

Process Ownership in the Context of Process Intelligence: A Systematic Literature Review

Nur Aeni Hidayah ^{1*}, Riyan Ainur Rahman ^{2*}, Maizura Azizah Sekar Ayuningrum ^{3*}

* Sistem Informasi, Fakultas Sains dan Teknologi, UIN Syarif Hidayatullah Jakarta, Indonesia
nur.aeni@uinjkt.ac.id ¹, riyan.ainur24@mhs.uinjkt.ac.id ², maizura.azzizah@uinjkt.ac.id ³

Article Info

Article history:

Received 2026-08-10

Revised 2026-09-11

Accepted 2026-10-09

Keyword:

*Process Ownership,
Process Intelligence,
Process Mining,
Business Process Management,
Artificial Intelligence*

ABSTRACT

Business Process Management (BPM) has been transformed by Process Intelligence, encompassing process mining, business process analytics, and Artificial Intelligence (AI). While the technological dimensions of Process Intelligence are well studied, the organizational implications, particularly the evolving roles, responsibilities, and competencies of process owners, remain fragmented and underexplored. Prior systematic reviews have addressed either process ownership in conventional BPM or the technical aspects of Process Intelligence in isolation, leaving a gap in understanding how Process Intelligence capabilities reshape process ownership as an accountability structure. To address this gap, this study conducts a Systematic Literature Review following the PRISMA 2020 guidelines, guided by four research questions covering publication characteristics, role evolution, conceptual themes, and research gaps. From an initial pool of 1,408 publications across two databases, 40 studies met the selection and quality criteria and were included in the final synthesis. A three-stage thematic coding process identified four overarching themes: data-driven process governance, human–AI collaboration, continuous process improvement, and organizational capability. Findings indicate a shift from technology-oriented discussions toward governance-oriented perspectives, with process owners evolving from administrative coordinators into data-driven decision makers operating within a Human-in-the-Loop framework. Three research gaps were identified: the absence of integrated conceptual frameworks, limited longitudinal and cross-sector empirical evidence, and underdeveloped governance mechanisms for AI-assisted decision-making. This study contributes a theoretically grounded synthesis of the process ownership–Process Intelligence nexus, offering conceptual insights for researchers and practical guidance for organizations implementing data-driven BPM.



This is an open access article under the [CC-BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.

I. INTRODUCTION

Digital transformation has pushed Business Process Management (BPM) beyond its traditional functions of documentation and control toward an analytics-based approach that supports continuous, evidence-driven decision-making, a shift reinforced by the growth of process mining, which enables the reconstruction and analysis of process behavior directly from event logs [1], [2]. This trajectory has been further accelerated by the integration of Artificial Intelligence (AI) into BPM, allowing organizations to generate predictive analyses, detect deviations, and produce

automated process-improvement recommendations [3]–[5]. The convergence of these capabilities has given rise to the concept of Process Intelligence, defined here as an organizational capability that integrates process mining, business process analytics, and AI-based techniques to continuously monitor, analyze, and generate evidence-based insights for process management and decision-making [1], [3], [5].

Within this landscape, the process owner holds end-to-end accountability for the performance, coordination, and continuous improvement of a business process that crosses organizational and functional boundaries [7], [8]. For the

purpose of this study, process ownership is defined as an accountability structure in which an individual holds end-to-end responsibility for the performance, coordination, and continuous improvement of a business process that crosses organizational and functional boundaries; this working definition, together with the definition of Process Intelligence given above, is used consistently throughout this review to delimit the scope of the studies considered. Kohlbacher and Gruenwald [7] showed that process ownership contributes to the effectiveness of process management and organizational coordination, while Danilova [8] identified the roles, competencies, and challenges faced by process owners in BPM implementation. The relationship between governance structures and BPM has also received attention in the broader literature, for instance through the examination of how governance mechanisms shape BPM practice [20]. However, these strands of research, whether centered on process ownership, process governance, or conventional BPM, have not accounted for the changing process environment shaped by real-time analytics, AI integration, and automated decision-making that characterizes the era of Process Intelligence [3], [5]. Conversely, existing reviews of Process Intelligence and process mining [1], [2] have concentrated primarily on technological and algorithmic developments, giving only incidental attention to organizational roles such as that of the process owner.

To the best of our knowledge, no systematic review has explicitly synthesized how specific Process Intelligence capabilities, namely real-time event-log analytics, AI-based recommendations, and human-in-the-loop decision support, are reshaping the roles, responsibilities, and competencies of process owners. This gap distinguishes the present study from prior process-ownership and process-governance research [7], [8], [20], as well as from technology-centric Process Intelligence reviews [1], [2], and constitutes the primary motivation for this work.

To address this gap, the present study adopts a Systematic Literature Review (SLR) following the PRISMA 2020 guidelines, ensuring a transparent, systematic, and reproducible process for identifying, screening, selecting, and synthesizing the relevant literature [9]. The review is guided by four research questions: RQ1, what are the characteristics of publications and the research landscape on process ownership in the context of Process Intelligence; RQ2, how have the roles, responsibilities, and competencies of process owners evolved with the adoption of Process Intelligence; RQ3, what conceptual themes emerge from the relationship between process ownership and Process Intelligence; and RQ4, what research gaps and future research directions can be identified based on the existing literature. The remainder of this paper describes the research methodology (Section II), presents the thematic findings and discussion addressing these research questions (Section III), and concludes with the study's main contributions and directions for future research (Section IV).

II. METHOD

The PRISMA-based review process comprised four main stages: formulating the research questions, performing the literature search, evaluating the quality of the selected studies, and extracting relevant data for subsequent synthesis. This study follows the PRISMA 2020 reporting guidelines [9] to ensure a transparent, systematic, and reproducible review process, distinguishing it from narrative reviews in which selection and synthesis procedures are not explicitly documented [23].

A. Research Questions

The Research Questions (RQ) were formulated based on the research gaps identified in the Introduction. The RQs serve as the foundation for developing the literature search strategy, the data extraction process, and the synthesis of findings, ensuring that all SLR stages are conducted in a focused and consistent manner. The Research Questions used in this study are presented in Table I.

TABLE 1.
RESEARCH QUESTIONS

ID	Research Questions
RQ1	What are the characteristics of publications and the research landscape on process ownership in the context of Process Intelligence?
RQ2	How have the roles, responsibilities, and competencies of process owners evolved with the adoption of Process Intelligence?
RQ3	What conceptual themes emerge from the relationship between process ownership and Process Intelligence?
RQ4	What research gaps and future research directions can be identified based on the existing literature?

B. Literature Search Strategy

The literature search was conducted in July 2026 using two academic databases: Scopus and Google Scholar. Scopus was selected for its broad coverage of peer-reviewed journals in information systems, business process management, and computer science [34]. Google Scholar was included to supplement Scopus coverage, particularly for conference proceedings and interdisciplinary publications relevant to organizational and management aspects of BPM [1]. Google Scholar searches were conducted using Publish or Perish (PoP) to retrieve and export bibliographic records systematically.

The search was performed on the title, abstract, and keyword fields using a Boolean search string developed from the two main concepts of this study, namely Process Intelligence [2], [3] and process ownership [7], [8]. To minimize the risk of missing relevant studies, the search string was constructed to encompass synonyms and terminological variants used across the BPM, process mining, information systems, and AI literature. The combination of keywords used is presented in Table II.

TABLE II.
SEARCH STRING

Concept	Keywords
Process Intelligence	"Process Intelligence" OR "Process Mining" OR "Task Mining" OR "Business Process Analytics" OR "AI-augmented BPM" OR "process analytics" OR "AI-enabled process management"
Process Ownership	"Process Owner" OR "Process Ownership" OR "Business Process Owner" OR "Process Governance" OR "Process Accountability"

The complete Boolean search string applied across both databases was: ("Process Intelligence" OR "Process Mining" OR "Task Mining" OR "Business Process Analytics" OR "AI-augmented BPM" OR "process analytics" OR "AI-enabled process management") AND ("Process Owner" OR "Process Ownership" OR "Business Process Owner" OR "Process Governance" OR "Process Accountability"). The search was restricted to the title, abstract, and keyword fields and was executed on 14 July 2026. The publication period was limited to 2016–2026 to capture the most recent developments in research on Process Intelligence and process ownership. Based on this search strategy, 1,408 initial publications were retrieved across both databases. The distribution of publications by year is shown in Figure 1.

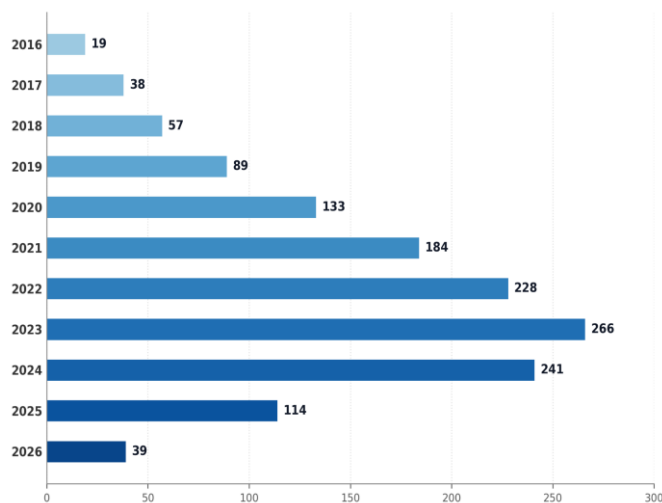


Figure 1. Distribution of Retrieved Publications by Publication Year (2016–2026)

C. Study Selection Criteria

Study selection criteria were established to ensure that the included literature was relevant to the research objectives and capable of answering the formulated research questions. These criteria comprise inclusion and exclusion criteria applied during the screening and eligibility assessment stages. The detailed selection criteria are presented in Table III.

TABLE III.
STUDY SELECTION CRITERIA

Parameter	Inclusion Criteria	Exclusion Criteria
Publication Year	2016–2026	Before 2016
Publication Type	Peer-reviewed journal articles and conference proceedings	Books, book reviews, editorials, short communications, industry reports, and grey literature
Language	English	Other than English
Topic	Studies that explicitly discuss the role, responsibilities, accountability, or decision-making of the process owner (or an equivalent role, e.g., process manager, process governance lead) in the context of Process Intelligence, process mining, business process analytics, or AI-augmented BPM	Studies limited to purely technical contributions (e.g., new mining algorithms, system architectures, or tool comparisons) without any discussion of organizational roles, governance, or human decision-making
Availability	Full text available	Full text not available

D. Study Selection Process

The study selection process followed the PRISMA 2020 guidelines [9], consisting of four stages: Identification, Screening, Eligibility, and Included. All stages were conducted by the first author. To reduce subjectivity inherent in single-reviewer screening, a consistency check was applied at each stage: a random sample of 10% of the screened records was re-evaluated after a two-week interval, and any discrepancies were resolved through discussion with the second author prior to proceeding to the next stage [23].

In the Identification stage, records were retrieved from Scopus ($n = 158$) and Google Scholar via Publish or Perish ($n = 1,250$), yielding a total of 1,408 identified records. After removing 56 duplicate records, 1,352 records remained for title and abstract screening. During the Screening stage, records were assessed against the predefined inclusion and exclusion criteria; 1,244 records were excluded as clearly irrelevant to the review scope, leaving 108 records for full-text eligibility assessment. In the Eligibility stage, each of the 108 records was evaluated using the Quality Assessment criteria described in Section II.E. Records scoring below the predefined threshold were excluded ($n = 68$), resulting in 40 studies that met all selection and quality criteria and were included in the final synthesis. The complete study selection flow is presented in Figure 2.

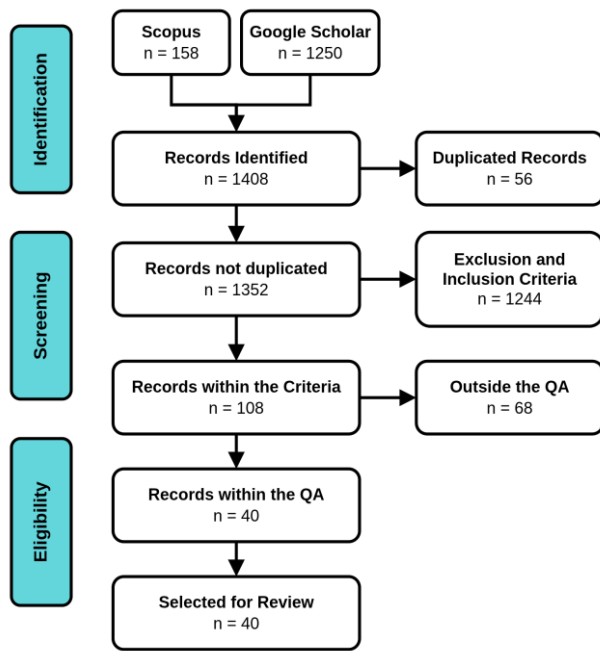


Figure 2. PRISMA Flow

E. Quality Assessment

To ensure the quality of the included studies, each article that passed the screening stage was evaluated using three quality assessment criteria [23]. This assessment was conducted to evaluate the clarity of the research objectives, the appropriateness of the methodology, and the validity of the reported findings. The quality assessment criteria are presented in Table IV.

TABLE IV.
QUALITY ASSESSMENT CRITERIA

ID	Assessment Question
QA1	Is the research objective clearly stated?
QA2	Is the research methodology adequately explained?
QA3	Are the research findings supported by adequate evidence?

Each criterion was scored as Yes = 1, Partially = 0.5, and No = 0, giving each study a maximum possible score of 3.0. Studies with a score ≥ 2.0 were retained for the data extraction and synthesis stages, while studies scoring below 2.0 were excluded from the analysis.

F. Data Extraction and Synthesis

Data from the 40 studies that met all selection and quality criteria were extracted into an analysis matrix to facilitate the grouping and comparison of studies. The information extracted included the author(s), year of publication, publication type, research method, Process Intelligence

technology used, aspects of process ownership discussed, key findings, and research gaps identified in each study.

The extracted data were then analyzed using a combination of descriptive analysis and thematic synthesis. Descriptive analysis was used to identify the characteristics and research landscape based on publication year, publication type, research method, research focus, Process Intelligence technology used, and implementation context, thereby addressing RQ1. Thematic synthesis was subsequently applied to identify and group findings with similar characteristics, following the three-stage coding procedure described by Thomas and Harden [23].

In the first stage, findings extracted from each of the 40 studies were coded line-by-line into the analysis matrix based on their descriptive content for example, statements regarding real-time monitoring, AI-based recommendations, or governance mechanisms. In the second stage, related codes were grouped into descriptive themes; for instance, codes such as "real-time process monitoring" and "event-log based performance evaluation" were grouped under the descriptive theme "data-driven monitoring." In the third stage, analytical themes were generated by interpreting relationships and patterns across the descriptive themes, resulting in the four overarching conceptual themes reported in Section III.D: data-driven process governance, human-AI collaboration, continuous process improvement, and organizational capability. This thematic synthesis procedure addresses RQ2, RQ3, and RQ4.

III. RESULT AND DISCUSSION

A. Literature Selection Results and Quality Assessment

Following the selection process based on the PRISMA 2020 guidelines, 1,408 publications were obtained at the initial identification stage across two databases. After removing 56 duplicate records, screening 1,352 titles and abstracts, and conducting a full-text eligibility assessment on 108 records, 40 studies were determined to meet all predefined selection and quality assessment criteria and were included in the final synthesis.

All 40 studies were evaluated using the Quality Assessment criteria described in Section II.E. The results show that all included studies obtained a score ≥ 2.0 , thereby meeting the established quality threshold. The distribution of QA scores is presented in Table V.

TABLE V.
QUALITY ASSESSMENT RESULTS

QA Score	Number of Studies
3.0	22
2.5	12
2.0	6
<2.0	0

The predominance of studies scoring 3.0 ($n = 22$) indicates that the majority of included studies clearly stated their research objectives, adequately explained their methodology,

and supported their findings with sufficient evidence. Studies scoring 2.0 ($n = 6$) were retained as they met the minimum threshold, though they exhibited partial adequacy in one assessment criterion.

B. RQ1: What are the characteristics of publications and the research landscape on process ownership in the context of Process Intelligence?

Based on the extraction results of the 40 studies, publication characteristics were analyzed to identify the research landscape on process ownership in the context of Process Intelligence. The analysis covered research focus, dominant technologies, research methods, implementation contexts, and temporal trends. A summary of the publication characteristics is presented in Table VI.

TABLE VI.
PUBLICATION CHARACTERISTICS AND RESEARCH LANDSCAPE

Aspect	Findings / Sub-Characteristics	Supporting Literature
Research focus	Role and capabilities of process owners in governance	[7], [8]
	Data-driven organizational culture and structure adaptation	[8], [12], [20], [36]
	AI-based operational and strategic decision-making	[3], [6], [15], [37]
	BPM maturity and digital transformation readiness	[32], [33], [40]
Dominant technology	Process Mining and Business Process Analytics	[2], [10], [17], [21], [25], [38]
	Machine Learning and AI-Augmented BPM	[3], [4], [5], [39]
	Integrated automation and Human-in-the-Loop AI	[18], [26]
	Robotic Process Automation (RPA)	[30]
Research method	Systematic Literature Review (SLR) and bibliometric analysis	[1], [4], [8], [10], [18], [19], [21], [34]
	Case studies and empirical organizational research	[6], [7], [11], [12], [16], [36]
	Delphi studies and expert surveys	[13], [14], [15]
	Conceptual and framework development	[31], [32], [33], [40]
Implementation context	Process governance	[7], [12], [20], [27], [28]
	Evaluation of success factors and impact of Process Mining	[11], [16]

	Business value creation and digital innovation	[6], [14], [31]
Research trends	Shift from technical aspects toward organizational governance	[8], [12], [15], [40]
	Cross-organizational Process Mining	[19]
	Human-AI Collaboration	[3], [18], [26]
	Data-driven culture and mindset	[36], [37]

Based on Table VI, research on process ownership in the context of Process Intelligence shows a clear shift from a dominance of technical aspects toward organizational and governance-related aspects. Earlier research focused more heavily on the use of Process Mining as a technological foundation for improving process transparency [2], [17]. However, more recent literature [3], [8], [12] consistently positions the process owner as a central actor who leverages AI-based analytical outputs (AI-Augmented BPM) [3], [5] to support strategic decision-making, process governance [20], and the integration of human and system capabilities (human-in-the-loop) [18]. This shift indicates that the implementation of Process Intelligence is no longer viewed merely as an analytical software innovation [21], but rather as an integrated approach that combines data analytics capability with organizational governance and digital transformation [6], [14], [15].

C. RQ2: How have the roles, responsibilities, and competencies of process owners evolved with the adoption of Process Intelligence?

The synthesis of the 40 included studies indicates that the adoption of Process Intelligence has brought substantive changes to the function of the process owner within organizations. The reviewed literature suggests that process owners have moved beyond coordinating process execution and ensuring procedural compliance toward a role centered on data-informed governance and continuous process improvement. A synthesis of this evolution across four dimensions is presented in Table VII.

TABLE VII.
EVOLUTION OF THE PROCESS OWNER'S ROLE, RESPONSIBILITIES, AND COMPETENCIES

Dimension	Synthesis Results / Sub-Indicators	Supporting Literature
Role	Shift from operational coordinator to data-driven decision maker	[7], [8]
	Integration of analytical capability into organizational process steering	[12], [15], [40]

	Expanded accountability across organizational and functional boundaries	[7], [20]
Decision-Making	Shift from periodic reporting to real-time monitoring	[2], [10], [38]
	Evaluation of decisions based on event logs and process analytics	[2], [17], [25]
	Use of predictive monitoring to anticipate deviations	[38], [39]
Responsibility	Expansion from procedural compliance to continuous improvement	[8], [20]
	Identification of deviations and data-driven corrective actions	[11], [16]
	Oversight of AI recommendation implementation	[18], [29]
Competency	Data literacy and analytical result interpretation	[15], [37]
	Understanding of AI and Machine Learning outputs	[3], [4], [5]
	Data-driven mindset and evidence-based reasoning	[36], [37]
Human–AI Collaboration	Process owner as the final decision maker	[3], [18]
	Human oversight of system generated recommendations	[6], [18], [26]
	Governance of algorithmic transparency and accountability	[27], [28], [29]

Table VII shows that the evolution of the process owner reflects a broader paradigm shift in process management. In conventional BPM, decision-making typically relied on periodic operational reports, resulting in largely reactive responses to process deviations [7], [8]. The integration of Process Intelligence enables process owners to draw on real-time event-log data to identify inconsistencies, evaluate root causes, and initiate corrective actions in a more timely manner [2], [10]. This shift is corroborated by evidence from multiple included studies, indicating that process decisions are increasingly grounded in analytical outputs rather than solely in managerial experience or intuition [2], [17], [38].

The expansion of responsibilities is equally well-documented in the synthesis. Beyond ensuring procedural compliance, process owners are now expected to oversee the quality of data-driven decisions, assess the reliability of AI-generated recommendations, and maintain alignment between process improvement efforts and broader organizational governance objectives [11], [16], [20], [29]. These findings converge with the observation that the locus of process management has shifted from operational control toward continuous improvement [8], [16].

The competency requirements associated with this transformation extend beyond conventional BPM knowledge [15]. The included studies consistently indicate that process owners need data literacy, familiarity with process analytics, and the capacity to critically evaluate AI outputs [3], [4], [5], [37]. Critically, the majority of studies emphasize that final decision-making authority is retained by the process owner within a Human-in-the-Loop framework [3], [18], [26], underscoring that technological capability alone is insufficient the governance readiness of human actors remains a determining factor [6], [36].

D. RQ3: What conceptual themes emerge from the relationship between process ownership and Process Intelligence?

The thematic synthesis of the 40 included studies identifies four overarching conceptual themes characterizing the relationship between process ownership and Process Intelligence. A summary is presented in Table VIII, followed by an analysis of the interrelationships among the themes.

TABLE VIII.
CONCEPTUAL THEMES IN THE RELATIONSHIP BETWEEN PROCESS OWNERSHIP AND PROCESS INTELLIGENCE

Theme	PI Manifestation	Role / Implication for Process Owner	Supporting Literature
Data-driven process governance	Event-log analysis and real-time monitoring	Using process data for monitoring, accountability, and governance decisions	[2], [10], [16], [20], [27]
Human–AI collaboration	AI-assisted analysis and recommendations	Validating AI outputs and retaining final decision-making authority	[3], [4], [5], [6], [18], [26]
Continuous process improvement	Continuous monitoring and deviation detection	Identifying performance gaps and implementing evidence-based improvements	[10], [11], [14], [16], [38]
Organizational capability	Process mining maturity, governance structures, and skill development	Building organizational conditions for effective PI integration	[11], [12], [13], [15], [17], [19], [32]

The four themes are complementary and mutually reinforcing. Data-driven process governance establishes the analytical foundation through which process owners access real-time event-log data for monitoring and accountability [2], [10], [16], [20], [27]. This capability is operationalized through human–AI collaboration, whereby AI-generated recommendations augment rather than replace human judgment, with the process owner retaining final decision-

making authority [3], [4], [5], [6], [18], [26]. The outputs of this governance collaboration dynamic are channeled into continuous process improvement: identified deviations and performance gaps are addressed through evidence-based corrective actions [10], [11], [14], [16], [38]. Underpinning all three themes is organizational capability the combination of process mining maturity, governance infrastructure, and human competency development that determines whether insights generated by Process Intelligence can be effectively translated into organizational action [11], [12], [13], [15], [17], [19], [32].

E. RQ4: What research gaps and future research directions can be identified based on the existing literature?

The synthesis of the 40 included studies identifies three interrelated categories of research gaps: conceptual, empirical, and governance related. Figure 3 illustrates the distribution of supporting studies across these gap categories, noting that several studies inform more than one gap.

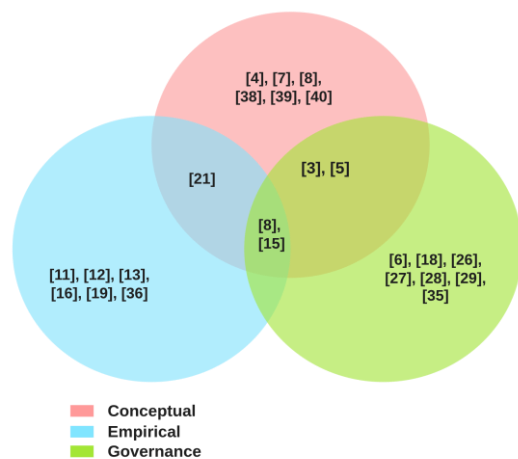


Figure 3. Distribution of Research Gaps by Category

From a conceptual standpoint, most included studies address either the technological dimensions of Process Intelligence such as process mining algorithms, task mining, and AI-based recommendation systems [4], [5], [38], [39] or the organizational dimensions of process ownership [7], [8] in relative isolation. Few studies have developed integrated frameworks that explicitly model how Process Intelligence capabilities transform the governance mechanisms, accountability structures, and competency requirements associated with process ownership [7], [8], [40]. This separation means that the relationship between technological capability and organizational role transformation remains under-theorized [3].

From an empirical standpoint, the included studies are dominated by single-organization case studies and sector-specific implementations [12], [19], which limits the generalizability of findings across diverse organizational contexts [11], [21]. Longitudinal studies examining how the process owner's role evolves following sustained Process

Intelligence adoption are notably absent [13], leaving the long-term impacts on process performance, decision-making effectiveness, and organizational capability insufficiently documented [16], [36].

A third gap concerns governance and accountability in AI-assisted decision-making. Although human–AI collaboration is a recurrent theme across the included studies [3], [18], [26], most do not clearly delineate the boundaries of authority between AI-generated outputs and human judgment [3], [6]. Questions regarding algorithmic transparency, decision accountability, and risk governance when AI recommendations are acted upon remain underexplored [27], [28], [29] despite their growing practical relevance as AI adoption in BPM accelerates [5], [35].

Based on these gaps, future research should prioritize the development of integrated governance frameworks that link Process Intelligence capabilities to process ownership structures [8], [15], [40]. Cross-sector and longitudinal empirical studies are needed to establish more generalizable evidence on the trajectory of process ownership transformation [12], [13], [36]. Research on the governance of human–AI collaboration in BPM encompassing transparency, accountability, and ethical dimensions of AI-based decision support also constitutes an important and underexplored direction [18], [29], [35].

IV. CONCLUSION

This study presents a systematic synthesis of process ownership in the context of Process Intelligence, conducted through a Systematic Literature Review (SLR) following the PRISMA 2020 guidelines. From an initial retrieval of 1,408 publications across two academic databases, 40 studies met the predefined selection and quality assessment criteria. The synthesis indicates that research in this field has shifted from technology oriented discussions toward process governance and data-driven decision-making, accompanied by the evolution of the process owner from an administrative coordinator into a data-driven decision maker operating within a Human-in-the-Loop framework. Four complementary conceptual themes characterize this relationship data-driven process governance, human–AI collaboration, continuous process improvement, and organizational capability with organizational capability serving as the enabling condition for the integration of the remaining three. Three research gaps were identified: the absence of integrated conceptual frameworks linking Process Intelligence capabilities to process ownership structures, limited longitudinal and cross-sector empirical evidence, and underdeveloped governance mechanisms for AI-assisted decision-making including algorithmic transparency and accountability.

This study contributes a theoretically grounded synthesis of the process ownership–Process Intelligence nexus, offering conceptual insights for researchers and practical guidance for organizations defining process owner roles and competencies in data-driven BPM implementation. Nonetheless, several

limitations apply: the search was restricted to Scopus and Google Scholar, only English language publications from 2016–2026 were considered, and screening was conducted primarily by a single reviewer with a consistency check applied to mitigate subjectivity. Future research should prioritize the development of integrated governance frameworks, longitudinal empirical studies across multiple sectors, and deeper investigation of human–AI collaboration governance in BPM contexts.

REFERENCES

- [1] H. Lizano-Mora, P. R. Palos-Sanchez, And M. Aguayo-Camacho, "The Evolution Of Business Process Management: A Bibliometric Analysis," *Ieee Access*, Vol. 9, Pp. 51088–51105, Jan. 2021, Doi: 10.1109/Access.2021.3066340.
- [2] W. Van Der Aalst And J. Carmona, *Process Mining Handbook*. 2022. Doi: 10.1007/978-3-031-08848-3.
- [3] M. Dumas Et Al., "Ai-Augmented Business Process Management Systems: A Research Manifesto," *Acm Transactions On Management Information Systems*, Vol. 14, No. 1, Pp. 1–19, Jan. 2023, Doi: 10.1145/3576047.
- [4] S. Weinzierl, S. Zilker, S. Dunzer, And M. Matzner, "Machine Learning In Business Process Management: A Systematic Literature Review," *Expert Systems With Applications*, Vol. 253, P. 124181, May 2024, Doi: 10.1016/J.Eswa.2024.124181.
- [5] M. Abbasi Et Al., "A Review Of Ai And Machine Learning Contribution In Business Process Management (Process Enhancement And Process Improvement Approaches)," *Business Process Management Journal*, Vol. 31, No. 4, Pp. 1414–1452, Nov. 2024, Doi: 10.1108/Bpmj-07-2024-0555.
- [6] A. Zebec And M. I. Štemberger, "Creating Ai Business Value Through Bpm Capabilities," *Business Process Management Journal*, Vol. 30, No. 8, Pp. 1–26, Apr. 2024, Doi: 10.1108/Bpmj-07-2023-0566.
- [7] M. Kohlbacher And S. Gruenwald, "Process Ownership, Process Performance Measurement And Firm Performance," *International Journal Of Productivity And Performance Management*, Vol. 60, No. 7, Pp. 709–720, Sep. 2011, Doi: 10.1108/17410401111167799.
- [8] K. B. Danilova, "Process Owners In Business Process Management: A Systematic Literature Review," *Business Process Management Journal*, Vol. 25, No. 6, Pp. 1377–1412, Dec. 2018, Doi: 10.1108/Bpmj-05-2017-0123.
- [9] M. J. Page Et Al., "The Prisma 2020 Statement: An Updated Guideline For Reporting Systematic Reviews," *Bmj*, Vol. 372, P. N71, Mar. 2021, Doi: 10.1136/Bmj.N71.
- [10] M. Imran, S. Hamid, And M. A. Ismail, "Advancing Process Audits With Process Mining: A Systematic Review Of Trends, Challenges, And Opportunities," *Ieee Access*, Vol. 11, Pp. 68340–68357, Jan. 2023, Doi: 10.1109/Access.2023.3292117.
- [11] A. Mamudu, W. Bandara, M. T. Wynn, And S. J. J. Leemans, "Process Mining Success Factors And Their Interrelationships," *Business & Information Systems Engineering*, Vol. 67, No. 3, Pp. 389–408, Mar. 2024, Doi: 10.1007/S12599-024-00860-Z.
- [12] L. Marcus, S. J. Schmid, F. Friedrich, M. Röglinger, And P. Grindemann, "Navigating The Landscape Of Organizational Process Mining Setups," *Business & Information Systems Engineering*, Vol. 68, No. 1, Pp. 137–158, Nov. 2024, Doi: 10.1007/S12599-024-00908-0.
- [13] N. Martin Et Al., "Opportunities And Challenges For Process Mining In Organizations: Results Of A Delphi Study," *Business & Information Systems Engineering*, Vol. 63, No. 5, Pp. 511–527, Oct. 2021, Doi: 10.1007/S12599-021-00720-0.
- [14] T. Grisold, J. V. Brocke, S. Gross, J. Mendling, M. Röglinger, And K. Stelzl, "Digital Innovation And Business Process Management: Opportunities And Challenges As Perceived By Practitioners," *Communications Of The Association For Information Systems*, Vol. 49, No. 1, Pp. 556–571, Jan. 2021, Doi: 10.17705/1cais.04927.
- [15] G. D. Kerpedzhiev, U. M. König, M. Röglinger, And M. Rosemann, "An Exploration Into Future Business Process Management Capabilities In View Of Digitalization," *Business & Information Systems Engineering*, Vol. 63, No. 2, Pp. 83–96, Mar. 2020, Doi: 10.1007/S12599-020-00637-0.
- [16] A. Mamudu, W. Bandara, S. J. J. Leemans, And M. T. Wynn, "A Process Mining Impacts Framework," *Business Process Management Journal*, Vol. 29, No. 3, Pp. 690–709, Feb. 2023, Doi: 10.1108/Bpmj-09-2022-0453.
- [17] J. V. Brocke, M. Jans, J. Mendling, And H. A. Reijers, "A Five-Level Framework For Research On Process Mining," *Business & Information Systems Engineering*, Vol. 63, No. 5, Pp. 483–490, Sep. 2021, Doi: 10.1007/S12599-021-00718-8.
- [18] K. Lazaros, A. G. Vrahatis, And S. Kotsiantis, "Human-In-The-Loop Artificial Intelligence: A Systematic Review Of Concepts, Methods, And Applications," *Entropy*, Vol. 28, No. 4, P. 377, Mar. 2026, Doi: 10.3390/E28040377.
- [19] J. Rott, M. Böhm, And H. Kremer, "Laying The Ground For Future Cross-Organizational Process Mining Research And Application: A Literature Review," *Business Process Management Journal*, Vol. 30, No. 8, Pp. 144–206, Jun. 2024, Doi: 10.1108/Bpmj-04-2023-0296.
- [20] M. R. Da Silva, N. De Souza Mayrink Resende, And E. P. Da Silva-Dias, "Connections Between Governance And Business Process Management – Bpm," *International Journal For Innovation Education And Research*, Vol. 10, No. 4, Pp. 221–235, Apr. 2022, Doi: 10.31686/Ijier.Vol10.Iss4.3733.
- [21] C. A. Kesici, N. Ozkan, S. Taşkesenlioglu, And T. G. Erdogan, "A Systematic Literature Review Of Studies Comparing Process Mining Tools," *International Journal Of Information Technology And Computer Science*, Vol. 14, No. 5, Pp. 1–14, Oct. 2022, Doi: 10.5815/Ijitsc.2022.05.01.
- [22] V. Braun and V. Clarke, "Using thematic analysis in psychology," *Qualitative Research in Psychology*, vol. 3, no. 2, pp. 77–101, Jan. 2006, doi: 10.1191/1478088706qp0630a.
- [23] J. Thomas and A. Harden, "Methods for the thematic synthesis of qualitative research in systematic reviews," *BMC Medical Research Methodology*, vol. 8, no. 1, p. 45, Jul. 2008, doi: 10.1186/1471-2288-8-45.
- [24] D. Moher, A. Liberati, J. Tetzlaff, D. G. Altman, and P. Group, "Preferred reporting items for Systematic Reviews and Meta-Analyses: the PRISMA statement," *PLoS Medicine*, vol. 6, no. 7, p. e1000097, Jul. 2009, doi: 10.1371/journal.pmed.1000097.
- [25] W. Van Der Aalst et al., "Process Mining manifesto," *Lecture Notes in Business Information Processing*, pp. 169–194, Jan. 2012, doi: 10.1007/978-3-642-28108-2_19.
- [26] M. H. Jarrahi, "Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making," *Business Horizons*, vol. 61, no. 4, pp. 577–586, Apr. 2018, doi: 10.1016/j.bushor.2018.03.007.
- [27] N. Diakopoulos, "Accountability in algorithmic decision making," *Communications of the ACM*, vol. 59, no. 2, pp. 56–62, Jan. 2016, doi: 10.1145/2844110.
- [28] D. Doneda and V. A. F. Almeida, "What is algorithm governance?," *IEEE Internet Computing*, vol. 20, no. 4, pp. 60–63, Jul. 2016, doi: 10.1109/mic.2016.79.
- [29] B. C. Cheong, "Transparency and accountability in AI systems: safeguarding wellbeing in the age of algorithmic decision-making," *Frontiers in Human Dynamics*, vol. 6, Jul. 2024, doi: 10.3389/fhumd.2024.1421273.
- [30] O. B. D. S. Moderno, A. C. Braz, and P. T. De Souza Nascimento, "Robotic process automation and artificial intelligence capabilities driving digital strategy: a resource-based view," *Business Process Management Journal*, vol. 30, no. 1, pp. 105–134, Nov. 2023, doi: 10.1108/bpmj-08-2022-0409.
- [31] Y. L. Antonucci, A. Fortune, and M. Kirchmer, "An examination of associations between business process management capabilities and the benefits of digitalization: all capabilities are not equal," *Business Process Management Journal*, vol. 27, no. 1, pp. 124–144, Jul. 2020, doi: 10.1108/bpmj-02-2020-0079.

- [32] M. Froger, F. Bénaben, S. Truptil, and N. Boissel-Dallier, "A non-linear business process management maturity framework to apprehend future challenges," *International Journal of Information Management*, vol. 49, pp. 290–300, Jun. 2019, doi: 10.1016/j.ijinfomgt.2019.05.013.
- [33] E. Gökalp and V. Martinez, "Digital transformation capability maturity model enabling the assessment of industrial manufacturers," *Computers in Industry*, vol. 132, p. 103522, Jul. 2021, doi: 10.1016/j.compind.2021.103522.
- [34] N. Donthu, S. Kumar, D. Mukherjee, N. Pandey, and W. M. Lim, "How to conduct a bibliometric analysis: An overview and guidelines," *Journal of Business Research*, vol. 133, pp. 285–296, May 2021, doi: 10.1016/j.jbusres.2021.04.070.
- [35] A. Batool, D. Zowghi, and M. Bano, "AI governance: a systematic literature review," *AI And Ethics*, vol. 5, no. 3, pp. 3265–3279, Jan. 2025, doi: 10.1007/s43681-024-00653-w.
- [36] A. M. Barbala, G. K. Hanssen, and T. Sporse, "Towards a common data-driven culture: A longitudinal study of the tensions and emerging solutions involved in becoming data-driven in a large public sector organization," *Journal of Systems and Software*, vol. 218, p. 112185, Aug. 2024, doi: 10.1016/j.jss.2024.112185.
- [37] M.-T. Huynh, "Individual Data-Driven mindset and Decision-Making performance: the mediating roles of effort and persistence," *Information Systems Frontiers*, vol. 27, no. 6, pp. 2511–2538, Oct. 2025, doi: 10.1007/s10796-025-10647-6.
- [38] A. E. Marquez-Chamorro, M. Resinas, and A. Ruiz-Cortes, "Predictive Monitoring of Business Processes: a survey," *IEEE Transactions on Services Computing*, vol. 11, no. 6, pp. 962–977, Nov. 2017, doi: 10.1109/tsc.2017.2772256.
- [39] W. Kratsch, J. Manderscheid, M. Röglinger, and J. Seyfried, "Machine learning in Business Process Monitoring: A comparison of deep learning and classical approaches used for outcome prediction," *Business & Information Systems Engineering*, vol. 63, no. 3, pp. 261–276, Apr. 2020, doi: 10.1007/s12599-020-00645-0.
- [40] M. Rosemann, J. V. Brocke, A. Van Looy, and F. Santoro, "Business process management in the age of AI – three essential drifts," *Information Systems and e-Business Management*, vol. 22, no. 3, pp. 415–429, Sep. 2024, doi: 10.1007/s10257-024-00689-9.