Exploring the Role of Visualization in Process Mining: A Systematic Literature Review

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Abstract. Visualization is an integral part of process mining. It can be used to visualize the process model or show information about process bottlenecks. This review gives an overview of the current usage of visualization for process mining. Additionally, we derive open research fields based on the current literature. We conduct a systematic literature review to reach this overview, including 33 papers. In addition, we define a taxonomy to categorize research within the field of visualization for process mining. Our results show a significant interest in process discovery and process monitoring, but fewer papers for process reengineering. The most used visualization type is the Directly Follows Graph. However, this is mainly used for control flow and not for other process mining perspectives. Instead, other types of visualization are used to cover the remaining perspectives. For future work, we propose stronger cooperation between the field of process mining and information visualization to combine the benefits of both areas and see open research in upcoming approaches like object-centric process mining.

Keywords: Process Mining · Visualization techniques · Literature Review

1 Introduction

Visualization is an integral part of process mining. It can be used, for example, to visualize the process model or show information about process bottlenecks. Nevertheless, it is often neglected in practice. At the same time, more efforts are made to bring information visualization and process mining closer together. Process mining bridges the gap between machine learning and data mining on one hand and process modeling and analysis on the other. Its primary objective is to uncover, monitor, and enhance real-world processes by extracting valuable insights from event logs obtained from systems. An event log is a list of activities recorded in a system during their execution. Each element is typically assigned to a case and has an activity name, a timestamp, and optional further properties. An elemental part of process mining is visualizing the mined models or generated

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results [1,2]. Information visualization is defined as a technology using human visual abilities to extract meanings from visual information. Combining color, size, position, or orientation of objects changes in visualizations can lead to faster and better analytic results and improve usability for process analysts [9,14]. To give an overview of visualization in process mining, we conduct a systematic literature review answer the following research questions:

– RQ1: What is the current state of research in visualizing process mining results?
– RQ2: Which visualization types are most commonly used in process mining research for which process mining type and perspective?
– RQ3: What are open research areas in visualizing process mining results?

To answer these questions, we define a taxonomy to categorize the review results. Based on the taxonomy, we create a concept matrix to assign each paper to its relevant categories. In addition, we identify open research questions and areas for future study based on the existing literature and the gaps in current research. To the best of our knowledge, this is the first work that provides a survey in the area of process mining and visualization with a combined view of process mining types and perspectives. In previous works like Sirgmets et al. [36] from 2018, an overview of two areas is given: 1) process mining techniques using visualization and 2) visualization types used for process mining. In contrast to our approach, the results are shown separately and not in a combined taxonomy, as well as without process mining perspectives. Another survey focusing on combining the research field information visualization and process mining is presented by Yeshchenko and Mendling [43]. While this work gives a comprehensive overview of the visualization of event sequence data, no mapping to process mining types and perspectives is provided. Additionally, this research focuses on six significant journals of information visualization and process mining, which could exclude relevant visualizations published at conferences.

This paper is separated into seven Sections. After the introduction, we briefly overview some relevant process mining concepts and define terms used in this review. In the third Section, we introduce our visualization taxonomy, which will be used to classify papers and create our concept matrix. Section 4 presents the literature review design, followed by the findings in Sect. 5. Finally, our discussion follows before the conclusion Section, and an outlook for future research is given.

2 Background

In this Section, we want to give an overview of important process mining topics and define related terms. The three main process mining types are process discovery, conformance checking and process reengineering. In van der Aalst [4], it was extended by a fourth type, operational support. In the context of this work, we define operational support as equivalent to process monitoring and will hereafter use only the term process monitoring. Process discovery is a technique to identify processes based on an event log without the need to provide information in advance. As a result, a process model, for example a petri net, is generated. During conformance checking, a comparison is made between the existing process model and an event log of the same process. This makes it possible to check whether the log follows the expected process and vice versa. The third type, process reengineering, extends or improves an existing process model based on the event log. As a result, an improved model is generated. Process monitoring aims to display recommendations or warnings about a process, preferably in real-time, to improve work with the process. Unlike process reengineering, the model is not changed [2,4].

Besides the process mining types, a process can be viewed from different perspectives. Four perspectives are defined in the process mining manifesto [1]. First is the control flow, often seen as the basis of the other perspectives [4]. This perspective visualizes the order in which the activities are executed. The second is the organizational perspective, including the information on which actors are part of the process and how they are connected. The time perspective covers all aspects of the timing and frequency of events. Lastly, the case perspective, sometimes called data perspective, includes the properties of objects used in the process [1]. Another form of process mining is the comparison of two process models, also known as comparative process mining. The goal is to recognize the difference between two processes. This is used, for example, in combination with process cubes that distinguish processes by various domains, e.g., regions. The processes from the different areas can then be compared to discover regional differences within a company [29].

3 Visualization Taxonomy

In this Section we introduce our taxonomy. The aim of this taxonomy is to categorize the works more easily according to their characteristics and to be able to find and compare similar works. An overview of the taxonomy is presented in Fig. 1. The taxonomy is based on the process mining types and perspectives presented in Sect. 2.

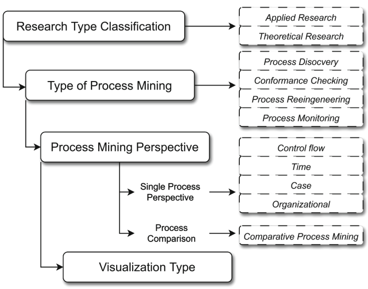


Fig. 1. Taxonomy for process mining visualizations

At the first level, a distinction is made between the research type of applied research and theoretical research. The applied research category includes all papers applying process mining and visualization to address business or social challenges or develop a tool for an existing visualization concept. In contrast, the theoretical research category includes all papers that develop new concepts of how visualization can be used for process mining or apply existing visualization for a theoretical process mining topic. In this work, we will focus on theoretical research, but we also want to emphasize the relevance of applied research in process mining and visualization. Following the research type classification, studies are further categorized by process mining type. The taxonomy includes all four process mining types as presented in Sect. 2. At the third level, a distinction is made between the process mining perspectives and a further differentiation between single process perspectives and process comparison. All results in the area of process comparison are assigned to the comparative process mining perspective. For the single process perspective, the categories from the process mining manifesto [1] are adopted in this categorization. In the context of this paper, the assessment of whether a perspective is included in a work is not based on which perspectives are addressed within a paper but exclusively on whether a perspective is taken into account in the visualization. The last level considers the visualization type. In addition to widely used business process visualizations such as Directly Follows Graph (DFG), petri nets or BPMN, new visualization approaches are also relevant. There is no active exclusion of visualization types, but newly developed or individual visualizations are assigned to a custom category instead of being added as their own category.

4 Literature Review Design

This Section outlines the methodological approach used for this literature review. As a guideline, this literature review follows a concept-centric approach presented by Webster and Watson [39]. Figure 2 presents an overview of our methodological process, which consists of four main steps. The process begins with identifying potentially relevant articles from Scopus, Web of Science, IEEE Xplore, ACM Digital Library and AIS eLibrary. The search string[1] was intentionally formulated without too many constraints to ensure that a broad overview of visualization topics in process mining is covered. We considered all papers published between January 2014 and December 2024. In total, 519 papers were found, of which 189 were identified as potentially relevant after removing the duplicates and checking the abstracts. The abstracts were screened by two reviewers independently of each other. Based on the identified papers, a full-text screening was conducted to categorize the results and assess their relevance to the review. The Concept Matrix, derived from Webster and Watson [39], is based on the taxonomy presented in Sect. 3. As additional exclusion criteria, all entries that are not in English or are not conference or journal articles have been withdrawn.

[1] The syntax between all databases is slightly different, but the search terms were chosen identically for all databases.

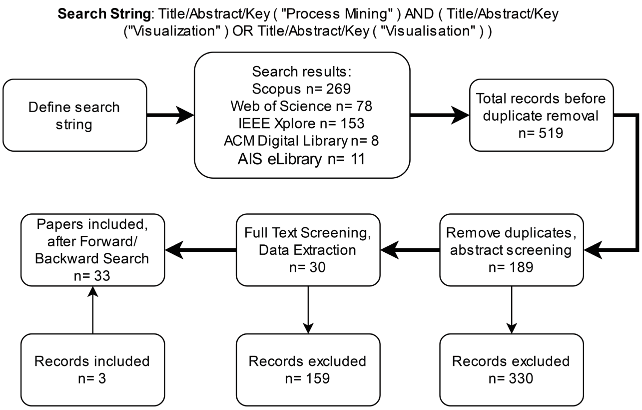


Fig. 2. Literature review process

For concepts that have been published in several formats (for example, journal, conference or workshop) by the same author, we have only included the journal version as long as no relevant content is lost. After the full-text screening, 30 papers remain relevant. A forward and backward search was conducted to find relevant articles that were not part of the search string. In this step, three papers were included. In total, 33 papers are included in this literature review.

5 Findings

In the following Section, the findings of our literature review are presented. The concept matrix is shown in Table 1. The table is structured such that the rows represent different visualization types, whereas the columns illustrate the process mining types, single-process perspectives, and comparative process mining. The papers in the table are assigned to the respective concepts based on their visualization type. It is important to mention that for papers with several visualization types, an assignment to a perspective only occurs if the specific type also visualizes it. In the following sub-sections, relevant developments in the area of process mining visualization based on the concept matrix are discussed.

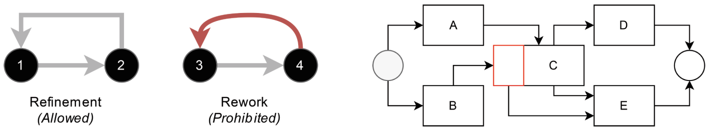
5.1 Directly-Follows Graph

The most commonly used visualization is DFG. This is plausible, as most process mining tools (e.g., ProM, Disco, Celonis) support this visualization. Surprisingly, petri nets and BPMN, which are also widely used process modeling notations, are minor or not represented. Despite the widespread use of DFG, its use in most papers is limited to the control flow [12,18,19,23,25,27,37,40,42]. Although DFG's are widely used, their adoption can be viewed critically. For example, van

Table 1. Concept Matrix: Theoretical Research

Visualization type	Type of Process Mining				Process Mining perspective				Comparative Process Mining	sum
	Process Discovery	Conformance Checking	Process Reeingeneering	Process Monitoring	Control flow	Time perspective	Case perspective	Organizational perspective		
DFG	[12, 23, 33, 37, 40]	[25, 42]	[19]	[18, 21, 26, 27]	∀	[21, 26]	[21, 33]	-	[25]	12
BPMN	-	-	-	-	-	-		-	-	0
Petri Net	[34]	-	-	[41]	∀	[41]	-	-	-	2
Gantt chart	[35]	[24, 31]	-	[24]	[24, 35]	[24, 31, 35]	[24]	-	-	3
Drift Map/Chart	-	[42]	-	-	-	[42]	-	-	-	1
Bar chart	-	-	[19]	[16, 18]	-	[18, 19]	[18, 19]	[16]	-	3
Dot plot	-	-	-	[18]	-	[18]	[18]	-	-	1
Sankey	-	-	-	[38]	[38]	-	-	-	-	1
Heatmap	-	-	-	[16]	[16]	[16]	-	[16]	-	1
Declare	[8]	-	-	-	[8]	-	-	-	-	1
Chevron diagram	[35]	-	-	-	[35]	[35]	-	-	-	1
Graph	-	[7, 15]	-	-	[7]	[7]	-	-	[7, 15]	2
Custom	[17, 20, 22, 32, 35]	[11, 28, 32]	-	[6, 13, 21]	$\forall x(x \neq$ [27])	[6, 13, 21, 28, 35]	[6, 21, 28]	[17]	[11, 28, 32]	10
sum	**12**	**9**	**1**	**10**	**29**	**14**	**7**	**2**	**6**	

der Aalst [5] discusses the disadvantages of DFG's. The main problem is that the simplification used to present DFG results could be misleading and result in false analytical results. To overcome these limitations, the papers Pfahlsberger et al. [27] and Wetzel et al. [40] present DFG extensions. Pfahlsberger et al. [27] proposes eight different path semantics and possible path combinations to add information about the process behavior. Two examples are shown in Fig. 3a. The arrow with a solid gray line and an angular course connecting nodes 2 to 1 represents an allowed backjump path. On the opposite, the arrow with a solid red line (nodes 4 to 3) and a curvilinear course shows a prohibited backjump path. The allowed and prohibited path combinations, in this example refinement and rework, can be used for further analysis of process flows. For example, prohibited process flows can be analyzed from time, cost, and quality perspectives to identify negative process impacts. In contrast, Wetzel et al. [40] focuses on so-called history dependencies. Figure 3b shows an example of the visualization. A history dependency based on this example means that activity D can't be executed if activity A is missing. Therefore, the trace $\langle B, C, D\rangle$ is not valid. A standard DFG can't visualize this dependency and can lead to false analytical results. Layout format optimization is another research direction to improve graph-based representations like DFG. In Mennens et al. [23] and Sonke et al. [37], two approaches are presented. Mennens et al. [23] presents an algorithm to generate a stable layout for the same process. While current industry-leading process mining tools could generate different visualizations for the same process, the presented algorithm transforms visualizations into a similar or same layout. The authors argue that this supports the analyst's mental model and generates better visualizations in total, based on the results from a user study. While the visualization in Mennens et al. [23] follows a top-down approach, Sonke et al. [37] present alternative layouts besides top-down approaches. The nodes are arranged both vertically and horizontally in order to make better use of the aspect ratio.



(a) Path semantics [27] (b) History dependencies [40]

Fig. 3. DFG extensions

While the presented approaches show promising approaches for reducing DFG shortcomings, they are currently in an early stage, and no production-ready implementation in widely used process mining tools exists.

5.2 Time and Case Perspective

Besides the control flow, the time perspective is the most researched perspective, with 14 distinct papers, followed by the case perspective with seven papers. The significant coverage of the time perspective is plausible since timestamps are a central component of the event log [1]. This distinguishes the time perspective from the organizational and case perspective, whose information must first be added to the log or process model. We found two focus areas regarding time perspective: 1) new approaches to visualize time-specific information, 2) adding time information for conformance checking. For the first focus area, Denisov et al. [13] present performance spectra to visualize all activities and cases individually over time, Schuster et al. [35] introduce chevron diagrams and a combination of points and vertical bars to visualize partially ordered event data, and Nagy and Werner-Stark [24] visualize processes as a gantt chart like diagram to improve time-related analysis. The second focus expands traditional conformance-checking methods, focusing on control-flow changes, to integrate time-related drift detection. For such changes, two visulisations based on gantt charts and drift maps/charts are proposed [31,42]. Both visualizations support process analysts in identifying temporal changes in their processes. As seen in all approaches, time is a challenging but also a relevant topic in adopting process mining to real world use cases. While new visualization approaches [13,35,42] show promising results, they require further research to enhance user-friendliness and practical tool support.

In contrast to the time perspective, we can't find focus areas for the case perspective. Especially new visualization approaches for the case perspective are missing. Instead, the case perspective is often used as a filter or attribute [18], visualized by established visualization types or text-based information beside the process diagram [6,19,21,24]. We only identified the work from Pini et al. [28] presenting an approach that integrates case information directly into process visualization. Unfortunately, due to missing data, the evaluation of a real-world dataset was not possible. While using established visualizations is not negative by default; the stronger integration of the case perspective into the visualization

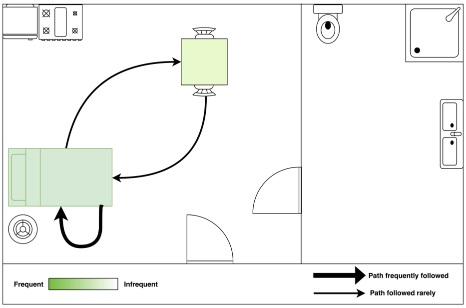


Fig. 4. Geo-aware visualization: Tiramisù approach [6]

could bring advantages. There could be interrelations to the emergence of object-centered process mining, which integrates process objects into the process model.

5.3 Geo-Aware Visualization

Standard process mining visualizations do not provide geographic context. While the first approaches for geo-awareness were presented, for example, by de Leoni et al. [21] in 2014, new approaches to extend this concept arose in 2024. Alman et al. [6], which extends previous process map approaches with additional dimensions, and Corea and Delfmann [12] present a new 3D geo-aware approach based on DFG.

The Tiramisù framework from Alman et al. [6] defines three layers. Firstly, the backdrop serves as the background for the visualization and provides a common context, represented by the room with furniture in Fig. 4. Secondly, the process representation shows the process flow via nodes and edges, shown by arrows and furniture in Fig. 4. The geo-awareness is represented by the nodes with fixed positions in the backdrop so that context-relevant information can be displayed. Finally, the Dimensions Layer augments the backdrop or provides additional information for the end user, for example, by coloring the furniture based on activity frequency. There is no limit to how many Dimension Layers are provided, but it should be possible to activate these dynamically to maintain clarity. The 3D-based geo-aware approach by Corea and Delfmann [12] uses a DFG combined with a 3D world as the basis. For example, the process is linked to a virtual hospital, whereby the process is displayed geo-aware in the hospital rooms. Both approaches open the possibility of creating visualizations optimized for a business domain and, therefore, increasing the value of the visualization. The main problem with both approaches is that a significant amount of domain knowledge is required to design suitable visualizations. Additionally, a high technical effort is needed to create an appropriate 3D environment based on the process map. As a future research field, it may be interesting to see how the generated 3D environments can be displayed using virtual or augmented reality.

5.4 Comparative Process Mining

Besides the main process mining types and perspectives, we also focus on comparative process mining. Although most of the work dates from 2015/2016, the topic is highly relevant from the authors' point of view because processes need to be adapted more and more dynamically, and visualizations of the differences can be highly relevant. In the identified papers, there is one focus on control-flow comparison [11,15,25,28,32] and another focus on time comparison [7,28]. In Gall et al. [15], a combination of color and symbolism is used to visualize the difference between two processes, showing the control flow of both processes together. This is similar to Cordes and Vogelgesang [11] using color and line patterning and Saito [32] using a 3D city metaphor. In contrast, Pini et al. [28] define a leading process variant as the basis and visualize if an activity is executed earlier or later in the compared variants, without showing the exact difference. While previous approaches are evaluated on small event logs, Neubauer et al. [25] focus on comparing complex processes after trace clustering. The analysis of complex event logs is a relevant research field, which we will discuss in Sect. 6. As for the control flow, there are approaches to compare time information in one single diagram [7,28] and multiple separated diagrams [28]. Bolt et al. [7] present an annotated transition system that uses colorization to indicate, for each activity, in which process a metric is statistically significantly higher. Currently, two metrics are supported: occurrence and elapsed time. In Pini et al. [28], both options are presented, whereas the single model visualization does not indicate whether the value is higher or lower but merely shows that the metrics differ. While multiple works were published in 2015/2016 we found limited research in the following years. This is surprising because multiple questions like comparing multiple process variants (more than three), enhancing process attribute comparisons, and comparing complex processes remain without further investigation.

5.5 Under-Researched Areas

The currently most under-researched areas are process reengineering (1 paper), conformance checking (excluding process comparison, 3 papers) and organizational perspective (2 papers). For process reengineering [19] and the organizational perspective [16,17] first approaches exist. While for the organizational perspective, first implementations based on ProM and custom development exist, there are no developed prototypes for process reengineering. In Kubrak et al. [19] the focus is on developing wireframe mock-ups to guide the development of usable tools. While this is an important step, developing usable process reengineering visualizations is still an open question. The third underresearched area is conformance checking, although nine works are assigned to the category. Without comparative process mining, only three papers remain for conformance checking [24,31,42]. Two papers [31,42] focus on identifying temporal changes, and Nagy and Werner-Stark [24] is the only identified work also visualizing control flow changes. The conformance checking results align with previous work from Rehse et al. [30].

Table 2. Future research areas

Future research areas
Investigate visualizations for process reengineering, conformance checking and case perspective
Adopt current or investigate new visualizations for object-centric process mining
Develop a framework to better integrate user evaluations into process mining visualization development processes
Development of a maturity model to quantify how effectively a perspective is covered in a visualization
Develop guidelines on how to choose the right visualization type for a specific process mining use case

5.6 Tool Usage

We also look at the question with which tools the found approaches are implemented. 10 papers used ProM[2]. The second most used approach, with 8 papers, is individual development for visualization. Individual development is defined as using a programming language with its associated frameworks (e.g., Python and Matplotlib) to visualize results. Three papers combine a custom development with the usage of ProM or PM4Py. PM4Py[3] is the third most used tool (4 papers). The remaining papers do not implement a visualization (5 papers), don't name the tool used (2 papers), or use other tools like Cortado or Noreja (1–2 papers each). For all papers, a trend toward open-source and easy-to-extend systems is visible.

6 Discussion

This Section presents the key findings of our research and discusses their implications for future studies. To answer the research questions outlined in Sect. 1, we create a taxonomy for classifying process mining and visualization papers and present a concept matrix mapping the results to these categories. The results indicate a strong interest in combining visualization and process mining. The most underresearched process mining type is currently process reengineering. We could not find a paper explaining why this is the case. A possible explanation could be that process reengineering partially relies on process discovery and conformance checking, and current research focuses on these types first. Another reason could be that research focuses on process monitoring, where the analytic results can also be used for process reengineering. Nevertheless, we believe focusing on specific process reengineering visualizations would be helpful. Regarding the perspectives, we identified control flow as the most researched area. This is

[2] https://promtools.org/.
[3] https://github.com/pm4py/pm4py-core.

plausible because the control flow is seen as the basis of the other perspectives [4]. Regarding the remaining three perspectives, we see increasing interest in the time perspective. Another important finding is that proposed visualization approaches are predominantly evaluated using small process models. Although first approaches [25] explore methods for visualizing complex processes or their abstractions, there is limited support for visualization techniques specifically designed for large and complex process models.

To answer the second research question, we mapped the process mining types and perspectives to the visualization types used. The most used visualization type through all researched categories is DFG. The focus on DFG or node-based visualization aligns with the previous work from Sirgmets et al. [36]. The visualization focus on DFG remains for research as well as most process mining tools, despite the remarks about their disadvantages [5]. Besides DFG, we found multiple works defining new visualization approaches. Classic visualization techniques such as bar charts, heatmaps, and graphs are also used. These mainly show information about the time and case perspective and are used beside a control flow visualization. Only in a few cases, such as chevron diagrams or gantt charts, the control flow is combined with another perspective in a single diagram. No explanation was found for the low usage of BPMN and petri nets. One possibility is that the existing focus on DFG in research and industry has promoted further research in this direction. Another reason could be that the comparatively easier representation as DFGs was considered adequate for most current process mining requirements.

The further integration of process mining and information visualization is an important aspect and is part of the third research question about current challenges. As suggested by Yeshchenko and Mendling [43] and Pini et al. [28], we also want to emphasize the need for stronger cooperation between these two fields. From deeper cooperation, all process mining types and perspectives could benefit. Our results show that the main research focus lies on case-centric process mining and only limited results for new approaches like object-centric process mining [3]. As a relatively new process mining approach, visualization is in its infancy. The increased complexity resulting from adding objects also increases the requirements for suitable visualizations. Adopting approaches from the information visualization domain could be advantageous here. Besides other, an essential aspect of information visualization is evaluating the proposed approach in a realistic testing environment [10]. 17 of all reviewed papers do not specify a user evaluation. The better integration of evaluations into the development of process mining visualizations is a relevant field of research for the future. To summarize the results from RQ3, an overview of open research directions is shown in Table 2.

While this study offers valuable insights into the synergy of process mining and visualization, it is crucial to recognize limitations that should be considered when interpreting the findings. The first limitation relates to our search string. Although our search string is very openly formulated, it is possible that we did not capture papers that used synonyms for visualization. The second limitation is the focus on scientific publications, excluding the features of commercial/open-source software tools. It cannot be guaranteed that functions identified as missing in this paper are present in existing software solutions. The last limitation refers to considering the different process mining levels (case, variant, process). For this review, we don't make any such differentiation but look only at the different perspectives presented.

7 Conclusion

Our research has two primary research contributions. First, we developed a taxonomy to classify papers in the field of visualization and process mining. This makes it easier to categorize literature and identify gaps and developments in different research areas. It can also be used in future reviews to track the development of selected fields. Secondly, we conduct a literature review to give an overview of the current research state of process mining and visualization. This review provides insights into under-researched areas and an overview of the used visualizations in process mining. Based on the results, we reveal open research areas for future researchers. Besides further research from a technical standpoint, quantifying the coverage of a process mining perspective would be a future area of improvement for our taxonomy. For example, the time perspective assignment currently does not capture how good the visualizations of, for example, bottlenecks are. Our next step is to investigate ways to combine information visualization and process mining more effectively to address the open gaps discussed in this review.

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