Process Automation with BPM and Emerging Technologies for Service and Industrial Process Optimization: Systematic Mapping

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Abstract

Context: The adoption of emerging technologies such as Artificial Intelligence (AI), Machine Learning (ML), Robotic Process Automation (RPA), and Process Mining (PM) is transforming business process management (BPM) and mainly its automation process, enhancing operational efficiency in services and industrial processes, and promoting innovation. Problem: The integration of emerging technologies with BPM faces organizational and technical challenges, including workforce adaptation, resistance to change and high costs, limiting its potential to increase efficiency and productivity. Solution: This article aims to investigate and analyze the approaches and structures that enable the integration of emerging technologies with BPM, addressing key questions of interest regarding their impact, implementation, and effectiveness in organizational settings. Information Systems Theory: This research was based on the aegis of the Diffusion of Innovations Theory, exploring how emerging technologies drive innovations in BPM, transforming organizational processes, accelerating automation and promoting operational efficiency and workforce reorganization. Method: We conducted a systematic mapping of studies published between 2019 and 2024, with a quantitative analysis of the selected studies. Summary of Results: The analysis highlighted AI, RPA, and Process Mining as the most cited technologies in BPM automation. However, gaps were identified in the integration of emerging technologies, pointing out technical challenges and opportunities for improvement. Contributions and Impact: This article provides insights into the integration of emerging technologies with BPM, addressing workforce adaptation and resistance to change. Its findings foster artifacts for IT managers and BPM professionals, promoting efficiency, competitiveness, innovation and new academic research.

CCS Concepts

• **Information systems** → *Information systems applications.*

Keywords

Business Process Management, Emerging Technologies, Process Automation, Diffusion of Innovations

1 Introduction

Business Process Management combined with emerging technologies, such as Robotic Process Automation, is increasingly adopted to enhance organizational efficiency, reduce operational costs, and improve service quality across diverse sectors. The integration of emerging technologies, such as Artificial Intelligence and machine learning, enables the handling of high-volume tasks, increasing efficiency and reducing costs. When combined with Business Process Management, these technologies present significant potential to transform workflows and improve service quality, meeting demands across various sectors [22]. BPM structures the modeling, analysis, monitoring, and optimization of workflows, enabling organizations to boost productivity and reduce operational errors. This methodology fosters a culture of continuous monitoring and collaboration among teams, supporting a dynamic and adaptive approach in response to advancements in Artificial Intelligence, Machine Learning, and other market-driven technologies. However, for these automation initiatives to be successful, it is essential to overcome organizational challenges, such as user resistance and the complexity of integrating RPA with the organization's strategic objectives. This explains the high failure rate in RPA implementations, which often result from managerial issues rather than technical ones Nielsen et al. [20].

Research Problem: Integrating emerging technologies with BPM presents organizational and technical challenges, including workforce adaptation, resistance to change, and high costs, which can limit the potential improvements in efficiency and productivity. **Central Research Question:** This study addresses the following question: *How are emerging technologies being integrated into BPM to optimize process automation in services and industries?* **Motivations:** The growing relevance of process automation underscores the need for consolidated practices and knowledge that can guide academia and industry in effectively integrating BPM with emerging technologies. **Objectives:** The study aims to investigate the current state of process automation with BPM in organizations by mapping key challenges, opportunities, impacts, and operational benefits to consolidate existing knowledge and provide insights that guide future research and practices.

2 Literature Review

This section contains a conceptual overview of the main technological innovations in the articles studied that have the potential to transform the management and optimization of business processes and its management. Technologies such as Robotic Process Automation, Artificial Intelligence, Process Mining, Machine Learning, Natural Language Processing (NLP), and Generative Pre-trained Transformer (GPT), which promote efficiency and increase operational precision, are highlighted. Next, analysis and discussion of the main works related to this research are carried out. It will be essentially focused on the articles related to the approaches that categorize the different emerging technologies with BPM. The theory used in this research on Information Systems is also presented.

2.1 Business Process Management

According to [28, p. 3], the concept of Business Process Management comes from management techniques focused on guiding and aligning business processes in line with the objectives of an organization and the needs of its customers. In a complementary way, according to [1, p. 303], "business process management involves the analysis, design, implementation, monitoring and optimization of business processes". There has been an evolution of BPM, according to [28], BPM has become a management discipline that approaches the management of business processes in such a way as to guarantee consistent results while taking advantage of opportunities for improvement.

2.2 Robotic Process Automation

As noted in [11, p.7], the majority of definitions provided in the reviewed articles describe traditional Robotic Process Automation as an emerging technology aimed at automating repetitive human tasks in both digital and physical environments. As stated in [31, p. 2], RPA is commonly used and frequently considered in relation to traditional automation solutions, as it operates directly on the graphical user interface (GUI), making it a non-intrusive technology that is easier to implement. Consequently, RPA is often applied to automate high-volume, repetitive tasks that follow consistent cycles and are based on predefined rules. Emerging technologies or advanced technologies applied to the business process ecosystem and its management have been the subject of study in the scientific community, which commercially reverberates in products and services in the organizations that implement them. As stated at the opening of this section, the scientific literature covered in this research reveals six main emerging technologies, and it is possible to find the distribution of various applications of these technologies for process automation with business process management. One of the emerging technologies in particular that has been adopted in the commercial and industrial sectors, in terms of process automation, is Robotic Process Automation. It's worth noting that this study found many scientific articles on the use of RPA applied to process automation in organizations. It is interesting to add, as can be seen in [25, p. 1], that people have an initial misconception about RPA, because this technology is not used with physical robots that carry out operational processes, but with digital robots, as mentioned previously [31, p. 2]. Some of the characteristics attributed to RPA are: a) Automation of Repetitive and Rule-Based Tasks; b) Interface with Legacy Systems via GUI; c) Scalability and Flexibility; d) Error Reduction and Increased Compliance; d) Cost-Effectiveness and Speed of Implementation [25]. These characteristics highlight the value added by RPA to Business Process Management, making the automation of processes in organizations more efficient, faster and enabling their operations to become scalable in an agile and sustainable manner.

2.3 Process Mining

Process Mining is cited by [31, p. 124] as being "the semi-automated approach to discovering process knowledge from event logs. It is also seen as a facilitator in other areas such as simulation, prediction and automation of robotic processes". Also according to [31] this emerging technology aims to obtain process models from event logs generated by process-aware information systems (PAIS) in an up-to-date and accurate manner, providing transparency for business process analysis [31, p. 124]. Process mining uses event logs from different IT systems in a company to map processes as they are. Event logs usually contain a case ID, the process activity and its timestamp. With this information, process mining can record the course and performance (e.g. time) of each process run [30, p. 422]. On-time delivery in order processing remains a key success factor for manufacturing companies. Process mining is a modern approach to data-driven process science, creating a digital process image from event logs [30, p. 422].

2.4 Machine Learning

As defined in [3, p. 2] "a computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.". This technique allows systems to identify complex patterns in data and adjust their actions based on accumulated knowledge. In consequence, the system's performance continually improves on similar tasks. The main characteristics of Machine Learning [3] specify Data-based models, Algorithms and training processes, Generalization and optimization and evaluation techniques. In addition, [3] cites that ML as being categorized in terms of learning methods as: Supervised, Unsupervised, Semi-supervised and "by Reinforcement". According to [1, p. 303], machine learning techniques can be used to improve BPM and help organizations achieve these goals. They can help organizations improve the quality of services offered, support scalability through automation, and reduce costs.

2.5 Artificial Intelligence

As [27] cites, "Artificial Intelligence is the field of Computer Science dedicated to the development of systems that simulate aspects of human intelligence, such as perception, learning, reasoning and decision-making". In addition, [29, p. 606] also defines Artificial intelligence is a collection of information communication technologies (ICTs) that imitate human intelligence for the primary purpose of improving jobs, creating greater efficiencies, and driving economic growth. AI involves techniques and algorithms that allow machines to perform tasks autonomously, usually by applying machine learning models to optimize their performance based on data, complements [27].

2.6 Natural Language Processing

Natural Language Processing is considered a subfield of Artificial Intelligence aimed at enabling computer systems to interpret, understand and generate human language in a relevant manner. [31, p.

126] cites that “the literature shows many examples of the utilization of NLP in order to enable RPA in the context of automating tasks that deals with unstructured data but are otherwise routine”. [10, p. 2] cites "One of the most important advantages is that integrating RPA with technologies like machine learning, Natural Language Process and data analytics enables digital software assistance to control, manage and improve business processes in real-time and optimize their efficiency".

2.7 Generative Pre-trained Transformer

Generative Pre-trained Transformer is defined by [2, p. 731] as “a state-of-the-art machine learning model capable of generating human-like text through natural language processing”. Also, [2] adds that the GPT model is trained on large volumes of textual data and utilizes deep learning techniques to recognize patterns and relationships in the data set, allowing it to generate consistent and contextualized text. There are automation processes that require natural language understanding. The integration of RPA width, for example, ChatGPT [13, p. 3249] makes this possible. The versatility of this technology enables various applications in the field of business process automation with a wide scope in the organization. There are some practical cases as stated in [13, p. 3244]:

- Text translation: when the automation process requires the use of several languages, such as sending personalized offers to customers around the world, analyzing competitor data from different regions or improving communication in an international environment.
- Assisting the HR department: a combination of RPA and ChatGPT can help with the entire recruitment process, from creating job advertisements, analyzing and shortlisting candidates, to scheduling questions and preparing for the interview process.
- Web text analysis: in the age of vast amounts of information on the web, such a combination can perform tasks unattainable for a human. RPA takes care of downloading and managing content, which is then transferred to ChatGPT for analysis. The result can be summaries, reports or content categorization.
- Mailbox automation: this integration brings tangible benefits to the flow of information. One example is analyzing the content of incoming emails and forwarding them to the appropriate departments with a certain level of priority. It is also possible to generate personalized responses, thus supporting customer service in the company.

2.8 A brief approach to Diffusion of Innovation Theory

This paper is based on the Diffusion of Innovation Theory (DOI) to analyze the adoption of emerging technologies in BPM, categorizing them and assessing their impact. The Diffusion of Innovation Theory, proposed by Everett Rogers [5] provides a framework for understanding how and why new technologies are adopted, considering factors such as relative advantage, compatibility, complexity, experimentation and observability. It was noted during the process of reading the articles that one of the important points highlighted regarding the adoption of new technologies, the so-called emerging technologies, for the optimization of services and industrial processes was the frequent mention of resistance by the workforce in organizations to the adoption of technological innovations. It was also noted, as noted in [28, p. 29], that in order to find a solution to this type of scenario, measures were adopted, such as implementing “Change Management” in the organizational culture and training employees to assimilate emerging technologies and continuous learning [9, p. 80].

2.9 Related Work

Robotic Process Automation (RPA) is one of the most cited emerging technologies in the articles reviewed, highlighting its potential to increase efficiency and reduce manual labor, especially in the accounting field [12]. However, there is still skepticism among professionals due to technical challenges and limitations in document processing [12]. Additionally, issues related to organizational change management and low initial employee adoption of innovations are frequently discussed [5], [28].

Research by [11] points to the lack of theoretical studies on the use of RPA in business processes and suggests the need for investigations into its direct and indirect effects on organizational performance. The paper by [35] explores the integration of RPA with ERP systems, showing benefits such as increased productivity and cost reductions, but also highlighting the complexity of this integration due to the variability of workflows and the constant maintenance required for RPA bots.

Other works, such as [31], propose cognitive frameworks for automating specific tasks, such as email data entry, using RPA and NLP (Natural Language Processing), while also discussing gaps in tools and approaches to integrate these technologies. In [33], the growing number of process mining (PM) tools on the market is noted, and the importance of combining human and machine intelligence for automating complex processes, such as those in ERP systems, is emphasized.

Criticism of Business Process Management (BPM) due to its rigidity and automation limitations is addressed in [36], which advocates for the use of AI to enable more adaptable and intelligent processes. The paper by [1] explores the use of ML (Machine Learning) to improve the discovery and modeling of processes, while [19] suggests that technologies like text mining, NLP, and speech recognition can enhance customer service interactions.

The potential to integrate RPA with technologies such as GPT is discussed in [13], highlighting benefits like improved customer interactions and streamlined workflows, while also addressing challenges related to maintenance and costs. The concept of Intelligent Process Automation (IPA), which combines ML and AI to optimize processes, is covered in [1], while [10] presents a strategic model for guiding IPA implementation in the context of digital transformation, proposing future research on orchestrating human and digital interactions. Finally, intelligent automation is defined as a combination of RPA, AI, and Soft Computing, which can significantly improve operational efficiency and decision-making [19].

3 Methodology

This section details the methodological approach used to conduct the systematic literature mapping. The approach follows the structured guidelines proposed by Kitchenham, Budgen, and Brereton [15], which serves as a basis for systematic research practices.

The study is descriptive in nature, aiming to systematically map and analyze recent literature on the application of business process management and process automation in organizations. It takes a quantitative approach to evaluate and synthesize data collected from selected scientific databases, ensuring that the research remains evidence-based.

Figure 1 provides an overview of the methodological process, which is divided into three main phases: Planning, Selection, and Execution.

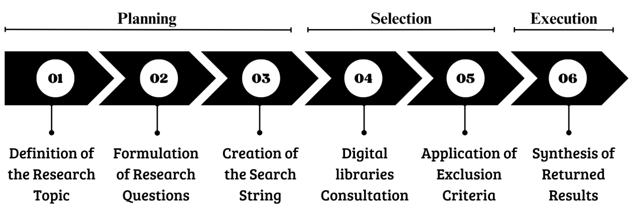

Figure 1: Flowchart of the Methodological Process

3.1 Secondary research questions

From the central research question, three secondary questions were formulated to explore emerging technologies, technical and organizational challenges, and best practices for integrating BPM in different organizational contexts.

- **RQ1**: What are the main emerging technologies utilized in process automation across various sectors?
- **RQ2**: What technical and organizational challenges are associated with the implementation of BPM using emerging technologies?
- **RQ3**: What are the best practices for successfully integrating emerging technologies with BPM in organizational contexts?

3.2 Inclusion Criteria

The inclusion criteria ensure that selected studies are recent, peer-reviewed, and relevant to the research questions. The criteria are as follows:

(1) Studies must have been published in the last 5 years (2020-2024).
(2) Only peer-reviewed journal and conference articles were included.
(3) Studies that explicitly address the application of process automation with BPM in organizations, answering at least one of the specific research questions.

3.3 Exclusion Criteria

The exclusion criteria were applied to remove studies that do not align with the scope or relevance of the research:

- **EC1: Language**: Articles written in languages other than English.
- **EC2: Type of Publication**: Grey literature, including theses, dissertations, books, book chapters, technical reports, and industry reports that are not peer-reviewed.
- **EC3: Content Relevance and Availability**: Studies that do not directly address BPM and process automation with emerging technologies, or that have less than three pages or unavailable full texts.

3.4 Search Strategy and Execution

The search strategy was designed to identify studies related to Business Process Management and its applications in process automation and optimization. The following search string was applied across multiple digital libraries to retrieve relevant literature:

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(("Business Process Management" OR BPM OR
"Process Management") AND ("Process Automation"
OR "Business Process Automation" OR "Process
Optimization"))
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This query was executed on three major databases: ScienceDirect, Scopus, and IEEE Xplore. The initial search yielded a total of 975 papers, as shown in Table 1.

Table 1: Number of papers retrieved from digital libraries (Initial Results)

Database	Number of Papers
ScienceDirect	647
Scopus	261
IEEE Xplore	67
Total	**975**

The results were then subjected to a systematic filtering process based on predefined exclusion criteria, focusing on relevance to BPM and automation. Papers were excluded if they were duplicates, not peer-reviewed, or outside the research scope. Figure 2 illustrates the article selection process, showing the initial retrieval counts, exclusions by criteria (EC1, EC2, and EC3), and the total number of articles included after filtering.

The remaining papers were then evaluated in a second filter involving full-text reading, where articles were further excluded if they did not meet the research relevance criteria. Table 2 summarizes the results after the second filter (full-text reading).

Table 2: Results of the Second Filter (Full-text Reading)

Database	Excluded	Included
IEEE Xplore	3	17
ScienceDirect	25	25
Scopus	19	16
Total	**47**	**58**

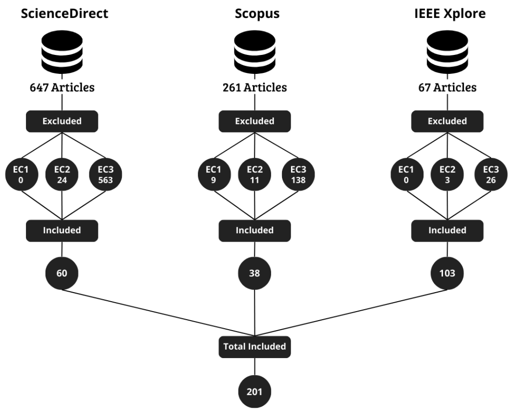

Figure 2: Article Selection Process for Systematic Review - First Filter

After the second filter, a total of 58 articles were accepted for final analysis, representing studies that directly address the research questions related to BPM and process automation with emerging technologies.

3.5 Selected Articles Per Year

Figure 3 presents the distribution of selected articles per year, offering insights into the systematic mapping process and highlighting the concentration of relevant research studies on integrating Business Process Management with emerging technologies. The data spans from 2019 to 2024, representing the number of articles chosen after applying the defined inclusion and exclusion criteria.

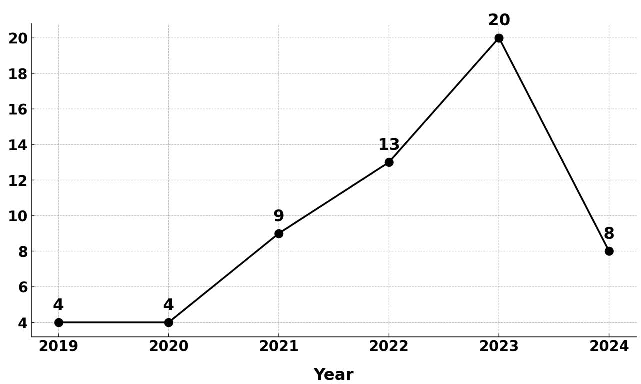

Figure 3: Number of selected articles per year (2019–2024).

3.6 Threats to Validity

The assessment of threats to validity is essential to ensure the credibility and reliability of the results of this systematic mapping study. Based on the classification proposed by Wohlin et al. [34], we consider four main categories of threats to validity: conclusion validity, internal validity, construct validity, and external validity. Conclusion validity is related to the ability to identify statistically reliable relationships between the variables analyzed. In our case, issues such as low statistical power, due to study selection, or the use of inappropriate statistical tests, may arise. To minimize this, we applied rigorous criteria for selecting the articles and used appropriate analyses to identify patterns in the data. Internal validity concerns the ability to establish that an observed effect is truly caused by the factors under analysis, and not by other elements. An identified risk is the inappropriate selection of studies or external influences that may distort the results, such as historical factors specific to each article. To mitigate this issue, we followed a careful screening and data analysis process. Construct validity is related to the adequacy between theoretical concepts and the study's observations. A challenge was ensuring that concepts such as "emerging technologies" and "process automation" were clearly defined and understood. To address this, we based our definitions on recognized sources and used a well-founded theoretical framework. Finally, external validity considers the possibility of generalizing the study's results to other contexts. One risk is that the studies analyzed may only reflect practices specific to certain sectors or regions. To reduce this limitation, we sought to include articles from different sectors and contexts, broadening the applicability of the conclusions. These measures were taken to ensure that the results obtained are reliable and can make a meaningful contribution to advancing the integration of emerging technologies in BPM.

4 Results

This section presents the results of the systematic literature mapping, structured to address the central research question: *How are emerging technologies being integrated with BPM to optimize process automation in services and industries?* The results are divided into three parts related to specific research questions (RQ1, RQ2 and RQ3), defined below.

4.1 RQ1: What are the main emerging technologies utilized in process automation across various sectors?

The first research question examines the main emerging technologies used in the automation. Our quantitative analysis of the selected studies highlights the technologies often associated with BPM implementation, including robotic process automation, artificial intelligence, machine learning, and process mining.

Table 3: Emerging Technologies in Process Automation

Technology	Articles Mentioned
Robotic Process Automation	44
Machine Learning	40
Artificial Intelligence	36
Process Mining	29
Deep Learning	14
Others Technologies	4

Table 3 shows the frequency of each technologies occurrence across articles.

Data shows that AI and RPA are the most widely used BPM-based automation methods. The research analyzed shows that this technology is more widespread in sectors such as finance, medicine and production, where it is necessary to improve organizational performance.

Robotic Process Automation: RPA is commonly highlighted as a transformative tool in automating repetitive tasks across sectors. For instance, [25] describes RPA's role in reducing time spent on routine tasks, allowing auditors to focus on more complex analyses. Similarly, [29] emphasizes the importance of systematic risk assessments in RPA implementations to ensure both security and efficiency. Furthermore, [7] applies a multi-criteria analysis (AHP-TOPSIS) to identify processes for automation, evaluating criteria such as complexity, frequency, and maturity.

Machine Learning: ML enables the prediction and analysis of future trends and operational outcomes. [8] examines ML's role in predictive analytics within process mining, illustrating how algorithms are used to anticipate operational challenges. Further, [30] explores the utilization of clustering and classification techniques to identify inefficiencies in workflows. The deployment of deep learning in [23] showcases its application in predictive process monitoring, including anomaly detection and next-step predictions in business processes.

Artificial Intelligence: AI plays a crucial role in creating intelligent, adaptable systems that enhance decision-making in dynamic environments. [21] highlights AI's contributions to organizational efficiency through its ability to handle complex data scenarios. Moreover, [13] demonstrates the integration of AI models like GPT with RPA, streamlining tasks such as text analysis, customer service, and translation, exemplifying AI's versatility and transformative potential.

Process Mining: Process mining offers tools to analyze and optimize workflows using event log data. [30] highlights process mining's role in identifying inefficiencies within production flows, while [26] demonstrates the use of predictive analytics to anticipate operational issues, such as flight delays, thereby improving performance. Additionally, tools like Alpha Miner and Inductive Miner are used in [17] to provide insights into real-time process execution.

Deep learning

Deep learning has significantly improved anomaly detection capabilities in Robotic Process Automation (RPA) systems. According to [18], integrating deep learning into RPA systems allows for enhanced detection of anomalies within business processes by leveraging advanced pattern recognition techniques. The study highlights the role of unsupervised learning models, which can identify anomalies without predefined labels, making them particularly effective in dynamic environments where traditional methods fall short.

Other Technologies: Additional studies highlight technologies such as no-code platforms, which empower non-technical users to automate processes with minimal coding, supporting digital transformation initiatives [6]. Furthermore, [14] explores the use of BDI (Belief-Desire-Intention) intelligent agents that autonomously adapt business processes in response to environmental changes, thereby creating a self-adjusting BPM framework.

> In summary, the reviewed studies underscore the diversity of emerging technologies applied in BPM-driven automation, each contributing unique capabilities to process optimization across various industries.

4.2 RQ2: What technical and organizational challenges are associated with the implementation of BPM using emerging technologies?

The second research question investigates the technical and organizational challenges associated with implementing BPM alongside emerging technologies. The reviewed studies reveal that integration issues, data management, and resistance to change are prominent barriers in such implementations.

Table 4: Key Challenges in BPM Implementation with Emerging Technologies

Category	Challenge
Technical	System Integration
Technical	Data Quality
Organizational	Resistance to Change
Organizational	Skills Gap
Security and Privacy	Data Sensitivity

Technical Challenges: Studies indicate that one of the primary technical challenges in BPM with emerging technologies is the integration of disparate systems and handling data complexities. [25] highlights the need to standardize data formats for RPA bots, particularly when dealing with optical character recognition (OCR) in document processing (pp. 6-7). [29] discusses the difficulties of adapting RPA bots in response to changes in legacy systems and managing risks in complex IT environments (pp. 189-191). Furthermore, [7] warns about the improper selection of processes for automation, which can lead to unsuccessful RPA implementations due to inadequate decision criteria (pp. 6-7).

Process mining faces similar challenges, as noted in [30], which cites the difficulty of integrating data from multiple IT systems and the lack of specialized knowledge among employees as obstacles to broader adoption (p. 420). [23] further emphasizes the importance of data preprocessing to ensure prediction model accuracy, noting that model performance is highly sensitive to data quality and adaptability (pp. 4-5).

Organizational Challenges: Organizational challenges often stem from cultural resistance to change, skills gaps, and privacy concerns. According to [21], employees may resist AI-powered systems due to concerns over new knowledge integration and the impact on existing workflows, which necessitates a supportive environment and effective training programs. Additionally, [16] points out that implementing Lean practices before automation can mitigate resistance but requires a significant cultural shift within the organization (pp. 7-8).

[14] discusses the need for strategic alignment between automated process models and organizational goals, coupled with a

cultural readiness to accept automated decision-making systems (pp. 7, 9). [19] underscores that technological readiness, cultural adaptation, and reskilling are essential for successful BPM implementation, suggesting a gradual integration approach to avoid operational disruptions.

Security and Privacy Concerns: Security and privacy challenges are also frequently cited, especially when sensitive data is involved. For example, [4] addresses auditors' resistance to new technologies due to the risks associated with handling confidential information (pp. 6-7). In the context of generative AI, [13] notes concerns about the legality and security of using AI models like ChatGPT in data-sensitive environments, particularly in European markets with stringent privacy regulations (pp. 3250-3251).

In summary, the reviewed studies highlight a range of challenges in BPM implementations involving emerging technologies. Technical difficulties often relate to data management, system integration, and model maintenance, while organizational challenges focus on change resistance, skill requirements, and privacy issues. These findings suggest that successful BPM implementations require both technical preparedness and organizational adaptability.

4.3 RQ3: What are the best practices for successfully integrating emerging technologies with BPM in organizational contexts?

To ensure a successful integration of emerging technologies with Business Process Management, organizations need to adopt a range of best practices that address both the technical and organizational aspects of the implementation. The analysis of selected studies reveals various practices that have proven effective in maximizing the benefits of process automation. These best practices are categorized into the following key points:

Table 5: Best Practices for BPM Integration with Emerging Technologies

Practice
Process Standardization and Prototyping
Risk Management and Prioritization
Simulation and Resource Allocation
Employee Training and Knowledge Transfer
Lean Process Analysis Before Automation
Adaptive and Holistic Process Modeling
Interactive Visualization Tools
Decision Support Systems and Performance Indicators
Gradual and Phased Integration
Pilot Programs and Iterative Testing
Sustainable Decision-Making Models
Change Management and Continuous Learning
Stakeholder Engagement and Cross-Functional Collaboration
Establishing Performance Metrics and Continuous Monitoring

Process Standardization and Prototyping: Before implementing automation solutions like Robotic Process Automation, it is essential to standardize processes and create prototypes to validate the technology. Standardized processes facilitate smoother automation, reducing the likelihood of inconsistencies and errors. For instance, [25] emphasizes the importance of process standardization and suggests the creation of prototypes to test RPA implementations. Additionally, decentralizing bot governance—allowing each business area to manage its bots—enhances adaptability and simplifies ongoing maintenance.

Risk Management and Prioritization: Effective risk management is crucial for the successful integration of RPA and other BPM technologies. Schlegel et al. [29] recommends the use of an impact and uncontrollability matrix to identify and prioritize risks in RPA projects. This approach enables project managers to develop targeted risk mitigation strategies, focusing on factors that most influence project success. Similarly, Costa et al. [7] advocates using AHP-TOPSIS as a structured decision-making tool for selecting processes that are well-suited for automation, thus minimizing the risks of unsuccessful implementations.

Simulation and Resource Allocation: To ensure resource allocation aligns with process needs, simulation-based methods can be used to test strategies before real-world application. Durán et al. [8] highlights the use of simulations to optimize resource provision, which allows organizations to adjust resource allocation in advance, enhancing efficiency in automated processes.

Employee Training and Knowledge Transfer: Developing training programs and learning environments, such as "learning factories," can make complex technologies like process mining more accessible and comprehensible. Schuh et al. [30] suggests that such environments help employees understand the practical applications of process mining, improving their capacity to optimize workflow using this technology. In addition, predictive analytics and topic modeling can be employed to anticipate trends and fine-tune machine learning integrations with BPM, as noted by [23].

Lean Process Analysis Before Automation: Conducting a Lean analysis prior to RPA implementation allows organizations to identify non-value-added activities and simplify workflows. This ensures that only efficient and value-driven processes are automated, as recommended by Mamede et al. [16]. By refining processes beforehand, companies achieve more effective and sustainable automation.

Adaptive and Holistic Process Modeling: A holistic, adaptive approach to process modeling allows organizations to adjust automated processes as business needs evolve. Kir and Erdogan [14] emphasizes the importance of integrating intelligent agents and knowledge-intensive process modeling to allow for dynamic adjustments. Continuous refinement through process mining helps in identifying patterns in execution logs, enabling organizations to update their processes based on real-world data.

Interactive Visualization Tools: Providing interactive visualization tools can make complex workflows more understandable to non-technical users, fostering better insights into real-world process flows. Merkoureas et al. [17] recommends developing user-friendly interfaces that allow users to explore and analyze processes, which enhances comprehension and decision-making across organizational levels.

Decision Support Systems and Performance Indicators: Incorporating rule-based decision support models and defining clear performance indicators can improve decision-making and facilitate process optimization. Chhor et al. [6] suggests holding workshops with specialists to establish actionable recommendations, while process mining techniques help monitor and adjust processes continually, ensuring that any changes are systematically captured and analyzed.

Gradual and Phased Integration: A gradual approach to integrating RPA and more complex solutions, such as Intelligent Process Automation, enables organizations to make incremental adjustments. Ng et al. [19] underscores the importance of a phased implementation that prioritizes simpler technologies, allowing employees to adapt gradually. Human-in-the-loop (HITL) strategies—where humans oversee and intervene in automated tasks as needed—further enhance the effectiveness of this approach, especially in complex scenarios.

Pilot Programs and Iterative Testing: Starting with pilot implementations helps organizations assess the impact of new technologies before scaling up. For instance, Jasińska et al. [13] highlights the benefits of integrating RPA with AI models like GPT for complex language-processing tasks, recommending initial pilot projects to evaluate integration outcomes. Such pilots provide valuable insights that inform broader deployments, allowing organizations to refine their strategies based on observed results.

Sustainable Decision-Making Models: When implementing RPA and other BPM technologies, decision-making models that consider social, environmental, and economic impacts help ensure sustainable outcomes. Patrício et al. [24] emphasizes the importance of decision models that go beyond economic benefits, advocating for a holistic approach to sustainable automation that benefits various aspects of organizational well-being.

Change Management and Continuous Learning: Change management strategies are essential for fostering a culture that embraces technological change. Organizations should invest in employee training and support continuous learning to bridge the gap between traditional workflows and automated systems. Ivančić et al. [11] suggests that fostering a mindset of adaptability within the organizational culture can help mitigate resistance to change, which is a common barrier to successful integration.

Stakeholder Engagement and Cross-Functional Collaboration: Engaging stakeholders early in the implementation process and promoting collaboration across departments are critical for aligning technological initiatives with organizational goals. Szelągowski and Lupeikiene [32] recommends starting with small, cross-functional teams and scaling gradually, which enhances project success by integrating diverse expertise and fostering shared responsibility.

Establishing Performance Metrics and Continuous Monitoring: Defining and monitoring performance metrics allows organizations to measure the effectiveness of BPM integrations continuously. Szelągowski and Lupeikiene [32] highlights the importance of establishing clear indicators to assess automation outcomes and making iterative improvements based on feedback and performance data. This approach ensures that the integration remains aligned with organizational objectives and adapts to evolving requirements.

In summary, the reviewed studies underscore a range of best practices essential for the successful integration of emerging technologies with BPM. These practices emphasize a strategic, phased approach that involves stakeholder engagement, continuous monitoring, and comprehensive training. By adopting these strategies, organizations can enhance their ability to implement automation solutions that are not only efficient but also adaptable to future challenges and opportunities.

5 Discussion

The integration of Business Process Management with emerging technologies, such as Process Mining, Artificial Intelligence, Machine Learning, and Robotic Process Automation, highlights a promising shift in organizational efficiency, especially in sectors where agility and operational resilience are critical. Our systematic review underscores that technologies like RPA and AI are among the most commonly implemented within BPM frameworks, driven by demands for enhanced automation, predictive analytics, and data-driven decision-making. However, the adoption of these technologies also reveals a set of technical, organizational, and strategic challenges.

Role of Emerging Technologies in BPM: The review indicates that RPA and AI are widely implemented due to their ability to automate routine tasks and enable complex data analysis, respectively. Process Mining is recognized as a crucial tool for real-time process analysis and optimization, enabling organizations to identify inefficiencies and streamline workflows. AI and ML, on the other hand, allow for adaptive, predictive process adjustments that align with evolving business goals. The use of Intelligent Process Automation, which combines RPA and AI, further illustrates the shift toward cognitive automation capable of handling both structured and unstructured data, supporting decision-making in complex scenarios.

Challenges in BPM Technology Integration: A significant barrier to the successful integration of BPM and emerging technologies is the complexity of data and system integration. Many studies, such as [25] and [30], emphasize the need for standardized data formats and compatibility between legacy systems and modern automation tools. Furthermore, cultural resistance to change, highlighted in studies like [21] and [16], remains a persistent obstacle, often stemming from workforce apprehensions and inadequate training resources. Security and privacy concerns, particularly around AI and data-sensitive environments, underscore the importance of establishing robust data governance policies, as noted in [4] and [13].

Best Practices for Effective BPM Integration: Our findings suggest that best practices for BPM integration with emerging technologies should focus on strategic, phased approaches that prioritize employee engagement, training, and continuous monitoring. Process standardization and prototyping, as recommended by Perdana et al. [25], lay a stable foundation for automation, reducing inconsistencies. Risk management practices, such as impact and uncontrollability matrices for RPA projects [29], and simulation-based resource allocation [8], also contribute to a more resilient automation framework. Finally, incorporating Lean analysis before automation [16] and using interactive visualization tools [17] can improve user comprehension and organizational alignment.

Strategic Implications and Future Directions: The successful integration of BPM with technologies like RPA, AI, and ML not only optimizes processes but also promotes a data-driven culture that is essential for sustaining competitive advantage. Future research could focus on long-term cost-benefit analyses to quantify the economic impact of these technologies and investigate more advanced integrations, such as the potential of combining RPA with advanced AI language models like ChatGPT to streamline text-heavy processes. Furthermore, exploring the role of sustainable decision-making models, as suggested by Patrício et al. [24], could ensure that BPM technology adoption aligns with broader organizational values, including social and environmental considerations. In summary, our findings suggest that the integration of BPM with emerging technologies can drive substantial efficiency gains and support organizational agility. By adopting a structured, employee-centered approach and addressing technical challenges proactively, organizations can optimize the impact of BPM-driven automation. Future research should focus on further refining these best practices and exploring the dynamic interplay between BPM and technological advancements in evolving business environments.

6 Conclusions and Future Work

This systematic mapping study has highlighted the growing impact of process automation and emerging technologies integrated with BPM across various industries. Technologies such as Robotic Process Automation, Artificial Intelligence, Machine Learning, and Process Mining have shown considerable potential to streamline workflows, reduce operational costs, and increase service quality, particularly in sectors like finance, healthcare, and public administration. These tools enable enhanced productivity by automating repetitive tasks, facilitating data analysis, and supporting decision-making through predictive and adaptive models.

The findings emphasize the importance of careful selection and prioritization of processes for automation, considering both organizational goals and resource constraints. Incorporating risk management strategies, such as impact and uncontrollability matrices, is essential for ensuring stability and resilience in BPM implementations. Future research could further refine these frameworks, examining the long-term cost-benefit of RPA and related technologies to quantify their economic impact over extended periods.

Emerging trends suggest a promising trajectory for combining RPA with AI and ML, enabling increasingly intelligent automation that not only executes tasks but learns and optimizes over time. This integration could transform RPA into a dynamic knowledge source within organizations, allowing robots to evaluate and continuously improve processes. Additionally, the use of ML for predictive analytics can enhance BPM by anticipating workflow demands and adjusting processes accordingly, which is especially beneficial in high-stakes environments.

Despite the benefits, challenges remain in the complexity of designing ML models, particularly for organizations with limited resources. The development of scalable, cost-effective machine learning solutions that can adapt to smaller or resource-constrained environments remains a critical area for future investigation. Moreover, the potential for integrating generative AI models like ChatGPT with RPA offers a novel pathway for automating tasks requiring natural language understanding, such as customer support, document processing, and internal communications. This could be especially useful in organizations with semi-structured IT infrastructures, where manual data interpretation remains a bottleneck.

In conclusion, while the integration of BPM with emerging technologies holds immense promise, its success depends on strategic planning, employee training, and a phased approach to adoption. Future studies should focus on refining the best practices identified in this review, exploring advanced applications of AI and ML within BPM, and assessing how these integrations impact long-term organizational goals. The dynamic nature of these technologies suggests that BPM-driven automation will continue to evolve, providing new opportunities for operational efficiency and competitive advantage in an increasingly data-driven world.

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