Emerging Narratives of AI-Enabled Process Mining: A Topic Modeling Analysis of Practitioner Discourse*

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Abstract

Artificial Intelligence (AI) is increasingly embedded in technologies to analyze, improve, and automate business processes. Yet, despite growing interest in AI-enabled process mining, limited research has examined how these developments are framed within professional communities. We investigate how AI-enabled process mining is articulated in practitioner-oriented discussions. We apply BERTopic topic modeling to analyze a dataset of 343 LinkedIn posts, including associated comments and pulse articles. The analysis reveals 22 topics grouped into seven recurring themes, including AI automation and agents, customer value and service improvement, domain-specific transformation, human-AI collaboration, innovation and business value, process intelligence, and system architecture. By uncovering how AI-enabled process mining is framed in these discussions, this study contributes to Business Process Management (BPM) research. By mapping these topics and higher-level themes onto the process mining lifecycle and BPM capability domains, this study provides a structured perspective on how AI-enabled process mining is currently understood in practice and highlights directions for future research.

Keywords

Process Mining, BPM, adoption, Artificial Intelligence, Agentic AI, Topic Modeling, BERTopic

1. Introduction

Process mining has emerged as a prominent approach for analyzing and improving business processes based on event data extracted from information systems and allows organizations to discover and enhance business processes [1, 2]. Within the broader field of business process management (BPM), process mining has become a key technique for enabling data-driven process analysis and supporting organizational process improvement initiatives [3–5]. As organizations increasingly rely on digital infrastructures and data-driven decision-making, process mining is gaining importance as an analytical capability, supporting operational transparency and continuous process improvement [6, 7]. Recent advances in AI have begun to extend the analytical capabilities of process mining and highlight how AI-enabled techniques (such as predictive monitoring, intelligent automation, and advanced analytics) can enhance process mining by enabling more adaptive and anticipatory forms of process management [8–10]. These developments have increased interest in AI-enabled process mining, where emerging AI technologies (such as generative AI and intelligent agents) are integrated with traditional process mining techniques to support more advanced forms of process analysis and operational improvement. Recent advances in agentic AI highlight autonomous, goal-directed agents operating within constrained process-aware frameworks [11]. At the same time, discussions on AI-enabled process mining among LinkedIn users engaging with process mining and AI-related topics (hereafter referred to as practitioners) are increasingly visible across professional and industry contexts. These discussions frequently emphasize emerging use cases, expectations, and narratives concerning the transformative potential of AI for process mining and organizational process improvement. However, despite the increasing visibility of these discussions, limited research has systematically examined how practitioners conceptualize the role of AI in process mining, and which topics and themes dominate these emerging narratives. To

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address this gap, we analyze practitioner discourse on AI-enabled process mining using topic modeling techniques applied to publicly available practitioner content. By examining these discussions, this study aims to identify the dominant themes through which AI and process mining are framed in practice. Specifically, the study addresses the following research question:

RQ: *How is AI-enabled process mining framed in practitioner discourse?*

We review literature on AI-enabled process mining in section 2, and describe the methodology in section 3. We then provide and discuss the results in section 4 and 5, and conclude in Section 6.

2. Theoretical Background

Process mining research conceptualizes process analysis as a sequence of analytical activities in which event data are transformed into insights about organizational processes [1, 2, 6]. This analytical workflow is commonly described through the process mining lifecycle, which structures how event data are extracted, analyzed, and translated into process improvement [2, 6]. Within this lifecycle, analytical techniques (such as process discovery, conformance checking, and enhancement) allow organizations to reconstruct process behavior from event logs and identify opportunities for operational improvement [1, 4]. Conceptualizing process mining through lifecycle stages highlights that process mining represents an integrated analytical workflow rather than a single technique, and enables organizations to systematically analyze process execution using event data [5]. Beyond analytical techniques themselves, prior research emphasizes that the successful implementation of process mining initiatives depends on a broader set of organizational capabilities. Process mining adoption typically requires technological infrastructures for extracting and integrating event data from multiple information systems, governance mechanisms (that coordinate analytical initiatives across organizational units), and organizational competencies that enable stakeholders to interpret and apply analytical insights [3, 19]. A broader view is consistent with BPM research, which emphasizes that process-related initiatives rely on multiple organizational elements such as strategic alignment, governance, methods, information technology, people, and culture [7].

To capture this broader perspective, [7] propose a BPM capability framework that identifies several capability domains required to implement and sustain process mining initiatives in organizations, including strategic alignment, governance, methods and information technology, people and culture. Viewing process mining through capability domains highlights that the value of process mining technologies depends not only on analytical methods but also on the alignment of technological resources, organizational structures, and human expertise supporting data-driven process improvement. Interpreting developments in AI-enabled process mining through these capability domains therefore provides a broader perspective on how emerging analytical technologies may influence the organizational conditions under which process mining initiatives are implemented. Information systems research suggests that digital technologies are not only technical tools but also organizational resources that enable value creation and strategic outcomes [13]. It emphasizes that the impact of information technologies depends on the organizational capabilities and purposes they support rather than on technological features alone. From this perspective, digital technologies are often deployed to achieve broader organizational goals such as coordination, value creation, and transformation [14]. This view provides a useful lens for interpreting how AI-enabled process mining is framed in practitioner discourse, where emerging technologies may be associated not only with analytical techniques but also with broader organizational purposes.

3. Methodological Approach

The methodology consisted of three main steps. In step one, the empirical analysis was collected from LinkedIn posts (including associated comments and pulse articles) in 2025-2026, using the query #processmining AND (#AI OR #GenAI). LinkedIn has increasingly been used as a relevant source for examining professional expectations, competencies, and practitioner-oriented process mining discourse [12,19]. The dataset consisted of publicly available LinkedIn posts authored by a diverse set of users, including professionals sharing opinions, experiences, and informational content related to AI in the context of process mining. We retrieved 638 posts through two extraction rounds and removed duplicates based on 70% similarity, resulting in 430 records. By manually screening for relevance, we retained 364 records, and 343 after excluding non-English content. Each textual component (post, comment, pulse article) was then treated as a separate entry for analysis, resulting in a final corpus of 514 textual records representing practitioner discussions on AI-enabled process mining.

In step two , we performed a structured preprocessing pipeline commonly applied in text mining research [15] to standardize textual representations and reduce noise in the dataset. This included lowercasing, tokenization, removing url, html, punctuations, numbers, special characters and English stop words. Literature on text mining suggested that, beyond standard stop words, domain-specific terms could dominate topic representations while offering limited discriminative value across documents [16]. Accordingly, we removed domain-specific stop words (such as process, business, enterprise, intelligence, automation, mining, AI, platform) to improve semantic differentiation between records.

In step three, we applied BERTopic, suited for short textual corpora [16], to identify topics in the corpus and generate document embeddings using sentence-BERT for robust semantic representations. Subsequently, we reduced the embedding dimensionality using Uniform Manifold Approximation and Projection (UMAP) to preserve semantic structure while improving cluster separability. We then applied HDBSCAN, a density-based clustering algorithm suited for heterogeneous textual corpora, which allowed documents that did not belong to coherent clusters to remain unassigned and thereby helped handle noisy social-media content [18]. BERTopic then generated topic representations using class-based TF-IDF (c-TF-IDF), which identified representative keywords for each cluster by emphasizing terms that appeared frequently within a cluster but less frequently across the corpus [17]. To improve topic coherence and interpretability, we tuned several parameters iteratively. We controlled cluster granularity through HDBSCAN parameters (min_cluster_size=10 and min_samples=3), balancing topic stability with sensitivity to heterogeneous texts. We varied the UMAP parameter n_neighbors to explore the trade-off between local and global document structure [19], and specified random_state=42 to ensure reproducibility and vectorization stage to use 1-3 gram representations.

Although BERTopic automatically extracted topics, meaningful interpretation still required a qualitative review. Therefore, we conducted a manual analysis of the model output following common practices in topic modeling research [15, 19, 20]. We inspected each topic using its representative keywords and associated documents. We removed topics that primarily captured noise or lacked semantic coherence, and reviewed the remaining topics to identify conceptual similarities and overlaps. Consequently, we identified 22 topics out of the initial 32 topics as meaningful for further analysis. The interpretation of topics followed an established qualitative approach, where model outputs were iteratively examined and labeled based on their semantic coherence. For improving interpretability and discussion, we grouped related topics into broader themes that reflected recurring patterns in the practitioner discourse.

4. Findings

The topic modeling analysis of the LinkedIn corpus provided insights into how AI-enabled process mining is framed in practitioner discourse, thereby addressing the research question. The findings are structured along the key dimensions summarized in Table 1, demonstrating the 22 identified topics grouped into seven broad themes. This included (1) AI automation & agents, (2) process analytics & intelligence, (3) process design & system architecture, (4) human-AI collaboration & teamwork, (5) customer value & service improvement, (6) innovation, strategy & business value, and (7) domain-specific transformation. Each topic was characterized by representative keywords extracted from topic modeling algorithm. For example, AI automation topics emphasized "workflows", "automate", and "agents", whereas the analytics topics highlighted "data-driven", "analytics", and "insights". The collaboration topic stressed "teams", "collaboration" and "human machine", while the strategic topic included "transformation", "value", and "vision". Domain-specific themes covered contexts such as "clinical workflows" and "logistics". Topic distribution was balanced and the most frequent topics appeared in ~10% of documents, indicating that no single narrative dominated. Some keywords such as "insight" and "data-driven" spanned multiple themes, highlighting their relevance to both technical and business concerns. These patterns reinforced the socio-technical perspective, suggesting that AI-driven process mining was viewed as a multifaceted phenomenon combining automation, analytics, human collaboration, and strategic objectives.

Table 1

Interpreted Topics and Their Associated Themes

Theme	Topic Label	Top 10 Topic Terms
AI automation & agents	Automating human workforce with AI agents (T1)	workflows, tech trend, tech trends, automate, workforce, agents, tasks, tech, agent, tools
	Intelligent automation combined with RPA to create smart and end-to-end business processes (T2)	enterprises adopt, innovation, automate, workflows, enterprises, technologies, automates, automating, intelligent end, sap
	Building technologies for better process automation by AI agents (T3)	automate, innovation, technologies, areas automate, work agents, work agents new, tools, research, systems, tech trends
	Autonomous agents and machines for task innovation and value creation (T4)	enterprises, machines, static workflows, innovation value creation, organization, innovation value, autonomous, tasks, autonomous agents, organizations
customer value & service improvement	Tools to provide better insights for customer improvement(T5)	industries, customer improvement opportunities, tools, technology, improvement opportunities hour, easy customers improvement, leveraging, customers improvement, insights, execs
	Tools to increase value to customers (T6)	tech industry, manager value engineering, high tech industry, tech, value engineer, value engineering, driving transformation data, high tech, engineering, senior value engineer
	Tools with process orchestration to better serve customers (T7)	enterprises, applications, software, tools, agents, step, crm, systems, orchestration need, orchestration
domain-specific transformation	Improving the throughput of knowledge-intensive workflows, e.g., healthcare (operational resilience versus bureaucracy) (T8)	workflows, clinical workflows, expertise, applications, leveraging, capabilities, bureaucratic, operational resilience, flow throughput, patient flow throughput
	Advancing process innovation in supply chain and logistics (T9)	logistics, data driven, business sustainably transform, build data driven, consultant supply chain, future supply chain, innovation, technology, consultant supply, expertise
human-AI collaboration & teamwork	Innovative human-machine collaborations (T10)	processmining, tasks, machines, leveraging, technology, innovation, tools, human machines, exploring, operational
	Advanced collaborative enterprise platforms (T11)	sap, microsoft, innovation, innovations, infosys brings advanced, asos partners microsoft, tasks, operational, apps, collaboration
	Streamlining workflows for team collaboration (T12)	workflows, streamlined workflows, transforming insights, technology, organizational, leveraging, tools, teams streamlined workflows, insights, audit

Theme	Topic Label	Top 10 Topic Terms
innovation, strategy & business value	Proactive and data-driven approaches in process innovation projects (T13)	proactive data driven, innovation project, operational excellence, data driven, inefficiencies, performance data, innovation, operational, performance, operational data
	Innovative approaches for cost reduction strategies (T14)	approaches deliver cost, approaches deliver, cost optimization strategies, sap, future innovation, deliver cost optimization, successfully organizing, successfully organizing visionary, value transforming future, client industry
process analytics & intelligence	AI integration for work optimization (T15)	futureofwork processmining, processmining, machinelearning processmining, businessintelligence, processoptimization, approaches managing, aiintegration lots exciting, aiintegration lots, analyze optimize operations, services
	Integrating AI in BI tools for deeper strategic insights in process inefficiencies (T16)	workflows, discovery, comprehensive, tools, bi tools, strategic initiatives, flow, learning, insights, inefficiencies
	Leveraging machine learning to optimize data-driven insight by AI agents (T17)	automated, agentic workflows, workflows, data insights, feature engineering, inefficiencies optimize workflows, analytics, leveraging machine, data driven, insights
	Deeper capability for predicting and assessing risk and issues (T18)	predictive analytics, operational, tools, operational risk, issues addressing underlying, deeper systemic issues, integration capability gaps, integration capability, analysis, audit
	Enabling agile process analytics and prediction (T19)	data driven operations, agile bi, analytics centric, driven operations, agile, enterprises, data driven, aware enabling predictive, analytics centric platforms, strategic
process design & system architecture	Agent-driven process modeling (T20)	bpmn, software ag, software, operate, digital service, services, agents, knowledge, agents drive, agentic
	Technological landscape optimization by integrating tools (T21)	theory optimize workflows, tools insights need, technology analyzing, tools insights, corporate technological, technology analyzing proper, technologies deliver, currently innovator early, currently innovator, corporate technological waste
	Facilitating alternative process designs and decision making (e.g., retail sourcing) (T22)	deep industry, industry, insights retail, decisions sourcing, sourcing, industry specific, technology, alternatives lead times, design decisions sourcing, retail technology

5. Discussion

This study provided insight into how the emerging role of AI in process mining is framed and conceptualized in practitioner discourse. Rather than focusing solely on isolated technical improvements, our findings highlighted both enhancements to the analytical phases of the process mining lifecycle [21] and broader organizational purposes for which AI-enabled process mining is applied. This section extends the findings by examining them through two complementary analytical and organizational lenses. While the lifecycle perspective explains how the identified topics relate to different process mining operational phases, examining the findings through capability domains provides insight into the broader areas in which AI-related developments may influence the implementation and application of process mining in organizations. Considering both perspectives enables a more comprehensive interpretation of the findings by linking analytical developments to the broader capability structures that are required to implement and sustain process mining in organizations. To support this interpretation, the topics are therefore reinterpreted and reorganized onto the process mining lifecycle model [21] and the BPM capability framework proposed by [7]. Interpreting the findings through these complementary perspectives helps clarify how AI may reshape the role of process mining in contemporary organizational settings.

5.1. AI-Enabled Process Mining across Lifecycle Phases and Purposes

Figure 1 distinguishes between two dimensions emerging from the findings, namely: process mining lifecycle phases and organizational purposes of adopting AI-enabled process mining. Together, these dimensions reflect how practitioner discourse positions AI-enabled process mining both within analytical process workflows and in relation to broader organizational objectives. Figure 1 focuses on topics that can be directly mapped to the process mining lifecycle, while other identified patterns that do not align with this perspective are not visualized. Rather than concentrating on a single stage, the findings suggest that AI is primarily discussed as influencing multiple phases of the process mining workflow, indicating a perception that AI enhances the overall analytical pipeline rather than an isolated analytical technique. This lifecycle interpretation suggests that practitioner discourse frames AI as strengthening end-to-end process mining activities spanning data preparation, analysis, prediction, and operational response. From this perspective, AI-enabled process mining is conceptualized as a more integrated analytical approach in which insights can be generated, interpreted, and acted upon more effectively across the lifecycle.

Beyond analytical workflow support, the findings also reveal a second dimension related to the organizational purposes and intentions associated with AI-enabled process mining, as well as the outcomes practitioners expect these technologies to support. Therefore, the lifecycle phases represent *where* AI is perceived to intervene within the analytical workflow of process mining, whereas the purposes reflect *why* organizations apply these capabilities and what they expect to achieve from adopting AI-enabled process mining technologies. Importantly, these purpose-oriented themes do not correspond directly to individual analytical phases in the lifecycle. Instead, they reflect broader organizational objectives that span multiple lifecycle stages simultaneously. For example, themes related to customer value and service improvement may combine AI-enabled analytics, intelligent orchestration, and automated workflows to support enhanced customer interactions and operational responsiveness. This observation highlights an important distinction between *phases* and *purposes*. Thus, lifecycle phases describe the analytical mechanisms through which process mining operates, whereas purpose-oriented themes reflect the organizational motivations for applying these techniques. Rather than merely applying existing frameworks, this dual interpretation reveals how AI-related developments can simultaneously reshape multiple dimensions of process mining, highlighting interdependencies that are not fully captured when these frameworks are considered in

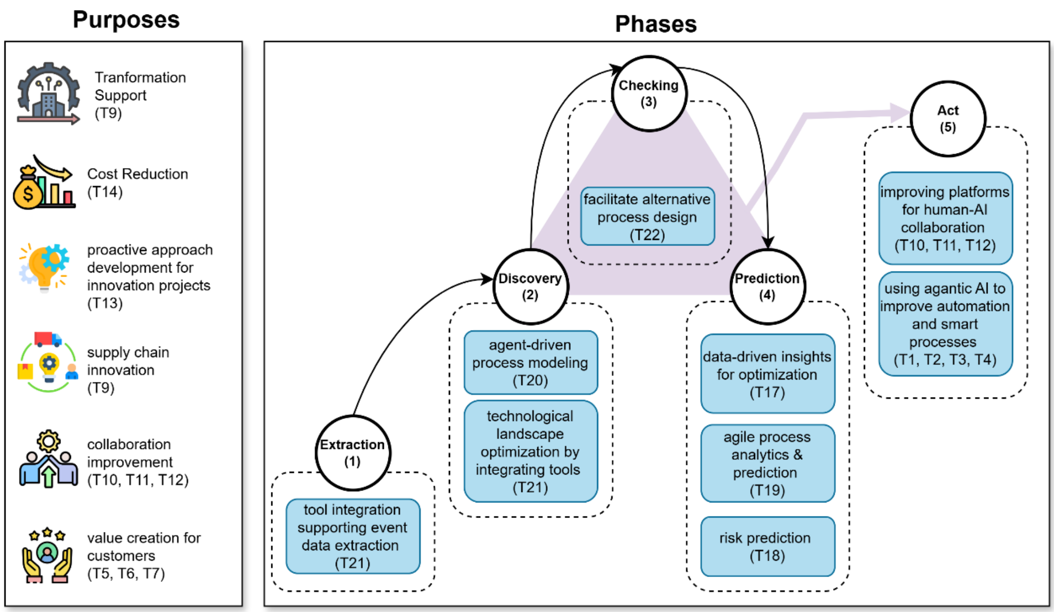

Figure 1: Dual perspective on AI-enabled process mining: lifecycle phases vs. organizational purposes

isolation. Furthermore, it suggests that in current discourse, the value of AI-enabled process mining is primarily articulated through cross-phase outcomes rather than through improvements within individual lifecycle stages.

5.2. AI-enabled Process Mining across Capability Domains

While the lifecycle perspective in Section 5.1 explains how AI-enabled process mining is framed across analytical activities and organizational purposes, it provides limited insight into the broader organizational capabilities required to support these developments. This is because process mining adoption and implementation typically depend on a combination of technological, methodological, and organizational capabilities. To capture this broader perspective, our findings are therefore also interpreted using the BPM capability framework [7]. In other words, whereas the lifecycle perspective focuses on *how* process mining analyses are performed, the capability framework highlights *which capability domains* are influenced by the integration of AI into process mining initiatives.

Interpreting the findings through this lens suggests that AI-related developments are primarily associated with the methods and information technology capability domains. As shown in Figure 2, several themes emphasize advanced analytics, intelligent modeling, and technological integration. This indicates that today's practitioner discourse largely frames AI-enabled process mining as extending the technological and methodological foundations of process analysis. This distribution indicates that AI-enabled process mining is predominantly framed through technical and analytical capabilities, while organizational and governance dimensions receive comparatively less explicit attention. In particular, topics related to AI automation, intelligent analytics, and tool integration suggest that AI is typically perceived as strengthening the analytical infrastructure that supports process mining initiatives. At the same time, the mapping also reveals links to strategic alignment capabilities. Themes related to innovation initiatives, business value, and domain-specific transformation suggest that AI-enabled process mining is frequently positioned as supporting strategic improvement efforts and organizational transformation. In practitioner discourse, process

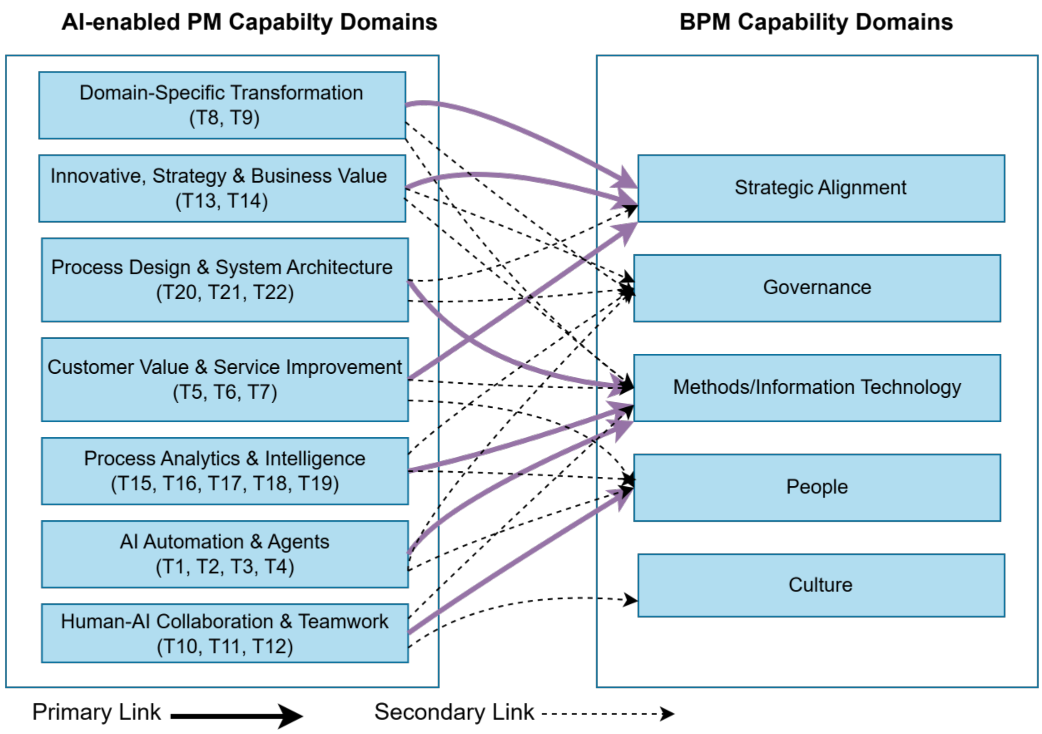

Figure 2: AI-enabled process mining influencing/supporting BPM capability domains of [7]

mining therefore appears not only as an analytical technique but also as a mechanism that supports strategic decision-making and value creation. The findings further highlight the relevance of people and collaboration capabilities. Next, topics related to human-AI collaboration indicate that the effective application of AI-enabled process mining depends on the ability of organizations to coordinate analytical insights across different stakeholders. These discussions suggest that AI-enabled analytical environments require collaborative practices in which process experts, analysts, and decision-makers jointly interpret and apply analytical insights. This perspective highlights that the integration of AI into process mining extends beyond analytical improvements and may reshape the broader capability landscape required to support process mining initiatives.

5.3. Limitations and Future Research

This study has some limitations that provide opportunities for future research. Although we have extracted records using queries combining process mining with AI-related terms (AI or GenAI), some practitioner posts may still discuss process mining in broader BPM contexts rather than explicitly focusing on AI-enabled process mining. In addition, the analysis relies on practitioner discourse from LinkedIn, which may reflect emerging expectations, narratives, or a "hype" around AI-enabled process mining rather than actual implementations in organizational practice. Furthermore, the LinkedIn corpus may introduce biases such as a tendency toward more promotional or optimistic narratives, limited visibility of critical perspectives, and a potential overrepresentation of certain industries or vendors. As a result, we acknowledge that the findings may emphasize more optimistic and forward-looking interpretations, potentially underrepresenting challenges, failures, or critical viewpoints. The dataset also covers publicly accessible LinkedIn content retrieved through keyword-based queries. However, not all LinkedIn posts are publicly available, as some content is restricted to user networks or private settings. Future research could therefore complement these findings by examining empirical cases of AI-enabled process mining adoption within organizations and by extending the analysis to additional practitioner or industry sources to further investigate how AI influences the organizational capabilities and how their purposes influence their aim to apply AI-enabled process mining. In addition, longitudinal studies could examine how practitioner narratives evolve over time. Lastly, future research could incorporate sentiment analysis to examine whether discussions are predominantly positive, critical, or forward-looking.

6. Conclusion

In this paper, we examined how AI-enabled process mining is framed in practitioner discourse by applying topic modeling to practitioner-generated content. Our findings suggest that contemporary practitioner narratives emphasize both enhancements to analytical phases of the process mining lifecycle and broader organizational purposes such as collaboration, value creation, and transformation. Interpreting these themes through the process mining lifecycle perspective further suggests that AI-enabled process mining is increasingly conceptualized as supporting integrated, end-to-end analytical activities across multiple lifecycle phases rather than isolated analytical techniques. In addition, examining the findings through BPM capability domains highlights that practitioner discourse positions AI-enabled process mining not only in relation to analytical and technological capabilities, but also in relation to broader organizational dimensions including strategy, collaboration, and organizational transformation. By combining these complementary perspectives, this study provides a more structured understanding of how emerging AI-related developments relate to established process mining concepts. These insights contribute to ongoing discussions on how AI may reshape the evolving role of process mining in organizational process improvement initiatives.

Declaration on Generative AI

Author 1 used GPT-5.3 to improve the conciseness of some of the text. All outputs were reviewed and edited as needed, and the author takes full responsibility for the final content of the publication.

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