munzner 2014). Following this, we split the ‘How’ dimension into two individual ones: Depiction (Marks) and Appearance (Channels). By splitting up this dimension, the taxonomy with its dimensions and characteristics increased in comprehensibility and conciseness. Additionally, a clearer distinction for the ‘How’ is now possible. For example, a ‘Symbol’ can now be described in more detail by specifying the appearance that is used, such as the ‘Shape’ or ‘Size’.

Last iteration (empirical-to-conceptual approach)

Finally, our goal was to verify the taxonomy with all its different dimensions and characteristics. Therefore, we again examined the visualizations in all tools and compared them with the developed taxonomy, confirming the completeness of the different dimensions and characteristics. Throughout this process, no adaptations were made, so the objective ending conditions were fulfilled. Regarding the subjective ending criteria, we did a further assessment, which showed that the taxonomy was concise and comprehensive as the dimensions and characteristics were kept to a minimum and were clearly defined. The taxonomy could also be extended by adding new dimensions or characteristics. As the dimensions and characteristics are labeled precisely, as simply as possible, and on the required differentiation level, the taxonomy also appeared to be self-explanatory and robust. Hence, we concluded the development process as all subjective and objective ending conditions were fulfilled from our perspective. The taxonomy at this state was published in our previous work (Häge and Rehse 2024).

Evaluation

To evaluate this first complete version of the taxonomy, we configured and performed an evaluation to assess whether the evaluation goals were met. Therefore, we evaluated the taxonomy with experts in semi-structured interviews, which ultimately led to minor adjustments to the taxonomy. Thus, we again checked the ending conditions and the achievement of the evaluation goals, which were then met based on our assessment and resulted in the final taxonomy, shown in the [The final taxonomy](#) section. The results and further details of the evaluation are outlined in the [Evaluation of the taxonomy](#) section.

Moreover, we applied the taxonomy to exemplary visualizations, which are described in the [Demonstration of the taxonomy: individual exemplary visualizations](#) section as general examples, and used it for an assessment of different tools in the [Demonstration of taxonomy: assessment across tools](#) section to identify the most common visualizations in the tools. This further validated the usefulness of the taxonomy.

Communication

After the evaluation, we now report on our final taxonomy (see [The final taxonomy](#) section), including all its dimensions and characteristics. This should make the taxonomy accessible and support a deeper understanding of existing visualizations than was previously possible.

Evaluation of the taxonomy

After developing the taxonomy according to the method described in the [Method](#) section, we evaluated it by means of expert interviews, a possible evaluation method suggested by Kundisch et al. (2021). In these interviews, we conducted a detailed analysis of the taxonomy with experts from the field of conformance checking and visual analytics. This analysis was aimed at assessing if the taxonomy fulfills the evaluation goals which we set prior to the development (see [Method](#) section): The taxonomy should enable its users to adequately describe and classify conformance checking visualizations, in order to gain a detailed overview of the visualization and its components. Further, we used the insights from the interviews to evaluate the taxonomy on specific desirable properties of taxonomies, postulated by Kundisch et al. (2021): completeness, correctness, understandability, simplicity, consistency, ease of use and value of use. In the following, we present the evaluation setup and the obtained results.

Evaluation setup

We designed the evaluation as semi-structured interviews, each consisting of three parts. In the first part, the interviewer introduced the interviewee to the topic and presented and explained the taxonomy. Next, the interviewees were asked to apply the taxonomy to classify four visualizations (outlined as exemplary visualizations in the [Demonstration of the taxonomy: individual exemplary visualizations](#) section), allowing for comparability between the participants' assessment and the one conducted by the authors. The interviewees were asked to think out loud, ask questions if anything was unclear, and mention if they disagreed with certain elements of the taxonomy. Finally, we asked the interviewee questions on the evaluation criteria to receive general feedback and identify improvement potentials. The interviews were conducted face-to-face in April 2025, two in person and the others via Microsoft Teams, with a time duration between 30 and 50 min.

Participants

The interview participants were drawn from a purposive sample (Etikan et al. 2016) of researchers and practitioners from our professional network. We conducted interviews with 8 participants, 5 researchers from the field of process mining and 3 employees from process mining tool vendors. They all had expertise in conformance checking and process mining visualizations, which was our necessary selection criterion. Table 1 provides a detailed overview of the participants.

Table 1 Participants in the evaluation interviews

ID	Job role	Professional Background	Interview duration (minutes)
P1	Professor	Researcher	40
P2	Professor	Researcher	30
P3	Doctoral Student	Researcher	39
P4	Professor	Researcher	33
P5	Doctoral Student	Researcher	35
P6	Software Developer	Employee at Tool Vendor	31
P7	Software Developer	Employee at Tool Vendor	32
P8	Product Lead	Employee at Tool Vendor	50
Average			36.25

Coding

The interviews of all participants were transcribed and analyzed. For further analysis, we used a template coding approach (Mayring 2014), which facilitated an alignment with the interview structure and a focus on predefined relevant information, such as the taxonomy and the evaluation goals. Consequently, the second part where the experts categorized the different visualization, provides a detail view of the applicability of the taxonomy. For each participant, the selected characteristics of the taxonomy for the different visualizations were encoded and can be found online in the supplementary data.⁵ Due to time constraints, P2 and P8 were not able to apply the taxonomy to all four exemplary visualizations. The last part of the interviews was then coded based on our predefined evaluation goals and desirable properties.

Evaluation results

Overall, the interviews showed that the taxonomy fulfilled the set evaluation goals. However, they also revealed some of its weaknesses regarding the taxonomy's accessibility and interpretability. In the following, we present these results in detail, including the insights regarding the evaluation goals and desirable properties. We also outline the (minor) adaptations we made to improve the taxonomy based on the participants' feedback as well as their recommendations for future work.

Insights regarding the evaluation goals

After a short explanation, all interviewees understood the structure and the elements of the taxonomy and were able to apply it. Thus, for experts with domain knowledge in conformance checking and visualization, the goal of adequately describing and classifying conformance checking visualizations was achieved. However, we also saw that different users interpret some characteristics slightly differently, also dependent on their background. As many taxonomy dimensions are not mutually exclusive, some of the participants selected more characteristics compared to others. For example, for the task type, P5 chose 'Explain & Diagnose Deviation' and 'Break Down & Compare' for Fig. 8. Other participants also considered selecting more tasks but eventually decided on one of them. Moreover, for the 'What' dimension, we noticed that the necessary background knowledge on conformance checking was essential to differentiate between the different characteristics. If clear definitions of each characteristic would be accessible to the user of the taxonomy, this dependency could be reduced.

⁵ [Appendix A: Taxonomy Categorization of all Interview Participants](#)

We also noticed that in applying the taxonomy, some interviewees focused only on those elements that were directly related to conformance checking, fading out the other ones. For example, P2 did not select symbols and shapes as they only relate to the underlying BPMN, not the conformance checking itself. This shows that the taxonomy can be applied to different avails and that it is important to define this prior to using the taxonomy, to extract only the relevant information. This also aligns with P4's feedback, who stated that they focused, especially in the 'What' dimension, on specific characteristics that were of interest to them.

Overall, all participants were able to apply the taxonomy and also stated that it was possible without any issues. When comparing the participants' classification of the exemplary four visualizations with that of the authors, only the above-described slight differences could be found, which can also be attributed to the general interpretability of certain elements within visualizations. We can conclude that the taxonomy is applicable to different conformance checking visualizations and can be used to categorize and describe them.

Insights regarding the desirable properties

To analyze the taxonomy in more detail, we also asked our experts whether it fulfilled the desirable properties of a taxonomy, postulated by Kundisch et al. (2021). Table 2 shows an overview of these properties as well as their degree of fulfillment as judged by the interviewees, supported by some exemplary quotes.

Table 2 Desirable properties, their fulfillment and exemplary participants' quotes

ID	Desirable property	Fulfilled	Quotes
DP1	Completeness	Completely	"No, I think it captures everything." (P1) "I think it's like a good summarization of what there is." (P7) "All the dimensions feel very complete to me." (P2) "I think you already have a comprehensive view." (P8)
DP2	Correctness	Completely	"I think, the domain, it's covered, nicely and comprehensively." (P5)
DP3	Understandability	Partially	"So I think it was definitely enough information to apply." (P6) "Very understandable." (P2) "A more detailed explanation that would help. I think it's just some background on conformance checking because I know the basics, but I don't know what the exact differences are between like a nonconformity or a deviation or a violation but it's all in terminology." (P3)
DP4	Simplicity	Completely	"I think it was also not that hard." (P3) "100%." (P2)
DP5	Consistency	Partially	"For this one thing that I mentioned also before with per month because this is very specific it would be better to change it to time per unit." (P6) "There are a lot of chart or graph possibilities. So whether there it might be helpful to have either that as a starting point, but there might exist also more or to have more general categories that could be the two options here." (P4)
DP6	Ease of Use	Completely	"So I found the the procedure of applying the taxonomy straightforward and the concepts were also clear." (P5)
DP7	Value of Use	Completely	"I found this to be very helpful, also to get a view for how information-rich is a visualization." (P5) "It's an helpful approach to also analyze the visualizations and also to see problems, like we discussed, based on the taxonomy or challenges of the visualizations." (P4)

Regarding the first property, *completeness*, none of participants missed any information. They thought that the taxonomy covered the domain very well, concluding that it is complete. *Correctness* was also verified as nobody disagreed with the taxonomy, its dimensions and characteristics. For *understandability*, some participants would have preferred more detailed explanations of the individual characteristics. For example, P3, who had more expertise in visualizations than in conformance checking, would have appreciated more details for some characteristics in the ‘What’ dimension to assess them correctly. P8 also mentioned that some guidance would have been helpful. We conclude that this property has room for improvement, although we note that when using the taxonomy in a real life scenario, users would have more time and could also independently collect more information on the characteristics.

Considering *simplicity*, participants stated that the taxonomy and its use were straightforward. For *consistency*, P1, P4 and P6 highlighted that some of the characteristics are on different granularity levels, so that it is only partially fulfilled. For example, P6 stated that the characteristic ‘Case Conformance Per Month’ is too detailed, in comparison to the more general description of the other characteristics, and suggested to abstract it to any possible time unit. P4 mentioned that the ‘How-Depiction’ contains information on different complexity levels, e.g., charts are more complex than a simple line.

The remaining two properties, *ease of use* and *value of use*, both relate to usability. For both, the feedback was positive across all participants. *Ease of use* was described as intuitive and clearly correlated with their assessment of simplicity. Participants also mentioned that the taxonomy with its dimensions and characteristics was clear and the steps to apply it were ‘straightforward’. Regarding *value of use*, all participants viewed the taxonomy as an important contribution and highlighted its value for different applications, such as understanding the conformance checking visualizations in more detail but also gaining a different perspective on visualizations by thinking in these dimensions. For P6 and P7, the taxonomy provided a holistic view of what the different tools currently include and how they may differ, which they found very valuable. P5 also appreciated the taxonomy’s support in identifying how rich in information the different visualizations are as well as how underlying algorithms could be visualized and on what information they should or could focus on. Also, P4 liked the taxonomy to identify problems in existing visualizations.

Adaptations to the taxonomy

Based on the participants’ feedback, we decided to make minor adjustments to the taxonomy, listed in Table 3. In that table, we specify the dimension and, if applicable, the subgroup(s) affected by the change, the affected characteristics, the change type, the new characteristic, and an explanation for the change.

Recommendations for future work

Two participants, P2 and P6, suggested to extend this work by “building a tool or system” where a user can select the input for the first three dimensions of the taxonomy and then gets possible outputs for the last three dimensions. This would allow them to gain even further insights on the currently used combinations. Currently, the taxonomy does not provide these insights, but it could indeed serve as a foundation for such an implementation of common combinations. P4 also highlighted that specific interdependencies

Table 3 Final changes to taxonomy based on evaluation results

Affected dimension: [Subgroup]	Affected characteristic(s)	Change type	New characteristic	Explanation for change
What (Data Abstraction): [(1) Conformity]	(#) of Conforming vs. Non-Conforming Cases	Deleted		Redundant as it is also covered when selecting both of these characteristics individually (suggested by P1)
What (Data Abstraction): [(1) Conformity]	Case Conformance Per Month	Adapted	Case Conformance Over Time	Adaptation to generalize it and achieve a higher consistency between the characteristics in this subgroup (suggested by P6)
What (Data Abstraction): [(7) Violation]		Newly Added	Violation Details	Addition to align with the structure of the other subgroups
What (Data Abstraction): [(8) Moves]	Model Move; Log Move; Synchronous Move	Adapted	[(8) Steps] Inserted Event; Missing Event; Correct Event	Adaptation to generalize it and decouple it from the underlying technique
What (Data Abstraction): [(9) Path]	Start/End Paths; Paths (excl. Start/End Path)	Combined	Paths	Summarization to ensure the same granularity level
How - Depiction	Bar Chart; Donut Chart	Combined	Chart (Flow/Bar/Donut/...)	Summarization to ensure the same granularity level and include all possibilities (suggested by P4)
How - Depiction	Dotted Graph; Bullet Graph	Combined	Graph (Dotted/Bullet/...)	Summarization to ensure the same granularity level and include all possibilities (suggested by P4)
How - Depiction		Newly Added	Complex, Simple and Dependent Marks as Subgroups	Addition to highlight the different complexity levels (suggested by P4)

within the taxonomy are also of interest and could be analyzed or captured in future work. An additional suggestion from P8 was to weigh the characteristics differently, as some aspects might be more relevant to conformance checking, e.g., the overall conformance rate compared to case conformance per month.

Conformance checking visualization taxonomy

We set out to develop a taxonomy that can describe and classify individual conformance checking visualizations, in order to gain an overview of the contained information and the used visualization components. After the evaluation showed that our developed taxonomy fulfills those goals, we now use this section to communicate it to the relevant target groups (Kundisch et al. 2021).

Therefore, we first report on the final taxonomy with all dimensions and characteristics in [The final taxonomy](#) section. To make the taxonomy more tangible, we then demonstrate how it can be used to describe and classify conformance checking visualizations, to provide potential future users with examples to support its practical application. During the expert interviews, different participants stated that such application examples would have helped them to apply the taxonomy. Hence, we first demonstrate how it can be applied to describe and classify individual exemplary visualizations in the [Demonstration of the taxonomy: individual exemplary visualizations](#) section. Then, we use the taxonomy for an assessment of different tools to identify commonly used

conformance checking visualizations in the [Demonstration of taxonomy: assessment across tools](#) section.

The final taxonomy

The final version of our taxonomy for conformance checking visualizations is shown in Fig. 4. It fulfills all ending conditions and evaluation goals. In this section, we report on the taxonomy, including its dimensions and characteristics, to the relevant target group, particularly researchers working with conformance checking. This makes the taxonomy accessible and demonstrates its value, as described and recommended by Kundisch et al.

Task Type	Quantify Conformance	Localize & Show Deviation	Break Down & Compare Conformance	Explain & Diagnose Deviation		
Data Granularity Level	Log	Variant	Single Trace	Deviation Category	Attribute	Deviation
Process Model Notation Type	DFG	BPMN	Petri Net	Chevron Diagram	No Model	
What (Data Abstraction)	<div style="display: flex; flex-wrap: wrap;"> <div style="width: 25%;"> <p>(1) Conformity</p> <ul style="list-style-type: none"> Conformance Rate (# of) Conforming Cases (# of) Non-conforming Cases # of Selected Cases Case Conformance Over Time </div> <div style="width: 25%;"> <p>(2) Deviation</p> <ul style="list-style-type: none"> Deviations Deviation Type Deviation Details </div> <div style="width: 25%;"> <p>(3) Variant</p> <ul style="list-style-type: none"> Variants Variant Details </div> <div style="width: 25%;"> <p>(4) Fitness</p> <ul style="list-style-type: none"> Avg. Fitness Max. Fitness Min. Fitness Fitness Per Month </div> <div style="width: 25%;"> <p>(5) Activity</p> <ul style="list-style-type: none"> Activities Activity Name Activities per Case Activity Details </div> <div style="width: 25%;"> <p>(6) Frequency</p> <ul style="list-style-type: none"> Case Frequency Path Frequency Variant Frequency Activity Frequency </div> <div style="width: 25%;"> <p>(7) Violation</p> <ul style="list-style-type: none"> Violations Violation Details Root-cause Analysis </div> <div style="width: 25%;"> <p>(8) Steps</p> <ul style="list-style-type: none"> Inserted Event Missing Event Correct Event </div> <div style="width: 25%;"> <p>(9) Path</p> <ul style="list-style-type: none"> Paths Path Details </div> <div style="width: 25%;"> <p>(10) Perspective</p> <ul style="list-style-type: none"> Resource Perspective Time Perspective Control-flow Perspective Data Perspective </div> <div style="width: 25%;"> <p>(11) Granularity Level</p> <ul style="list-style-type: none"> Adjustable Granularity Level for Paths Adjustable Granularity Level for Activities Adjustable Granularity Level for Variants </div> <div style="width: 25%;"> <p>(12) Additional</p> <ul style="list-style-type: none"> Throughput Time Case Cost Alignment Statistics </div> <div style="width: 25%;"> <p>(13)</p> <ul style="list-style-type: none"> Visualization explanation </div> </div>					
How – Depiction (Marks)	<div style="display: flex; flex-wrap: wrap;"> <div style="width: 33%;"> <p>(1) Complex marks</p> <ul style="list-style-type: none"> Chart (Flow/Bar/Donut/...) Graph (Dotted/Bullet/...) Table </div> <div style="width: 33%;"> <p>(3) Dependent marks</p> <ul style="list-style-type: none"> Legend Filter Bar </div> <div style="width: 33%;"> <p>(2) Simple marks</p> <ul style="list-style-type: none"> Number Text Percentage Symbol Line </div> </div>					
How – Appearance (Channels)	<ul style="list-style-type: none"> Color Hue Color Luminance Color Saturation Size Shape None 					

Fig. 4 Conformance checking visualization taxonomy

(2021). The taxonomy has six dimensions, with four to 41 characteristics per dimension. In the following, we describe each dimension and its characteristics in detail.

Task type

Any conformance checking visualization within the tools aims to achieve one of the four conformance checking tasks: *Quantify Conformance*, *Localize and Show Deviation*, *Break Down and Compare Conformance*, and *Explain and Diagnose Deviation* (Rehse et al. 2023). Even though the visualization will have one task in focus, it might also be able to support another task. Therefore, the characteristics are not necessarily mutually exclusive.

Data granularity level

Data is needed as input for each visualization. This data will be refined to a certain granularity level, as shown within the visualization. For conformance checking data, six granularity levels are used: *Log*, *Variant*, *Single Trace*, *Deviation*, *Deviation Category*, and *Attribute* (Carmona et al. 2022; Rehse et al. 2023). *Deviation* and *Deviation Category* are separated as one *Deviation* is a subgroup of a *Deviation Category*. As only one data granularity level can serve as the input for a visualization, this dimension is mutually exclusive.

Process model notation type

Many, but not all, conformance checking visualizations incorporate process models. Due to their dominance and importance across the different tools, this dimension includes their use and a detailed differentiation based on their notation. If a visualization does not contain a process model, it falls under the characteristic *No Model*. Otherwise, the right notation will be selected, which is either a *DFG*, *BPMN*, *Petri Net*, or *Chevron Diagram*. Thus, this dimension is also mutually exclusive.

What (data abstraction)

Every visualization includes some type of information. This dimension describes what information is shown within the visualization. As one visualization can depict multiple pieces of information, selecting multiple characteristics is possible. Thus, the characteristics in this dimension are also not mutually exclusive. Due to the wide range of information depicted across tools, this dimension includes many characteristics with different level of detail. Some rather focus on technical information, such as the fitness characteristics, whereas others consider more general aspects, such as deviation, which only offers on a high-level view on whether there is a deviation in the process or not. To simplify this, the characteristics are clustered into several groups:

- (1) *Conformity information* provides general insights on the conformity of the process, such as the *Conformance Rate* and the *Number of Conforming or Non-Conforming Cases*.
- (2) *Deviation information* provides insights on the deviations, including *Deviations*, their *Types*, and more *Details*.
- (3) *Variant information* shows the affected or selected *Variants*, and might provide further *Details*.

- (4) *Fitness information*, including *Average*, *Maximum*, *Minimum*, or *Per Month*, provides details on how well the process model aligns with the event log or the selected filtered log.
- (5) *Activity information*, including their *Names* and more *Details*, shows further details on activities in the visualization and of relevance to conformance checking.
- (6) *Frequency information*, either for the *Case*, *Path*, *Variant* or *Activity* level, provides us with the amount of affected data from the overall dataset.
- (7) *Violation information* shows *Violations*, and more *Details*. Sometimes a *Root-Cause Analysis* is also offered with details on potential causes for the occurring violations.
- (8) *Steps information* highlights *Inserted*, *Missing*, or *Correct Events* for a specific trace. *Inserted Events* occur only in the trace and not in the model, whereas *Missing Events* are necessary in the model but do not occur in the trace. *Correct Events* are the ones that are allowed in the model and occur as well in the trace.
- (9) *Path information* provides insights on *Paths* and more *Details*.
- (10) *Perspective information* differentiates between *Control-Flow*, *Time*, *Resource*, and *Data*. The tools sometimes also provide the option to switch between them.
- (11) *Granularity level information*, adjustable for *Paths*, *Activities*, or *Variants*, provides further options to filter the information by selecting specific groups or single components.
- (12) *Additional information*, such as *Throughput Time*, *Case Cost*, and *Alignment Statistics*, provides further details.
- (13) *Visualization explanation* provides detailed descriptions on the visualization and on its individual components.

How dimensions

The How Dimension is divided into two sub-dimensions, allowing for a better structure and leading to a higher comprehension. However, they are interconnected, as one depiction can be supported by a specific appearance.

How – depiction (marks) This sub-dimension of ‘How’ shows what graphical elements are used for the visualization. For conformance checking visualizations, 10 different characteristics can be applied. We divided them into three subgroups to highlight the different complexity levels and the dependence of some of the characteristics.

- (1) *Complex marks* are *Tables*, *Charts*, e.g., bar or donut charts, or *Graphs*, such as dotted or bullet graphs.
- (2) *Simple marks* include *Number*, *Text*, *Percentage*, *Symbol*, or *Line*. Complex marks can be made out of them but simple marks can also exist by itself.
- (3) *Dependent marks* are a *Filter Bar* or *Legend*. These graphical elements only occur in combination with another graphical element, as they play a supportive role.

As these characteristics can be dependent and multiple of these can be selected at once, they are also not mutually exclusive.

How – appearance (channels) This sub-dimension supports the previous one and emphasizes the used depiction. Characteristics of this dimension are visual channels used for conformance checking visualizations, including *Color Hue*, *Color Luminance*,

Color Saturation, Size, and Shape. However, none of these possible visual channels have to be used, leading to the additional characteristic *None*. These characteristics are also not mutually exclusive.

Demonstration of the taxonomy: individual exemplary visualizations

For the first demonstration of the taxonomy, we selected different individual exemplary visualizations, each fulfilling a different conformance checking task type, to showcase how it can be used to describe and classify a variety of known conformance checking visualizations (Kerracher and Kennedy 2017). For the first exemplary visualization, shown in Fig. 5, we include the whole taxonomy, highlighting the selected options in blue and also showing the non-selected options. Later, we only include the selected options due to redundancy and simplicity.

Quantify conformance

The first exemplary visualization is shown in Fig. 5, together with its classification in the taxonomy. The *Task Type* is 'Quantify Conformance'. Concerning the *Data Granularity Level*, the provided information considers the whole 'Log'. For the *Process Model Notation Type* 'No Model' is selected, as the shown visualization does not include one.

To identify what information is provided in the visualizations, we turn to the dimension *What (Data Abstraction)*. As this dimension is not mutually exclusive, multiple characteristics can be selected. Concerning the first subgroup (1) *Conformity*, the visualization shows the conforming cases in percentage, which is the same as the 'Conformance Rate'. Furthermore, the 'Number of Conforming and Non-Conforming Cases' is provided and, consequently, selected in the taxonomy. For (2) *Deviation*, we select 'Deviations' as well as 'Deviation Type'. Deviations include the identified violations as well as the allowlisted violations, which are violations that have previously been marked as allowed by the user. However, both deviate from the to-be process, which is why they constitute two different types of deviations: negative deviations, which show unwanted behavior and are therefore called violations, and accepted or even potentially positive deviations, which show behavior that is tolerated or might even be beneficial in certain situations. Furthermore, we can gain information on the 'Violations' in the visualization, which are part of the subgroup (7) *Violation*. No further information is provided in the visualization.

To understand *How* the information is visualized, we analyzed the *Depiction*. Three characteristics are part of the visualization, which all refer to simple marks. First, 'Numbers' or 'Percentage' present the information characteristics. 'Text' is used to state what type of information is shown and provides the necessary supporting information. Lastly, for *Appearance* only different 'Color Hue' is used, in particular blue (conforming), red (non-conforming) and black for supporting information.

Through this classification of the visualization with the given taxonomy, we obtain an overview of the different visual elements and information. Moreover, we see what information is not contained, which could potentially be included or provided with the help of other existing visualizations.

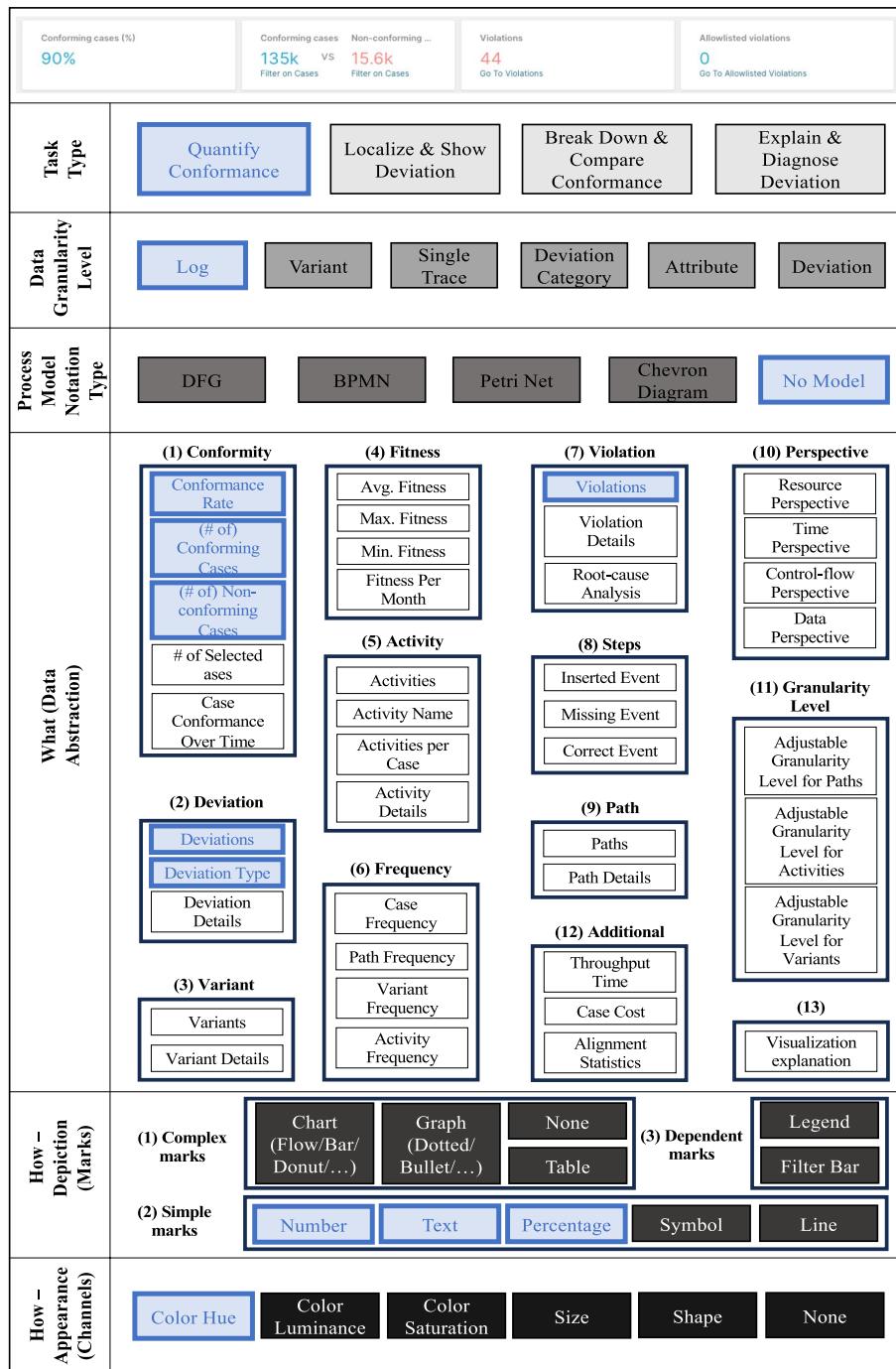


Fig. 5 Application to exemplary visualization of quantify conformance (screenshot of own dataset almost identical to Celonis Inc. (2024))

Localize & show deviation

The next example, shown in Fig. 6, considers the *Task Type* ‘Localize & Show Deviation’. As this task follows a different goal, also a completely different visualization is used compared to the first exemplary visualization. The selected visualization is a ‘BPMN’ *Process Model* and highlights the different ‘Variants’ of the process flow on the *Data Granularity Level*. This allows to identify whether the selected variant includes one or multiple deviations and, if existent, where the deviations are located.

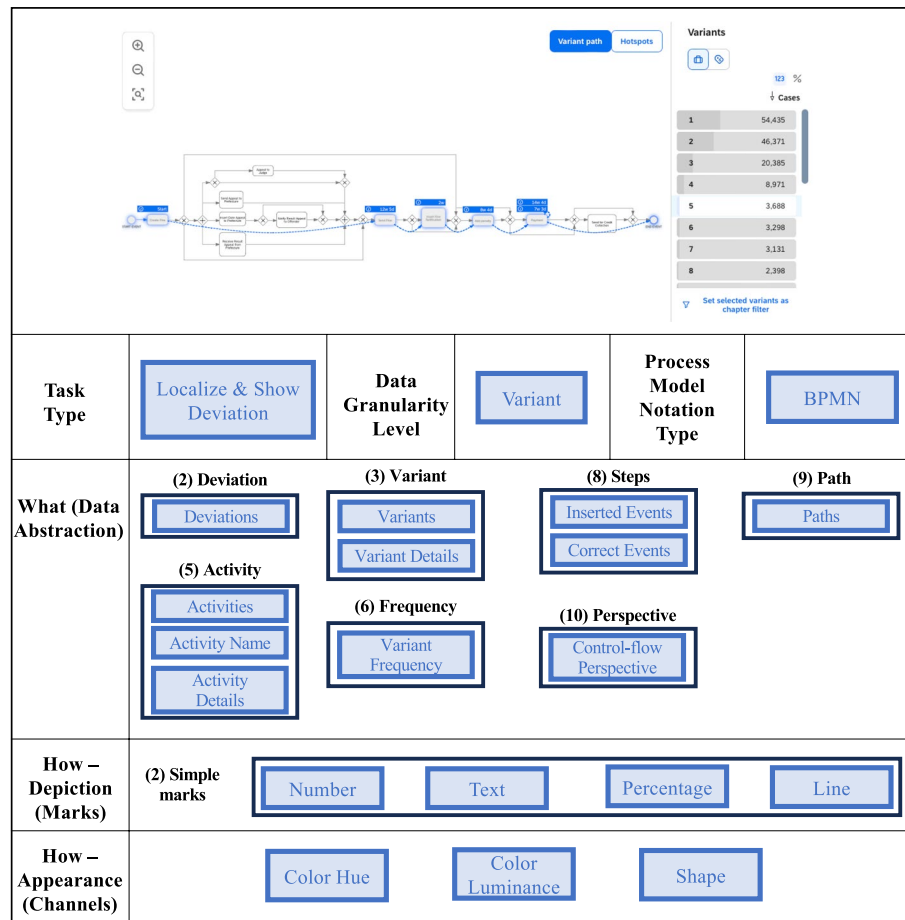


Fig. 6 Application to exemplary visualization of localize & show deviation (screenshot of own dataset almost identical to SAP Se (2025))

To fulfill this task, the visualizations includes specific information, which we characterize according to the *What (Data Abstraction)* dimension. As part of the subgroup (2) *Deviation*, ‘Deviations’ are shown in the model for the selected ‘Variant’. It is difficult to detect but the activity ‘Payment’ can be repeated in the trace (indicated by a loop), which constitutes a deviation as it is not allowed in the underlying to-be model. Additionally, for (3) *Variant*, the visualization includes ‘Variant Details’, e.g., the number of affected cases. Concerning the (5) *Activities*, the BPMN shows all possible ‘Activities’ and the variant’s ‘Activities’ with their ‘Activity Names’. Furthermore, we have ‘Activity Details’, as for the activities that are part of the chosen variant, the activity duration is shown above the activity. On the right side of the visualization, we can identify the (6) *Frequency* for each ‘Variant’, showing how many cases are part of it. Within the model, the different (8) *Steps* are shown. ‘Inserted Events’ can be identified, in this case the event ‘Payment’, which occurs multiple times. ‘Correct Events’ need to be mapped individually by the user between the activities of the BPMN model in the background and the blue highlighted activities in this visualization. If both align, a ‘Correct Event’ exists. Also, (9) *Paths* are shown in the BPMN. The information in the visualization considers the ‘Control-Flow’ (10) *Perspective*.

Next, we identified *How* the information is visualized. For the *Depiction*, the BPMN model includes ‘Numbers’ to provide the time duration or the variant frequency, ‘Text’

for the activity names, ‘Symbols’ for the different gateways, and ‘Lines’ to show the paths. All are simple marks. For *Appearance*, the channels ‘Color Hue’, ‘Color Luminance’ and ‘Shape’ are used. Only blue is used for ‘Color Hue’ to show the selected ‘Variant’ and the time duration. The outline of the activities that are part of the variant are illuminated. The notation BPMN consists of multiple elements, which are represented through different ‘Shapes’, e.g., gateways are always diamond-shaped. Also, the lines have different shapes, such as straight or curved.

With the selection of the relevant characteristics, we can structure the information and grasp all relevant information. Furthermore, this example shows how much detailed information can be included in a visualization and highlights how this can be emphasized through different depictions and appearances of the information.

Break down & compare conformance

For the *Task Type* ‘Break Down & Compare Conformance’, the aim is to get more details on the conformance of the process. In the visualization in Fig. 7, more detailed information is given on the overall conformance per month.

The visualization shows the information on the *Data Granularity Level* of the entire ‘Log’. It does not break it down based on the data granularity level but by time and provides information on the ‘Case Conformance Over Time’, in this case per month, on the *What (Data Abstraction)*. To illustrate this information, a ‘Chart’, specifically a bar chart (complex mark) with a ‘Legend’ (dependent mark), is used as the *Depiction*. This highlights the dependency between these marks, as a ‘Legend’ is only used to explain another mark, in this case a ‘Chart’. We also do not see a specific *Process Model Notation Type*, which leads to the selection of ‘No Model’. For *Appearance*, this example uses only different ‘Color Hue’, in particular blue for the conforming and red for the non-conforming cases, which is stated in the ‘Legend’. Black is used for supporting information.

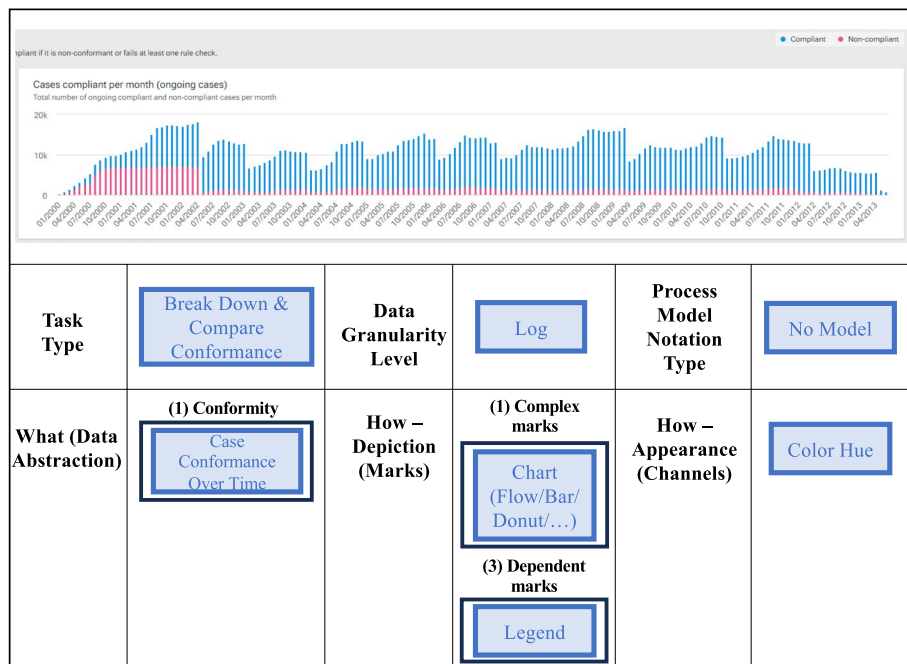


Fig. 7 Application to exemplary visualization of break down & compare conformance (screenshot of own dataset almost identical to Software GmbH (2024))

This example shows that a conformance checking visualization can also be very focused on providing information on one aspect, in this case the ‘Case Conformance Over Time’, and this have a rather low information density. The taxonomy and the selection also help to realize this.

Explain & diagnose deviation

Last, we applied the taxonomy to a visualization for the *Task Type* ‘Explain & Diagnose Deviation’, which is shown in Fig. 8. It aims to provide further insights on the deviation, including effects of the deviation on the whole process.

The visualization provides information on the *Data Granularity Level* of the ‘Deviation’, as for each individual ‘Deviation’ explanations or further diagnoses are stated. We have again ‘No Model’ for the dimension *Process Model Notation Type*. Concerning the dimension *What (Data Abstraction)*, we have multiple characteristics. As on the left the ‘Number of Selected Cases’ is shown, in this case of non-conforming cases, we selected this in the subgroup (1) *Conformity*. The list provides insights and ‘Violation Details’ on the ‘Violations’, which are specific ‘Deviations’. Thus, we selected this for the subgroup (7) *Violation* as well as ‘Deviations’ and ‘Deviation Type’ for the subgroup (2) *Deviation*. Furthermore, we selected ‘Deviation Details’ as this is provided in the visualization e.g., what ‘Activities’ are affected by the deviation. Based on this, for (5) *Activity*, ‘Activities’ and ‘Activity Name’ was chosen. Another characteristic we selected was ‘Case Frequency’ in the subgroup (6) *Frequency* because the number and percentage of affected cases is provided on the left. Due to the description of the deviation in form of what

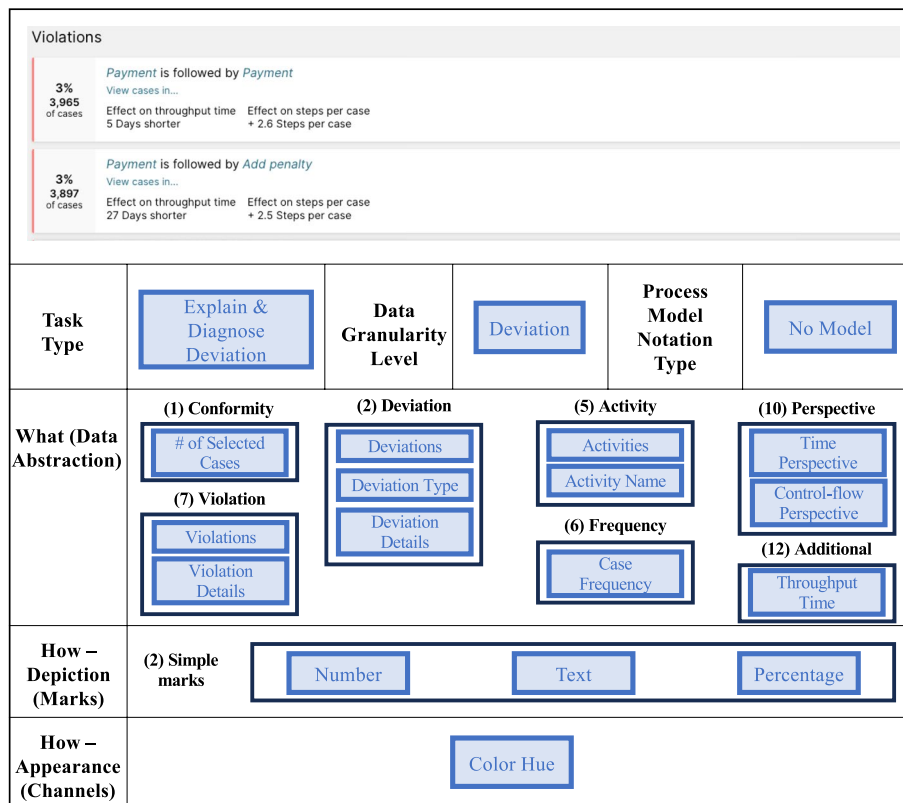


Fig. 8 Application to exemplary visualization of explain & diagnose deviation (screenshot of own dataset almost identical to Celonis Inc. (2024))

activity follows another and the detailed information on the effect on steps per case, for (10) *Perspective* we chose ‘Control-Flow Perspective’. In addition, the ‘Time Perspective’ is considered by stating the effect on ‘Throughput Time’, which is part of the subgroup (12) *Additional*.

Considering *How* the information is depicted, we selected for the *Depiction* ‘Number’, ‘Text’ and ‘Percentage’, all being simple marks. For the *Appearance*, only ‘Color Hue’ is used to highlight information. In this visualization, blue is used for the affected activities and probably clickable and red is only used to highlight the deviation as a violation on the left.

The categorization of this visualization into the taxonomy shows that the taxonomy is also applicable to more text-based visualizations. These visualizations are still processed visually by the users and specific visual components are used to emphasize or highlight important aspects. Furthermore, when looking at the overview in the end, there are characteristics for the *What (Data Abstraction)* that partially overlapped e.g., time perspective and throughput time. However, a clear distinction into these separate groups is necessary as the existence of one characteristics does not directly lead to the existence of the other in a visualization.

Demonstration of taxonomy: assessment across tools

In this second demonstration, we use the taxonomy to describe and classify different tools, with the goal of identifying, first, the most commonly used conformance checking visualizations and, second, the process model notation types used. This two-step analysis provides different examples of how a taxonomy can be used to gain insights on a higher level. In this demonstration, we do not consider all dimensions of the taxonomy, but focus on the most relevant ones for a high-level assessment: *Task Type*, *Data Granularity Level*, *Process Model Notation Type*. This allowed us to achieve an appropriate level of abstraction and focus on the (most) relevant dimensions for an assessment across different tools.

Starting with the eleven tools listed in the [Method](#) section, we used the taxonomy to analyze what individual visualizations they provide for conformance checking. Then, we classified and described each visualization with the help of the taxonomy. Afterwards, we clustered them into groups that fulfilled the same combinations of characteristics for the different dimensions. Since our analysis follows a two-step approach, we first considered only the first two dimensions of the taxonomy, *Task Type* and *Data Granularity Level*, to identify the most common combinations. In the second step, we included the third dimension *Process Model Notation Type* to assess whether process models are used, and if so, what notation types are applied. The results are outlined in the following.

Occurrences of the task type and data granularity level combinations

First, we categorized the existing visualizations from the different tools into the combination of *Task Type* and *Data Granularity Level*. We identified ten groups, shown in Fig. 9. For ‘Quantify Conformance’, only visualizations on the log level existed. ‘Localize & Show Deviation’ was considered in visualizations on log, variant, deviation category and single trace level. Visualizations for ‘Break Down & Compare Conformance’ were provided on log, variant and attribute level. When tools ‘Explain & Diagnose Deviation’, they only used visualizations on log and deviation level.

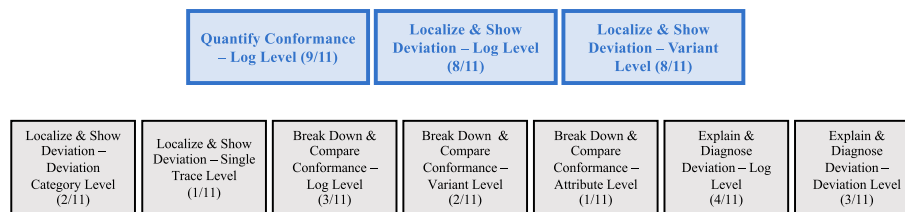


Fig. 9 Frequency of conformance checking visualizations considering first two dimensions and highlighting the most common ones

Moreover, we considered how many out of the eleven tools provided visualizations for these combinations, also shown in Fig. 9. This overview of currently used conformance checking visualizations shows that currently three tasks are predominantly visualized across most tools: ‘Quantify Conformance’ on the log level as well as ‘Localize and Show Deviation’ on the log and variant level. The first combination ‘Quantify Conformance – Log Level’ is offered by nine out of eleven tools. Eight tools offer visualizations for the other two combinations. The other combinations were only presented in one to four tools, e.g., ‘Break Down & Compare Conformance’ was only considered by two to three tools.

When analyzing this overview in more detail, it is noticeable that there is a strong connection between the *Task Type* and the role of this task in the overall analysis of process conformance. ‘Quantify Conformance’ is often the first task in conformance checking as it aims to gain an overview of the conformance information for the selected process. ‘Localize and Show Deviation’ on the log and variant level are also often used early when conducting conformance checking. In contrast, the other two task types are more specific and provide more detailed information. Therefore, it seems that most tools currently only cover the starting points of conformance checking. Moreover, for the data granularity level, we found that conformance checking tasks are always considered on the log level and often on the variant level. Therefore, these data granularity levels are currently predominantly visualized in the different tools, probably correlating with the used intensity of conformance checking. It can be assumed that most often, a top-down approach is followed, looking first at the log level data and then increasing the granularity level.

Occurrence of the different process model notations

For the second part, we also considered the third dimension of our taxonomy *Process Model Notation Type* to identify the process model notation types used. We had a closer look at the most popular combinations (‘Quantify Conformance’ on the log level as well as ‘Localize and Show Deviation’ on the log and variant level) and assessed whether process models were used and, if so, which notations. As ‘Quantify Conformance’ uses many different visualizations but no process models, this task was excluded from the further analysis (Fig. 10).

When analyzing ‘Localize and Show Deviation’ on the log level, three different process model notations could be identified: DFG, BPMN and Petri Net. Overall, four out of the eight tools offered DFGs as a process model notation and two tools used BPMNs. Petri Nets also occurred in two tools, but both were ProM visualizers, which produced a similar visualization of the Petri Net. For ‘Localize and Show Deviation’ on variant level, also DFGs and BPMNs were identified as process model notations, both occurring three



Fig. 10 Frequency of conformance checking visualizations considering also process model notation type and highlighting the most common ones

times in the tools. In comparison to the previous combination, chevron diagrams were used instead of Petri Nets, also generated by the identical ProM visualizers, resulting in identical chevron diagram visualizations.

Considering the frequency of the different process model notations, also across the tasks, we can recognize that DFGs and BPMNs are the predominately used process model notations. Between the two, DFGs are implemented slightly more often, but it seems that tools choose only one of them per task/granularity combination. The discrepancy between the frequency of process model notations used by tools is probably also related to the number of academic and research tools. Only research tools use Petri Nets and chevron diagrams, which leads to a lower frequency because there are also fewer research tools. In contrast, DFGs are only used in commercial tools, where there are several tool vendors.

Discussion

The developed and evaluated taxonomy for conformance checking visualizations generates an overview of the used conformance checking visualizations and its components, clusters the contained information systematically, and provides a foundation for future empirical research in order to reduce the current research gap of visual analytics in process mining. In the following, the contribution to research and practice, its limitations, and paths for future research are outlined.

Contribution to research

With the taxonomy, researchers can now describe and assess the visualizations they use or develop. This provides detailed insights on the visualizations and their components that are difficult to acquire without the taxonomy. Moreover, the taxonomy highlights how diverse and complex conformance checking visualizations are. It is one of the first artifacts that combines the foundations of visual analytics and process mining and provides detailed insights on the depicted conformance checking visualizations and visualization components across the different tools. Thus, we can reach a better understanding of what visualizations are currently used, what information they contain, and how they are depicted. This paper connects the research fields of visual analytics and process mining, contributing to a stronger exchange between them. The developed taxonomy can be used by researchers to deepen their understanding of visualizations and their relevance, and helps them identify information gaps that have not been identified so far.

In our second exemplary application ([Demonstration of taxonomy: assessment across tools](#) section), which assessed different tools, we identified a large range of visualizations for different task types and on different data granularity levels. However, only three of

them are common across the majority of the tools, showing that there is limited standardization. Additionally, the fact that we decided to exclude the last three dimensions of the taxonomy due to too many differentiations in the details shows the difficulty of a general assessment of the individual visualizations in the different tools, which offer numerous different types of visualizations fulfilling different tasks. This lack of defined standards across the tools might hinder the adoption of conformance checking. Thus, these newly gained insights might help research to further close this gap between user expectations and tool offerings by defining more clearly what conformance checking entails and what information the tools should provide.

Contribution to practice

For process mining users, the taxonomy provides an understanding of what conformance checking visualizations are made of and what information they cover. With the developed dimensions, they can gain deeper insights into the components of the visualizations and can increase their awareness of the tasks that the visualization should solve. Moreover, the taxonomy may help users assess whether existing visualizations include the information they seek when starting with conformance checking. This could support a more informed tool selection, potentially allowing for a better alignment between users' expectations and the information provided by visualizations across different tools. Furthermore, tool vendors can use the taxonomy to categorize their conformance checking visualizations and identify through the taxonomy what information or conformance checking task is not covered yet by the existing visualizations in their tool. Based on this, they could implement new visualizations or adjust existing ones within their tool to cover other task types or information. Furthermore, tool vendors can clearly state through this newly gained knowledge what conformance checking visualizations and information they provide to help the user during the tool selection process. Not only will this help the user, but it can also help tool vendors identify their competitive advantage.

The application examples of the taxonomy provide practitioners insights on how to apply the taxonomy themselves and on the conformance checking visualization focus across all tools. Almost all tools offer visualizations for 'Quantify Conformance' on the log level as well as 'Localize and Show Deviation' on the log and variant level. This can help during the tool selection process because if these combinations satisfy the practitioners' needs, they can select almost any tool. If the practitioners have specific requirements, they should select the tools carefully. Therefore, this overview can support the tool selection process, urging them to make more sophisticated decisions based on their newly gained knowledge. Furthermore, for 'Localize and Show Deviation' on the log and variant level, the more detailed analysis also identified the most common process model notations used. Practitioners can also analyze which of them fits their needs and preferences best. For tool vendors, the results help evaluate if they fulfill the standard and what additional information they provide or which ones they want to add to improve their competitive advantage and reach new customers.

Limitations

Our work is subject to multiple limitations. First, we focused on procedural conformance checking and excluded declarative and rule-based conformance checking visualizations, which are not used at all by industry tools. Also, object-centric conformance

checking visualizations are not included, as this research field just emerged during our tool analysis and none of the analyzed tools included fitting visualizations at this point in time. Moreover, the results are based on data acquired only during a specific time period. Therefore, all findings and information, especially from the tools, may have been subject to modifications.

Second, the information that underlies the taxonomy was gathered from a selection of tools. As we did not have access to all possible tools, important insights from these tools might be overlooked. Although the tool selection was done thoroughly, due to the fast-changing market of the tool providers, a tool might have been missed. However, with the covered tools in this paper, the majority of the market for conformance checking solutions was considered.

Third, the taxonomy only includes information on currently existing conformance checking visualizations. This means that it entails information derived from existing literature and the existing visualizations in the tools. Consequently, newly developed visualizations are not covered by this taxonomy and might contain information that is not included so far. This also implies that the taxonomy only covers what is currently available within the tools and does not cover what the user might need. We decided for this approach to achieve completeness of the current tools. Thus, we included all the information we found in the different tools but nothing more. This also secured consistency within the taxonomy and between the different dimensions.

Fourth, the taxonomy development method we used still cannot fully rule out a certain degree of bias. Through the evaluation by experts we attempted to increase the objectiveness and validity of our results. Nevertheless, a larger interview sample would lead to a higher generalizability of our results, especially because our evaluation only included researchers and employees from tool vendors. Moreover, we only showed the applicability for four different exemplary visualizations leading to a limited empirical validation. However, the selected exemplary visualizations cover significantly different visualizations and, therefore, show the applicability to a variety of conformance checking visualizations.

Further, the characteristics, especially of the *What (Data Abstraction)* dimension, have interdependencies and the selection of relevant ones inevitably involves interpretative judgment. Additionally, the *How - Depiction (Marks)* dimension includes not only interdependencies but also hierarchical dependencies, e.g., numbers are part of a chart, but can also be used by itself. Moreover, there are dependent marks, such as a legend, which are only used in combination with a complex or simple mark to provide the necessary explanation. These are just examples that show that not all dimensions of our taxonomy are mutually exclusive and a direct hierarchical structure is also not possible but that there are dependencies within the dimension, which contradicts the approach by Kundisch et al. (2021). However, such interdependencies and the resulting interpretability are inherent to visualizations and cannot be entirely eliminated. Thus, we excluded this ending condition, which allowed us to cover the domain in focus.

Last, relevant literature, visualization elements, or information within the tools could have been missed and might not be included in the taxonomy, even though we conducted several iterations and aimed to include all relevant information.

Future research

The taxonomy provides the foundation for multiple paths of future empirical research. First, the taxonomy's operationalization should be further validated empirically using more exemplary visualizations. Moreover, the evaluation of the taxonomy could be expanded with additional interviews, including also users of visualizations to consider their perspective as well. However, it would be difficult for them to assess certain desirable properties, such as completeness, due to their limited access to and knowledge of the different visualizations. Another path for future research would be to create a tool that shows the different inter-dependencies between the dimension and characteristics. This could be especially useful for researchers or software developers who try to create a visualization for a new underlying algorithm. With a pre-selection, they could then see what information is normally or should be depicted and what options exist to visualize it.

While we aimed to reduce the research gap of visual analytics in process mining, our findings also uncovered valuable questions and opportunities for future research. First, visual analytics emphasizes focusing on the user and including them in the analysis process. However, so far, there are no user studies for visual analytics in process mining, neither for conformance checking nor for other sub-disciplines. This provides an opportunity for empirical research to include the user when considering process mining visualizations and conduct research on it. Such research needs to check if the existing visualizations fulfill the users' needs for the different tasks, especially for conformance checking. The evaluation of the taxonomy revealed first insights on the user interaction with conformance checking visualizations, e.g., some of the existing visualizations were not directly understood by the users or needed additional interpretation about information that was not visualized. This highlights the need to look further into the visualizations, especially from the user perspective, and use empirical research to assess the visualizations and the user interaction. Therefore, researchers could conduct experiments where users evaluate visualizations to test the user's comprehension of the visualized process. This could be measured based on different metrics, such as response quality or time. It could also be achieved through interviews, similar to the ones we used to evaluate our taxonomy. Based on the knowledge gained from the empirical research, conformance checking visualizations could be improved and standardized. Moreover, new visualizations could be created and tested. This could also include the adaptation or new development of the underlying algorithms, precisely addressing the users' needs.

Conclusion

Organizations use conformance checking to identify deviations within their business processes. To effectively communicate these conformance checking results to their users, visualizations are essential. Researchers have acknowledged the need for improved visualizations (Gschwandtner 2017; Rehse et al. 2023; Klinkmüller et al. 2019; Mendling et al. 2021). However, current visualizations have mainly been developed by the tool providers and, thus, depict different information with different representations. As of now, it is very difficult to pinpoint these differences and understand what components the visualizations are made of and what information they contain.

To address this issue, we developed a taxonomy that provides a detailed overview of the existing breadth of characteristics of conformance checking visualizations. The

taxonomy consists of six dimensions and various characteristics. We used the results from eight expert interviews considering multiple desirable properties, such as ease or value of use, to evaluate the taxonomy from an external perspective. The final taxonomy presents, in a structured manner, what information is currently depicted for conformance checking and how this is visualized across the different tools. It now allows to describe and assess visualizations and its components in more detail. Its applicability was demonstrated through four individual exemplary visualizations, where we categorized different visualizations with the help of the taxonomy. Moreover, we used the taxonomy to assess different tools to identify the most common conformance checking visualizations and process model notation types used, highlighting the focus of the tools currently.

We discuss our results and provide potential future research avenues necessary to improve conformance checking visualizations. These include empirical research that aims to understand the cognitive perspective and the users' needs in more detail to derive from this visualization requirements that (new) visualizations should fulfill.

Overall, this paper with its taxonomy provides a foundation for future empirical research on conformance checking visualizations and, hence, is an important contribution, offering an initial understanding to be elaborated on. Following the path of research and extending it with empirical research on process mining visualizations, would have an significant impact on the adoption of process mining and would further advance the research of connecting visual analytics and process mining.

Authors' contributions

We specify the authors contributions by describing the respective contribution roles according to the CRediT Taxonomy: M.-C.H.: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Validation, Visualization, Writing - original draft, Writing - review & editing; J.-R.R.: Conceptualization, Funding Acquisition, Methodology, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing.

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Data availability

Supplementary materials are available through the provided links in the footnotes or upon request.

Declarations

Ethics approval and consent to participate

Participation in our interviews was entirely voluntary. Participants could withdraw at any time without providing a reason. Informed consent was obtained at the beginning of each session, including permission to record the interview and use the data for research purposes. All identifying information was anonymized during data collection.

Consent for publication

The intent of publishing the findings was made transparent by mentioning the connection to the research project at the beginning of the interview. 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.

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References

- Brinkman R, Mannhardt F, Mennens RJ et al (2024) Interpretability challenges for discovered process models: A user study and prototype solution. In: EuroVis. Eurographics, Eindhoven
- Carmona J, van Dongen B, Weidlich M (2022) Conformance checking: foundations, milestones and challenges. Process Mining Handbook. Springer, Cham, pp 155–190
- Celonis Inc. (2024) Analysis - conformance checker. <https://docs.celonis.com/en/analysis---conformance-checker.html>. Accessed 31 Mar 2025

- Cui W (2019) Visual analytics: a comprehensive overview. *IEEE Access* 7:81555–81573
- Dani VS, Freitas CMDs, Thom LH (2019) Ten years of visualization of business process models: a systematic literature review. *CSI* 66:103347
- De Weerd J, Wynn MT (2022) Foundations of process event data. In: *Process Mining Handbook*. Springer, Cham, pp 193–211
- Di Ciccio C, Miksch S, Soffer P et al (2024) Human in the (process) mines (dagstuhl seminar 23271). *Dagstuhl Rep* 13(7):1–33
- Dumas M, Rosa LM, Mendling J (2018) *Fundamentals of business process management*. Springer, Cham
- Emamjome F, Andrews R, Hofstede AH (2019) A case study lens on process mining in practice. In: *OTM*. Springer, Cham, pp 127–145
- Etikan I, Musa SA, Alkassim RS et al (2016) Comparison of convenience sampling and purposive sampling. *AJTAS* 5(1):1–4
- FAU (2021) Process mining survey. https://www.processmining-software.com/wp-content/uploads/2021/FAU2021_Process_Mining_Survey.pdf. Accessed 31 Mar 2025
- Gall M, Rinderle-Ma S (2021) Evaluating compliance state visualizations for multiple process models and instances. In: *BPM Forum*. Springer, Cham, pp 126–142
- García-Bañuelos L, Van Beest NR, Dumas M et al (2017) Complete and interpretable conformance checking of business processes. *TSE* 44(3):262–290
- Grohs M, van der Aa H, Rehse JR (2024) Beyond log and model moves in conformance checking: discovering process-level deviation patterns. In: *BPM*. Springer, Cham, pp 381–399
- Gschwandtner T (2017) Visual analytics meets process mining: challenges and opportunities. In: *SIMPDA*. Springer, Cham, pp 142–54
- Häge MC, Rehse JR (2024) A taxonomy for conformance checking visualizations. In: *ICPM Workshops*. Springer, Cham, pp 507–519
- Hoogmoed A, Vidgof M, Djurica D et al (2024) Visual representation of resource analysis insights for process mining. In: *BPMDs*. Springer, Cham, pp 117–128
- Kaouni A, Theodoropoulou G, Bousdekis A et al (2021) Visual analytics in process mining for supporting business process improvement. In: *NIDS*. IOS Press, Amsterdam, pp 166–175
- Keim D, Andrienko G, Fekete JD et al (2008) *Visual analytics: Definition, process, and challenges*. In: *Information Visualization: Human-Centered Issues and Perspectives*. Springer, Cham
- Kerracher N, Kennedy J (2017) Constructing and evaluating visualisation task classifications: process and considerations. In: *CGF*, vol 36. Wiley Online Library, Hoboken, pp 47–59
- Klessascheck F, Knoche T, Pufahl L (2024) Designing and evaluating a structural model for conformance checking visualizations. In: *EuroVis. Eurographics, Eindhoven*
- Klinkmüller C, Müller R, Weber I (2019) Mining process mining practices: an exploratory characterization of information needs in process analytics. In: *BPM*. Springer, Cham, pp 322–337
- Knoblich S, Mendling J, Jambor H (2024) Review of visual encodings in common process mining tools. In: *EuroVis. Eurographics, Eindhoven*
- Kriglstein S, Pohl M, Rinderle-Ma S et al (2016) *Visual Analytics in Process Mining: Classification of Process Mining Techniques*. In: *EuroVis. Eurographics, Eindhoven*, pp 43–47
- Kundisch D, Muntermann J, Oberländer AM et al (2021) An update for taxonomy designers: methodological guidance from information systems research. *BISSE* 64, 421–439
- Mayring P (2014) *Qualitative content analysis: theoretical foundation, basic procedures and software solution*. Klagenfurt. <https://nbn-resolving.org/urn:nbn:de:0168-ssoar-395173>
- Mendling J, Djurica D, Malinova M (2021) Cognitive effectiveness of representations for process mining. In: *BPM*. Springer, Cham, pp 17–22
- Munzner T (2014) *Visualization analysis and design*. CRC Press, Boca Raton
- Nickerson RC, Varshney U, Muntermann J (2013) A method for taxonomy development and its application in information systems. *EJIS* 22(3):336–359
- Oberländer AM, Lösser B, Rau D (2019) Taxonomy research in information systems: A systematic assessment. In: *ECIS*. AIS, Atlanta
- Rehse JR, Pufahl L, Grohs M et al (2023) Process mining meets visual analytics: the case of conformance checking. In: *HICSS*. ScholarSpace, Honolulu, pp 5452–5461
- Reinkemeyer L (2020) *Process mining in action: Principles, Use Cases and Outlook*. Springer, Cham
- SAP SE (2025) Process conformance. <https://docs.celonis.com/en/analysis---conformance-checker.html>. Accessed 31 Mar 2025
- Sirgmetts M, Milani F, Nolte A et al (2018) Designing process diagrams—a framework for making design choices when visualizing process mining outputs. In: *OTM*. Springer, Cham, pp 463–480
- Software GmbH (2024) Compliance check with aris process mining. <https://docs.aris.com/10.0.27.0/ymp-compliance-check-with-h-apm-guide/en/Compliance-Check-with-ARIS-Process-Mining.pdf>. Accessed 31 Mar 2025
- Szopinski D, Schoormann T, Kundisch D (2020) Criteria as a prelude for guiding taxonomy evaluation. In: *HICSS*. ScholarSpace, Honolulu
- Thomas J, Cook K (2005) *Illuminating the Path*. IEEE CSP, Piscataway
- Van Der Aalst W (2022) Foundations of process discovery. *Process Mining Handbook*. Springer, Cham, pp 37–75
- Van Der Aalst W (2022) Process mining: a 360 degree overview. In: *Process Mining Handbook*. Springer, Cham, pp 3–34
- Van Der Aalst W, de Leoni M, Hofstede A (2011) Process mining and visual analytics: breathing life into business process models. In: *BPM*. Springer, Cham, pp 699–730
- Van Der Linden S, de Fouw E, van den Elzen S et al (2023) A survey of visualization techniques for comparing event sequences. *CG* 115:522–542
- Weske M (2019) *Business Process Management - Concepts, Languages, Architectures*. Springer, Cham
- Yeshchenko A, Mendling J (2024) A survey of approaches for event sequence analysis and visualization. *Inf Syst* 120:102283

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