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Bridging the Gap: A Review of Robotic Process Automation and Process Mining Integration

Haythem Messai, Adel Bentayeb and Leila Zemmouchi-Ghomari*
Industrial Engineering and Maintenance Department,
National Higher School of Advanced Technologies, Algiers, Algeria.

(Corresponding author: Leila Zemmouchi-Ghomari)*
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ABSTRACT: Businesses have experienced substantial modifications in their operations due to digital transformation, with Robotic Process Automation (RPA) and Process Mining (PM) being among the prominent technologies for improving operational efficiencies and analytical capabilities. This paper reviews the literature on Robotic Process Automation and Process Mining, exploring their development, integration, and impact on business process management. The analysis includes a detailed examination of the methodologies employed in RPA and PM, their operational synergies, the resultant enhancements in process efficiency and data-driven decision-making in various industries, and the need for a nuanced understanding of their impact on organisational performance and strategy. This study categorises existing research into thematic areas, identifies current knowledge gaps, and suggests future research directions. Significantly, it highlights how the convergence of RPA and PM can provide strategic insights within organisations, augmenting processes that traditionally require intensive manual oversight. The findings indicate that the combined application of RPA and PM enhances operational efficiency and provides strategic insights that can lead to sustainable competitive advantages.

Keywords: Process Mining, Process Discovery, Event Logs, Conformance Checking, Process Automation, Robotic Process Automation.

INTRODUCTION

Digital transformation has led to significant changes in how businesses operate, with Robotic Process Automation (RPA) and Process Mining (PM) at the forefront of enhancing operational efficiencies and analytical capabilities (van der Aalst, 2021; Kassem, 2024). RPA and Process Mining, though distinct technologies are increasingly integrated to provide end-to-end business process improvements. RPA automates repetitive and rule-based tasks that were once manually performed by humans, thus reducing error and increasing efficiency. Meanwhile, Process Mining provides deep insights into business process performance, using existing data from IT systems to visualise and analyse how business processes are conducted in reality. This analysis helps identify bottlenecks and inefficiencies but also aids in pinpointing the optimal areas for RPA application, thereby ensuring targeted and effective automation strategies (El-Gharib & Amyot 2023; Vishnoi *et al.*, 2019).

RPA and process mining are potent tools for optimising business processes (Geyer-Klingeberg *et al.*, 2018). However, data quality, skewed data, and process complexity can hinder effective implementation. Incomplete or inaccurate event logs, data silos, and handling variations can hinder comprehensive analysis. Identifying suitable candidates for automation requires careful analysis and domain expertise. Integration and tooling can be challenging due to interoperability challenges, limited tooling support, and resistance to change. Organizational factors, such as resistance to change and lack of expertise, can also hinder successful implementation.

The current literature does not adequately explore the integration of process mining and robotic process automation (Choi *et al.*, 2022; El-Gharib & Amyot 2023). There is a lack of standardised frameworks to guide task discovery, and current methods often rely on manual efforts or subjective user inputs (Sahu & Nayak 2020). Data-driven approaches are needed to ensure accurate mapping of processes. Insufficient initial task assessment is also lacking, and the exploration of cognitive RPA is limited. Event logs are often inadequate for understanding task behaviour, and transparent criteria are needed to assess potential tasks. Real-world validation is lacking, and most existing frameworks rely on manual methods for discovery. The need for more robust, comprehensive, and practical frameworks that effectively integrate process mining with RPA is highlighted. The current state of research requires significant development to realise the potential of thoroughly combining process mining and RPA (Sallet, 2021).

A paper review can help bridge the gap between process mining and RPA by identifying and consolidating existing knowledge, highlighting research gaps, establishing the need for standardised frameworks, promoting data-driven approaches, and guiding the development of methodologies. It can act as a catalyst for progress in process mining and RPA.

This paper explores the interplay between RPA and Process Mining, focusing on their roles in automating and optimising business processes. A class diagram is proposed to facilitate the understanding of this interplay. This work attempts to bridge the gap between theoretical frameworks and practical RPA and Process Mining implementations. A mind map on primary challenges and solutions is provided to synthesise current knowledge, identify gaps in the existing research, and provide a comprehensive overview of the combined utility of RPA and Process Mining. In addition, KPIs are proposed to measure the benefits of the joint application of RPA with process mining.

This paper is structured into several sections. The first sections review the foundational concepts and technologies underlying RPA and Process Mining. Subsequent sections delve into integrating these technologies, exploring literature reviews and theoretical models highlighting their synergistic effects. The final section highlights the main findings and discusses their implications for future research.

PROCESS MINING

Data mining is a well-known concept that involves extracting valuable information from data for various purposes, such as decision-making and prediction. Process mining, on the other hand, is similar to data mining but specifically focused on managing processes.

Process mining is a research domain that develops innovative methods to gather insights from event logs (Van der Aalst, 2011). It involves applying specialised algorithms to event log data to identify trends, patterns, and details of how a process unfolds (Van der Aalst, 2016). This technique combines data science with process analytics to discover, validate, and enhance workflows, providing organisations with valuable insights to optimise their processes and drive better business outcomes.

Process mining techniques: Process mining provides various uses for process improvement using event data stored in today's information systems. These techniques encompass aspects such as business process intelligence, business activity monitoring, and business process management (BPM), but process mining is commonly used for three primary purposes:

(a) Process Discovery: A process mining technique derives process models from event logs devoid of pre-existing information. It is a primary technique within process mining to uncover the actual occurrences by scrutinising the recorded events in an event log. This method proves especially valuable in elucidating the genuine conduct of a process, distinct from its anticipated or optimal trajectory. Process discovery facilitates organisational comprehension of inefficiencies, bottlenecks, and deviations present within their processes, offering significant insights conducive to process enhancement (Van der Aalst *et al.,* 2012); there are many algorithms for process discovery, such as the heuristic miner (Ayutaya *et al.,* 2012). The evaluation of process model quality encompasses diverse perspectives and employs varied assessment methodologies, as underscored in (De Weerdt *et al.,* 2011). One such method involves utilising model-log metrics, which entails comparing the traces present in the event log and those derived from the mined model. Alternatively, another approach compares a pre-existing model with the model generated through mining, necessitating the presence of an a priori model (referred to as model-model metrics) (De Weerdt *et al*., 2011).

(b) Conformance Checking: According to the process mining manifest to (Van der Aalst *et al.,* 2012), this technique compares an existing process model with an event log of the same process. The aim is to determine if the behaviour recorded in the event log aligns with the behaviour described by the model and vice versa. This comparison can help identify discrepancies, deviations, or commonalities between the modelled and observed process behaviour. Different models, including procedural, organisational, declarative process models, business rules/policies, and laws, can be considered for conformance checking. Conventional methods of conformance checking include Token-Based Replay (Berti & van der Aalst 2021), Alignment-Based Techniques (Nagy & Werner-Stark 2022), and Declarative Conformance Checking, which compares an event log with a declarative process model instead of a procedural (Maggi *et al.,* 2020). In recent years, researchers have been trying to create more stochastic-aware methods to extract additional information and perform more in-depth analyses such as time and cost instead of control flow only. Conformance-checking techniques face significant challenges when applied to systems characterised by weak supervision, where limited data availability hinders the extraction of meaningful insights such as anomaly detection and process improvement opportunities. Krajsic and Franczyk (2021) propose an innovative approach utilising an activity-based Variational Autoencoder (VAE) with a Bidirectional Long Short-Term Memory (Bi-LSTM) architecture. A comparative analysis against established methods, including BiNet, Denoising Autoencoder, Conditional Probabilistic Model, and Anomaly-Free Automaton, demonstrates the superior performance of the Bi-LSTM VAE with Self-attention mechanism, as measured by precision and recall metrics. This study concludes that the proposed activity and weighted-based classification model effectively leverages the Bi-LSTM VAE with Self-Attention to outperform existing anomaly detection techniques in scenarios with limited data. This finding aligns with the results presented in (Elaziz *et al.,* 2023), which demonstrate the efficacy of the proposed approach in surpassing five competing methods by efficiently utilising scarce anomalous examples.

(c) Process Enhancement: Process enhancement denotes the augmentation or refinement of an extant process model by integrating insights derived from actual process data. This enhancement endeavour seeks to elucidate problematic process pathways, uncover deviations from the expected course, and explain their ramifications on organisational operations. Enriching process models enables enterprises to discern segments ripe for automation, conduct root cause analyses, and initiate process amelioration initiatives. Process enhancement is a pivotal facet of process mining, empowering organisations to refine their operations using empirical data and insights extracted from event logs (Van der Aalst, 2011).

Process mining algorithms: Research has shown that the most prominent algorithms in process discovery depend on features of event logs and process characteristics (Pérez-Alfonso *et al.*, 2015). Discovery algorithms in process mining encounter significant challenges when applied to real-world event logs, particularly those arising from unstructured processes. These challenges include noise, duplicate tasks, hidden tasks, non-free choice constructs, and loops, as De Weerdt *et al.* (2012) identified. The inherent complexity and variability of real-world processes (De Weerdt *et al.*, 2011) contribute to these issues and impact the performance of discovery algorithms. Consequently, the effectiveness of such algorithms is contingent upon the specific characteristics of the event log and the underlying process it represents.

(a) Alpha Algorithm: A foundational approach in process mining introduced to address the discovery of workflow nets from event logs. This algorithm identifies and analyses the workflow by examining the sequences of activities in a process, distinguishing between parallel and sequential operations. It works by extracting the starting and ending activities, identifying pairs of activities directly followed by each other, and discerning parallelism within the log. Based on these observations, the Alpha Algorithm constructs a Petri net that models the process, capturing the dynamics and concurrency of tasks. This model helps visualise the process flow, identify bottlenecks, and improve efficiency. The Alpha Algorithm's ability to directly represent a process from event data marks a significant advancement in process mining, providing a systematic approach to uncovering the underlying structures in the process log (Van der Aalst *et al.*, 2004).

(b) Heuristics Miner: The Heuristic Miner (HM) algorithm is pivotal in process mining for discovering the control-flow perspective of a process model primarily by analysing the order of events in a log rather than their timing or correlation across different cases. This algorithm utilises event logs to identify dependencies between activities, mapping out how one activity may precede another. The methodology of HM comprises three main steps: creating a dependency graph to visualise and assess the relationships between activities; detecting complex structures like AND/XOR splits or joins and non-observable tasks; and mining for long-distance dependencies that are less apparent but significant in understanding the process dynamics. By iteratively processing traces within the log, HM builds a refined model that highlights the most frequent patterns of behaviour, providing insights into the process structure that are invaluable for optimising operations and understanding workflow dynamics (Bakhshi *et al.*, 2023).

(c) Genetic Process Mining: The genetic algorithm for process mining represents a robust approach to modelling and optimising various business and healthcare processes (Santhoshkumar *et al*., 2019). This algorithm, a type of evolutionary algorithm, simulates natural selection to generate high-quality solutions for complex problems. It iteratively evolves a population of individual solutions to ward an optimal solution using operations like selection, crossover, mutation, and termination. In process mining, the genetic algorithm analyses event logs to discover, enhance, or check the conformance of the process models to real-world processes. It is beneficial in dealing with noisy, incomplete, or unusual data logs. The genetic algorithm stands out for its ability to handle diverse data and to model complex relationships within the process data, thus providing significant insights that can drive process optimisation and innovation.

(d) Fuzzy miner: The Fuzzy Miner algorithm, as outlined in the paper by Sarno *et al.* (2020), is a sophisticated tool used for process mining, particularly in detecting anomalies and fraud within business processes. This algorithm leverages fuzzy logic to handle process data's inherent uncertainty and variability, which is standard in dynamic and complex business environments. By constructing fuzzy models from event logs, the Fuzzy Miner algorithm effectively maps and analyses deviations from standard operating procedures (SOPs), identifying unusual patterns that may indicate fraudulent activities. The strength of this approach lies in its ability to adapt the level of detail and abstraction based on the fuzziness of the data, providing a flexible and robust framework for uncovering subtle yet critical irregularities that rigid, deterministic methods might overlook (Samo *et al.*, 2020).

Process mining assessment metrics: Evaluating process discovery methodologies is crucial for assessing the effectiveness and applicability of process models generated from event logs. This chapter discusses the primary dimensions and specific metrics used to evaluate these methodologies, focusing on accuracy and comprehensibility. It also introduces additional metrics that have gained prominence in recent research.

(a) Accuracy and Comprehensibility: Process discovery methodologies are evaluated along two main dimensions: accuracy and comprehensibility (Bakhshi *et al.*, 2023). Accuracy refers to the degree to which a process discovery technique accurately reflects the behaviour recorded in an event log. It challenges the balance between over-generalization, which can omit critical details, and excessive granularity, which may introduce noise and irrelevant elements into the model (Van der Aalst, 2011). Comprehensibility involves the understand ability of the discovered process models, emphasising their ease of interpretation and simplicity. This metric assesses the ability of stakeholders to grasp and utilise the process models in practical scenarios effectively (Van der Aalst, 2011).

(b) Conformance Checking Metrics: Conformance checking is integral to validating the accuracy of process models against actual event logs. Developing a

State-Based Deterministic Finite Automaton (SDFA) is a noteworthy method wherein the SDFA is constructed iteratively from an event log. Initially starting with a single state, this automaton expands by adding new states and transitions as it encounters new events in the log, thus forming a probabilistic model through normalised transition probabilities (Leemans & Polyvyanyy 2023).

(c) Precision and Recall: Precision and recall are critical metrics from information retrieval and classification. They evaluate the elements' specificity and completeness within a discovered model. Precision measures the proportion of accurately identified elements within the model, reflecting its specificity and exclusion of irrelevant details. Recall assesses the extent to which a model captures all relevant process elements, indicating its comprehensiveness. Balancing these metrics is crucial as an overemphasis on one can detrimentally affect the utility of the process model (Krajsic & Franczyk 2021).

(d) Additional Key Metrics: Recent studies have highlighted several other metrics that are essential for a holistic evaluation of process models:

- Fitness: assesses how well a model can reproduce the behaviour seen in the event log using various methods, such as token-based replay or behavioural alignment (Van Dongen *et al.*, 2009).
- Generalization: Measures the model's ability to predict unseen instances, ensuring it is not over-fitted to the training data.
- Simplicity: This evaluates the model's ease of understanding based on its structure and complexity.
- Overall Accuracy: This encompasses various aspects of model quality, including precision, recall, fitness, and generalisation, to provide a comprehensive evaluation of its effectiveness (Huang & Kumar 2012).

The selection of appropriate metrics (Table 1) depends on the specific goals and context of the process mining project. Considerations include the model's purpose, the complexity of the process, the stability of the process environment, and the quality of the event log. Through careful metric selection, researchers and practitioners can derive significant insights into the capabilities and limitations of discovered process models, thereby enhancing their practical applications in organisational contexts.

Table 1: Model Evaluation Parameters.

Parameter	Focus	Usage
Precision	Accuracy of positive predictions	Conformance checking, filtering evaluation, algorithm comparison
Recall	Completeness in capturing positive cases	Conformance checking, filtering evaluation, algorithm comparison
Fitness	Fittothe observed data	Overall model evaluation, model selection
Generalisation	Ability to handle unseen data	Overall model evaluation, model selection
Accuracy	Ease of understanding	Overall model evaluation, model selection, Communication
Simplicity	Overall correctness and reliability	Overall model evaluation, model selection

Process mining challenges: PM is an innovative analytical approach that leverages data mining techniques to analyse business processes. It has gained substantial attention due to its ability to provide detailed, data-driven insights and its applicability across various industries, including healthcare (Helm *et al.*, 2020), banking, finance (Werner & Gehrke 2015), and production industries (Lorenz *et al.*, 2021). One of the primary benefits of process mining is its reliability in extracting meaningful information from event logs generated by various information systems. This reliability stems from the objectivity of the data-driven approach (see Fig. 1), which minimises human biases and errors. Furthermore, its wide range of applications shows process mining's versatility. For instance, it aids in conformance checking, identifying the root causes of deviations, pinpointing bottlenecks, and predicting future trends or possible outcomes of process adjustments. These applications demonstrate process mining's critical role in understanding and optimising business processes.

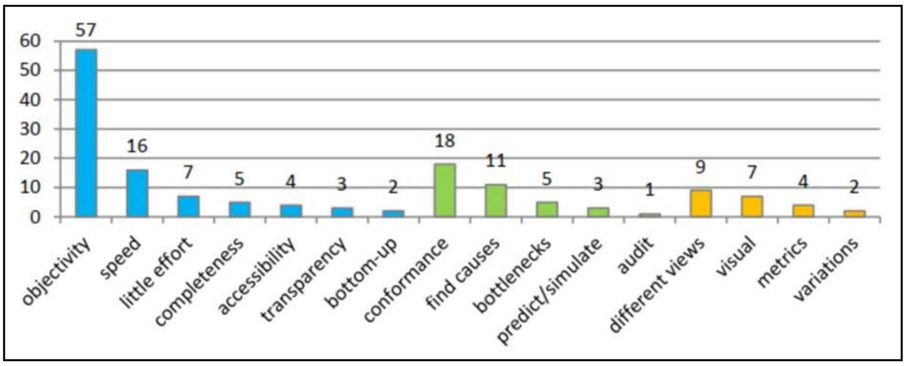

Fig. 1. Benefits of process mining techniques (42 questions, 94 respondents) (blue: characteristic, green: application, orange: representation) (Claes & Poels 2013).

Process mining significantly enhances transparency and process efficiency. It provides a bottom-up analysis approach, ensuring a comprehensive view of the organisational process. This is further supported by the ability to visualise process flows in various representations, which helps stakeholders understand complex data sets and process metrics with little effort. The visual representations and metrics developed through process mining make tracking a process's complete journey possible, promoting a transparent audit trail and facilitating continuous improvement.

The strategic benefits of process mining are realised through its impact on decision-making. Process mining supports strategic decisions that enhance productivity and efficiency by providing detailed insights into process performance and compliance. Simulating process changes before implementation also enables decision-makers to foresee potential impacts and proactively adjust strategies.

The adaptability of process mining extends its benefits across multiple sectors. In healthcare, process mining can improve patient flow and optimise treatment processes. In the banking and finance sectors, it enhances compliance and fraud detection. Moreover, process mining is instrumental in streamlining manufacturing processes and reducing waste in production industries. These examples highlight the broad applicability and significant advantages of process mining in improving operational efficiencies, contributing to cost reductions, and enhancing service delivery.

Despite its potential, process mining's adoption and effectiveness are hindered by several challenges (see Fig. 2). A primary obstacle in process mining is accessing the correct data and ensuring its quality. Research shows these are the most significant barriers organisations face when implementing process mining techniques. Poor data quality or incomplete data can lead to inaccurate process models, compromising the results' reliability and usefulness.

The complexity of process mining techniques and the usability of related tools also pose considerable challenges. For practitioners, especially those at the managerial level, the process mining tools may seem too complex or unintuitive, making them hard to use and understand. This complexity can discourage adoption, mainly when the benefits are not immediately apparent to decision-makers. In addition, integrating process mining tools with existing IT infrastructures is another significant challenge. This integration often involves substantial costs and requires technical expertise, which may not be readily available. Additionally, the overall cost of implementing process mining solutions, including training and maintenance, can be prohibitive for some organisations. Process mining outputs, such as process models and diagnostic analytics, can be challenging to interpret. For instance, complex models, often called "spaghetti models," are hard to understand and communicate to stakeholders. This lack of clarity can reduce the actionable insights derived from process-mining endeavours.

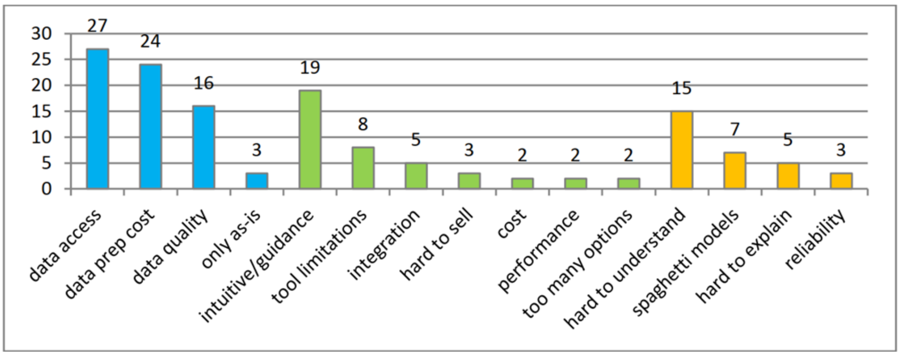

Fig. 2. Drawbacks of process mining techniques (question 5 2, 90 respondents) (blue input, green techniques, orange output) (Claes & Poels 2013).

Future directions in process mining: Looking ahead, the future of process mining lies in addressing these challenges while leveraging advancements in technology and methodology:

(a) Enhanced Data Management Techniques: Advanced data management techniques will improve data accessibility and quality. This includes developing more sophisticated data cleaning tools and methodologies to ensure the integrity and completeness of data used in process mining.

(b) User-friendly Tools: More intuitive process mining tools that cater to users with varying technical expertise are needed. Simplifying the user interface and providing more explicit guidance on using tools can help make process mining more accessible to a broader audience.

(c) Integration Solutions: Developing better integration solutions that reduce the cost and complexity of deploying process mining tools will encourage more organisations to adopt these techniques. This could evolve into creating more modular and scalable tools that can easily fit into different IT environments.

(d) Advanced Analytical Techniques: Future research should also focus on refining analytical techniques to handle complex data and provide more pre-case, interpretable models. Artificial intelligence and machine learning could play a significant role in developing these advanced techniques.

ROBOTIC PROCESS AUTOMATION

Robotic Process Automation is a rapidly growing approach to process automation that uses software robots to mimic human tasks. RPA automates repetitive tasks or workflows previously performed manually, streamlining business processes through technology and software (Geyer-Klingeberg *et al.*, 2018). According to Choi *et al.* (2021), RPA is a software tool that automates repetitive tasks involving structured data, rules, and user interface interactions. The primary objective of RPA is to minimise human effort in labour-intensive processes, thereby increasing the speed and efficiency of high-volume transactional tasks.

RPA vs. Conventional Automation: RPA is a means of automation similar to conventional script automation and the automation included in standard IT implementations. So, firstly, what are traditional automation and typical IT implementations? Conventional automation refers to automating it through conventional programming techniques or other tools. It involves direct integration with backend systems through APIs or other connectivity means. In general, this needs to be developed and maintained by IT staff who are highly expert in the systems and technologies underneath. Traditional automation, integrated much deeper into system architecture, handles many tasks, such as data processing, system operation, and complex business logic (Richardson, 2017).

Standard IT implementation encompasses the comprehensive deployment of IT solutions through a systematic process that includes planning, system requirements analysis, system design, development, integration, testing, and maintenance. This sequence aims to ensure the IT solutions meet business requirements effectively and adhere to predefined budgets and timelines. This process highlights the critical integration of new technologies within an organisation's IT framework to improve or replace existing functionalities (Murch, 2001). According to Rajagopal and Ramamoorthy (2023), IT implementation, such as CRM, is highly intricate. Implementation requires an expert as it involves complex integration at the data or application layers and concerns the whole business process. On the other hand, RPA implementation consists of training the bot directly on the software (e.g., UiPath) and affects only the application layer.

RPA operates on the front end, mimicking a human user's behaviour. On the contrary, conventional automation requires access to the backend as it involves controlling machines to conduct certain operations in certain phases (Table 2).

Table 2: Comparison of Conventional Automation and RPA.

Criteria	Conventional Automation	RPA
IT infrastructure adjustments	Necessary	Unnecessary
Human behaviour emulation	Incapable	Capable
Coding knowledge	Necessary	Recommended but not necessary
Customisation flexibility	High	Low
Speed	Fast	Slower compared to CA but still much faster Than manual

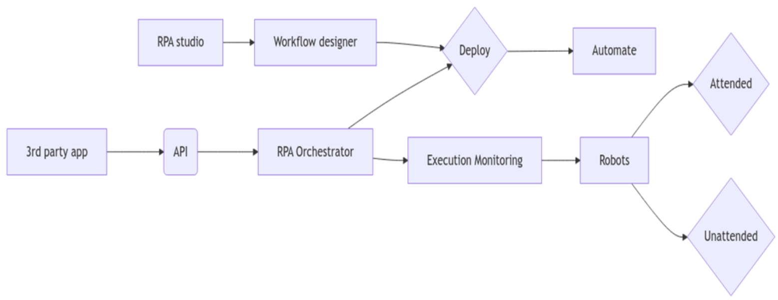

Fig. 3. Flow Chart of RPA Components.

RPA components: According to Choi *et al.* (2021), RPA can be divided into three components (see Fig. 3).

• **Robots:** Virtual software bots that perform mundane, repetitive tasks instead of human resources. They can be "attended" type bots, which work alongside their human counterparts, or "unattended" bots, which work independently and require little to no human involvement.

• **Orchestrator:** An RPA orchestrator is a management server that schedules, monitors, manages, and audits robots. It is used in the development, testing, and production (Khan, 2020). As a highly scalable platform that connects the studio to the robots, the orchestrator also bridges the development environment (studio) and the robots, enabling efficient and centralised control of automated processes.

• **Studio:** The RPA studio is a user-friendly, intuitive tool for designing and automating robotic processes. It also allows users to create and automate robot workflows.

RPA tools: Khan (2020) conducted a comparative study on the three most common RPA tools: UI Path, Automation Anywhere, and BluePrism. Other tools include Windows Power Automate, Taskt, Robo Corp, and many more. She specified that tools can have two types of architectures. It is either a client-server architecture, meaning that every node can be a client or a server. Alternatively, a web-based orchestrator that links automated tasks to create a unified workflow; a web-based architecture can be like the .Net Framework. We will now conduct a comparative study on some popular RPA tools: UiPath, Automation Anywhere, Blue Prism, and TASKT, a popular open-source solution. Then, we will briefly overview each tool, its components, and its advantages and disadvantages. Then, we shall compare these tools according to determined criteria (Table 3).

(a) Automation Anywhere (AA) is a software platform that enables businesses to automate their entire business processes using RPA. Automation Anywhere provides all the features needed for a company in RPA through its Control Room, serving bot development, configuration, and monitoring in one single and central environment. These bots can be used for many tasks, including data entry, validation, and complex calculations, mainly using AI and ML technologies (Andrade, 2020). AA supports three types of bot creation: Task Bots for rule-based tasks, Meta Bots for reusable building blocks, and IQ Bots for processing unstructured data. It also provides three types of recorders to automate functions by replicating user actions. It offers features such as BOT INSIGHTS for data visualisation and business insights, BOT FARM for usage-based RPA tool purchases, and BOT STORE for plug-and-play bots.

(b) Uipath is one of the top platforms for RPA, and it offers automation functionality combined with process discovery and analytics. UiPath platform facilitates the software robots (SRs) development, deployment, and management de- signed to perform automated repetitive and rules-based business tasks. Other vital components are the orchestrator of task management, workflow designers, and analytic tools (Dobrica, 2022). Components of UiPath are (Khan, 2020):

(1) Core RPA Capabilities: Allows accessible building and deployment. (2) Process Discovery and Analytics Tools: These are business-oriented ideas whereby the impact of the process on automation is provided. (3) Orchestrator: It shall be a central control that manages task assignments and performance appraisal. (4) Workflow Designer allows you to design processes with a drag-and-drop surface. These mimic human operations on digital systems and carry out robotic process automation—software Robots (SRs). The advantages of UiPath include improved efficiency, ease of company scaling, and performance analytics (Andrade, 2020). Disadvantages include the constant updating of the software, its complexity in set-up and management, potential high costs, and dependence on the current IT system. The UiPath software has been actively improved to integrate newer innovations like machine learning and AI as part of its advancing functions.

(c) Blue Prism is a robotic automation software used to automate the business processing system through the integration of presentation. This approach, formerly known as "screen scraping," has been remodelled to permit efficient interaction with various applications, simplifying business process automation. It empowers business analysts with the ease of low-technical skills to create and modify automation through direct interaction with application user interfaces. Blue Prism provides functionality that allows the automation of interfaces from contemporary web interfaces to the most mature mainframe applications, including interface automation (Chappell, 2017). Blue Prism mainly includes several components. (1) Visual Business Objects (VBOs) are application interface adapters that graphically create and execute specific tasks, such as logging in or entering data, without using coding through Object Studio. (2) Process Studio is a graphical tool for defining and sequencing the steps in a business process, using VBOs for application interactions.

(3) Control Room: This room oversees the execution of Blue Prism processes and handles process control, monitoring, and scheduling. (4) System Manager: Administer users, manage user settings, administer processes, deploy processes, and manage the overall system for successful, efficient, and secure operation. (5) SQL Server Database that stores the details about the processes and VBOs for management and audit purposes. One of the Blue Prism advantages is efficiency: Easily and fast, you can automate business processes easily and quickly through user interfaces without changing the applications. It is cost-effective: It is cheaper than the traditional way of doing things and can be applied in low-value processes. Also, adaptability: Easily variable to changing business changes. It has broad compatibility and can interface virtually any application with a user interface. It ensures robust security, such as safeguarding encrypted credentials and role-based access controls. One of the disadvantages of Blue Prism is performance issues: Complex multi-screen processes and extensive data retrieval can be a struggle. Also, UI Limitation: Only automates tasks that can be managed through the user interface, lacking direct backend access. In addition to some maintenance issues due to updates on the significant changes in application interfaces, Skill Dependency requires a sound fundamental understanding of cutting across the business processes and the Blue Prism tools for effective implementation.

(d) TASKT (formerly known as sharp RPA) represents the pioneering instance of a genuinely free, user-friendly, and open-source process automation tool developed within the .NET Framework using C#. TASKT empowers users to create and customise process automation workflows without coding application logic (Taskt, 2024). It offers an extensive suite of task management features, including subtasks, alerts and notifications, task visualisation tools, and comprehensive reporting and analytics capabilities. Additionally, its integrations seamlessly connect with other applications, enhancing workflow productivity and efficiency (Task Management Software Features, 2025). One of its advantages is that it is free and open-source, making it reachable even for small businesses and individuals. It provides an intuitive interface and accessible commands to automate tasks, making it easy for users to come up to speed quickly. It supports web and desktop applications, thus making it very flexible and allowing for different automation scenarios. One of its disadvantages is that, being a smaller project, it may not provide the same level of support or community activity as some of the more extensive commercial RPA tools. It is limited to the Windows environment, implying that this software would be ineffective when implementing a cross-platform functionality. It has the smaller scale of the project can mean less frequency and scope with which updates or new features are made.

(e) Robocorp: According to the Robocorp and Rpabotsoworld (Robocorp, 2025) website, Robocorp is an RPA open-source Python tool for automation across different platforms. This software, purposefully made for non-code and code user interfaces, targets developers and non-developers. That rests on the cloud-native architecture foundation, allowing it to handle data and execute tasks with fortitude, whether on-cloud or on-premise. Its components are the Robocode Lab, An IDE that supports the development of automation scripts, and the Control Room, a central dashboard for deploying, managing, and scaling bots and automation. The Robocorp Cloud offers cloud services for bot execution, making it easier to manage and deploy bots remotely. One of its advantages (Robocorp Reviews, 2025) is the flexibility and Open Source; Robocorp is perfectly poised to give users the ideal flexibility to connect an extensive range of Python libraries and APIs inside their automation workflow, making it functional and flexible. It is cost-effective and supports a consumption-based pricing model since its features are affordable for the user and what is only utilised. It supports scalability; the system will expand operations excellently and take in those of small and large businesses; it will do so without the need for colossal infrastructures. It provides community and documentation; the community is robust, and the guides are well-documented. New learners, hence, find the tool accessible for learning and troubleshooting. One of its disadvantages (Robocorp Reviews, 2025) is the complexity of setup; setting up the environment for Robocorp can be time-consuming and challenging for users who need it for quick deployment. Its interface and usability of the tool might not be straightforward for users who do not possess coding skills, therefore increasing the learning curve. Some users added that the tool could use huge memory and space, requiring robust systems specifications for better functionality.

RPA project lifecycle: Implementing RPA involves a structured six-phase lifecycle (see Fig. 4). The process starts with the Discovery Phase, where suitable processes for automation are identified. The Analysis Phase then assesses the feasibility of automating these processes. The specifications for the automated processes are outlined in the design phase. The Development Phase transforms these designs into actionable components. The Deployment Phase follows, where robots are executed in operational environments. Control and Monitoring oversee the robots' performance, while the Evaluation Phase evaluates their effectiveness, facilitating continuous improvement (Rajagopal & Ramamoorthy 2023).

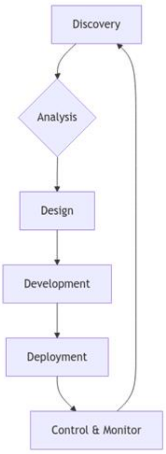

Fig. 4. RPA Project Lifecycle.

Table 3: RPA tools comparison according to some of the criteria mentioned by Rajagopal & Ramamoorthy (2023); Khan (2020).

Criteria	UiPath	Taskt	Robocorp	Automation Anywhere	BluePrism
Architecture	.NetFrame-Work	.NetFrame-work	Robot Framework and Jupyter Notebook	Client Server	Client Server
Availability	Community Edition (Bots cannot be distributed), 60-day free Trial (UI Path Pro)	Open Source	Consumption-based pricing with free trial; packages for various usage levels from personal to enterprise, costs vary based on usage.	One month Free trial (Industry edition), community edition (Bot Creator rights only)	One month free trial, Learning edition (1 digital worker, 15 processes)
Usability	Simple	Simple (ac-cording to Github)	Simple (for the paid version) Moreover, it offers some complexity for the free version.	Complex	Simple
Automatable Processes	back/front office	Back/front office	Back/front office	back/front office	Back-office
Recorders	Innovative, screen, and web (Desktop and web applications)	recorder available	It does Not have a recorder	Primary, web, desktop, image, and Citrix	No recorders
Cognitive ability	Medium	Medium	High Cognitive Ability due to AI integration	Medium	Low

RPA benefits and challenges: RPA presents numerous benefits that can significantly enhance business operations. Firstly, RPA enables rapid efficiency gains and cost savings, often within weeks or months of implementation (source). The initial investment and return on investment (ROI) are manageable and predictable, making RPA an attractive option for cost-conscious businesses. Furthermore, RPA provides a solution that requires minimal changes to existing applications and business processes, facilitating incremental improvements without substantial disruption (Syed *et al.*, 2020). RPA operates 24/7, ensuring continuous productivity and operational availability. This capability enhances efficiency and maintains consistent compliance with regulatory requirements. Additionally, RPA is scalable; as the system expands, it achieves more significant cost advantages and can support extensive data generation necessary for Lean Six Sigma programs, thereby improving process repeatability and reducing human error (Santos *et al*., 2020).

Despite its advantages, RPA faces significant challenges. The perception of RPA is polarised; some view it as a revolutionary advancement akin to artificial intelligence, while others dismiss it as overhyped by marketing efforts. One of the primary technical challenges is the maintenance required when underlying software updates occur. These updates can disrupt RPA by altering critical elements that the bots interact with, necessitating frequent adjustments to maintain functionality. Furthermore, RPA is particularly effective in environments with legacy systems that lack API or database access, functioning as a "glue" between disparate software applications. However, as more modern systems with better integration capabilities become prevalent, the utility of RPA may diminish, highlighting its suitability mainly for outdated systems.

There are alternative views on RPA's efficacy. Critics argue that RPA merely accelerates existing processes without addressing underlying inefficiencies. This perspective suggests that rather than relying on RPA, organisations should focus on reducing software fragmentation and improving process efficiency through more traditional automation techniques. This approach would streamline operations and mitigate the accumulating software burdens that could lead to future operational issues. In summary, while RPA offers substantial benefits in terms of efficiency, scalability, and compliance, it also faces challenges related to maintenance and relevance in modern IT environments. The debate continues on whether RPA represents a technological advancement or a temporary solution to deeper systemic issues.

RPA implementation frameworks: Implementing RPA necessitates a well-defined framework, as the complexity of these projects demands structured guidance to ensure efficacy and scalability. However, as RPA is a new technology and is relative to other IT technologies, it does not have many well-structured frameworks. We have picked the latest and most popular frameworks to discuss in our article.

A. Process mining-based RPA frameworks: Using a process mining-based framework for an RPA project: Unlike conventional frameworks, a PM-based framework leaves less room for guesswork and depends directly on data logs generated by process behaviour. Thus, it gives a better understanding of the process and detects RPA opportunities more effectively. Moreover, it helps during and after the implementation of the RPA bot (as described in the previous section). In what follows, we describe some frameworks that rely on process mining to implement RPA in organisations.

- **PLOST Framework:** Jongling (2022) created the "Prioritized List of Suitable Tasks" Framework. It utilises process mining and consists of eight qualitative and quantitative steps that must be performed chronologically (see Fig. 5).

First, the automation strategy should be determined to customise the framework to the organisation's needs. The automation strategy consists of two parts: prioritising the business values and determining the risk Level. Next, processes are gathered from the organisation through semi-structured interviews with domain experts, including various roles from managers to system administrators. In the third step, processes selected in the previous phase undergo assessment based on six mandatory qualitative criteria. These criteria are digital and structured input, easy data access, few variations, repetitiveness, clear rules, and maturity. In the fourth step, the process data is collected for the processes in the revised process selection from the previous step. With the event logs of the processes in the revised process selection, the next step is to apply process mining. The framework user can choose which process mining tool is used for this step. The Process Analysis step assesses the remaining processes from the revised process selection against different quantitative criteria. This happens at a high level. It is done with the help of the output of the previous step. The requirements are Cycle Time, Case Frequency, Activity Frequency, Standardization, Length, Automation rate, Human Error Prone. The task analysis step involves assessing individual tasks within the identified processes using specific quantitative criteria and focusing on the low-level details. The requirements are task-specific, and their values are obtained through visualisations in the fifth step, which ensures a detailed analysis of process components. The requirements are Activity Frequency, Case Frequency, Duration, Automation Rate, Human Error Prone, and Irregular Labor. The final step of the framework produces a prioritised list of tasks suitable for RPA automation. This output relies on two key components: the automation strategy established in the initial step and the task analysis conducted in the seventh step. The six criteria analysed in the previous step align with various business values outlined in the automation strategy, facilitating the final task prioritisation process.

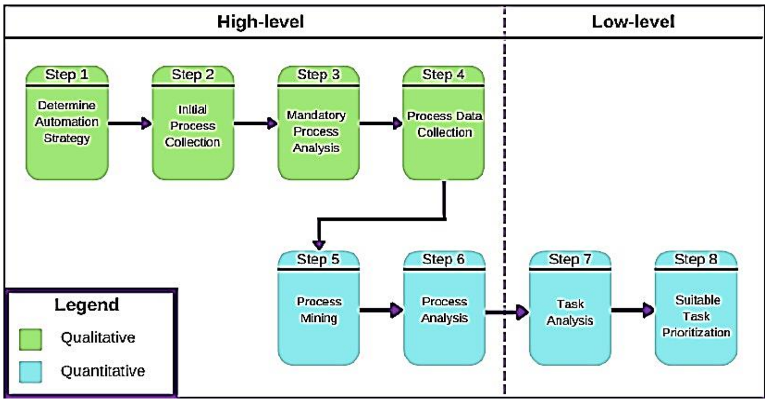

Fig. 5. The PLOST framework steps (Jongeling, 2022).

Comments on this framework: While this framework provides a detailed step-by-step guide to selecting suitable tasks for automation and focuses on repeatable tasks that match the criteria for automation, it misses the ROI (return on investment) in the process selection phase. Moreover, this framework is specialised for IT-related processes, and although it is still applicable in other functions, it may pose a challenge.

• **A framework for implementing Process Mining and RPA in Organizations** in 2023, a paper (El-Gharib & Amyot 2022) proposed a framework that depends on PM to assess tasks' suitability for automation; in said framework, the process mining helps implement RPA by (1) discovering Automation Opportunities: Process mining techniques analyse the collected event logs and identify candidate routines that can be automated. By analysing the process execution data, process mining can reveal patterns, bottlenecks, and inefficiencies. This analysis helps organisations identify which processes can benefit the most from RPA automation. (2) assessing Feasibility: Process mining helps assess the feasibility of automating identified processes using RPA. It provides insights into the execution frequency, the number of process variants, and the number of exceptions encountered. This information helps determine whether a process suits automation and provides a basis for decision-making. (3) Process Understanding and Improvement: Process mining enables organisations to understand their current processes deeply. It helps uncover hidden process variations, deviations, and inefficiencies that may not be apparent through traditional documentation or manual observations. This understanding is crucial for e actively implementing RPA, allowing organisations to optimise and streamline processes before automation. (4) continuous Monitoring: After implementing RPA, process mining continues monitoring the automated processes' performance. By comparing the actual execution of the automated processes with the expected process models, process mining can identify any deviations, errors, or unexpected behaviours in the RPA implementation. This monitoring capability helps organisations ensure their automated processes' accuracy, consistency, and efficiency.

Comments on this framework: This framework uses process mining to identify and assess opportunities for automation so that a suitable selection can be made for RPA. It also provides continuous monitoring to maintain the RPA-implemented process efficiency. However, it might lack the same treatment regarding the scale of RPA solutions and the cultural and change management aspects required for adoption success.

B. Frameworks that do not primarily rely on process mining: Frameworks not based on process mining require domain expertise and might depend on much guesswork. As a result, they may lead to a wrong task choice and the failure of the RPA project as a whole. They are necessary in enterprises that do not have well-structured data.

• **A framework for implementing robotic process automation projects:** Herm *et al.* (2023) proposed a robust and adaptable framework, offering a significant tool for organisations to approach RPA implementations systematically and effectively. The framework comprises four phases: Initialization, Implementation, Scaling, and Rollout. The initialisation phase identifies areas in the enterprise that can benefit from automation using RPA technology. The implementation phase involves selecting processes and RPA software, creating a pilot to test project feasibility, and evaluating the business case to determine the feasibility of full-scale implementation. The scaling phase involves rolling out the RPA project to cover other processes, increasing automation scale and percentage within tasks, and implementing RPA support processes to ensure reliable operation and maintenance. A Center of Excellence is set up to oversee the organisation's RPA-related activities, development, and enhancement. The framework ensures that RPA projects align with business objectives and are supported by mechanisms to ensure reliable operation and maintenance.

Comments on this framework: This framework is comprehensive and methodically structured to cover the breadth of considerations necessary for successfully adopting and scaling RPA technologies. It could be improved by incorporating specific identification methodologies, such as process mining and employee workshops, to discover automation opportunities systematically. This would help identify and prioritise suitable processes based on potential return on investment and ease of implementation.

Table 4: Stakeholders involved in each UiPath framework phase.

Stakeholder	Phases Involved
Solution Architect	Discovery & Kickoff, Process Analysis, Solution Design, Development & Unit Testing, Integration & UAT, Deployment & Hypercare
Project Manager	Discovery & Kickoff, Process Analysis, Solution Design, Development & Unit Testing, Integration & UAT, Deployment & Hypercare
Business Analyst	Process Analysis
RPA Developer	Development & Unit Testing, Integration & UAT

• **A proposed framework for UiPath Academy:** As mentioned earlier, Uipath is among the most popular RPA tools, and it is the only one to include a complete framework for RPA implementation in its academy training (Uipath Academy Learning Path Viewer, 2025).

The Uipath Academy framework outlines the different steps, deliverables, and team members included primarily in each step (Table 4). The automation process involves several steps, including discovery and kickoff, process analysis, solution design, development and unit testing, integration and user acceptance testing (UAT), deployment and hyper care, and deployment and hyper care. The setup team evaluates potential automation projects based on their complexity and intricacy, establishing schedules and resources for successful completion. Next, process analysis involves assessing the customer's process requirements and determining the degree of automation based on the study and complexity of the process. The technical team designs a future state flow and maps out various modules to complete the automation. The development and unit testing involves the creation of modules from the design using PDD and SDD papers, with each module tested individually in set situations before moving forward. The next step is testing and combining modules. The user acceptance testing (UAT) is conducted by users with oversight from the implementing team. Users coordinate with business groups to draft a test plan covering all expected and exceptional use cases. The end of UAT is marked by signoff. Finally, the deployment of robots and hypercare oversee the bots' running. The team reviews automation cases in daily meetings, ensuring errors or issues are fixed quickly.

Comments on this framework: This framework provides detailed information on the deliverables and responsibilities of each stakeholder in an RPA project and focuses primarily on BOT development. However, it lacks (compared to other frameworks) in process selection and identification of automation potential.

INTEGRATING PROCESS MINING ANDROBOTIC PROCESS AUTOMATION

The synergy between process mining and RPA lies in their shared objective of optimising business processes. They complement each other in several ways. Firstly, process mining aids in process discovery by uncovering accurate process flows through analysing event logs during RPA bot activities. This visibility enables organisations to identify inefficiencies and prioritise areas for automation, ensuring that RPA efforts are targeted and effective. Secondly, process mining enhances processes by evaluating logs to pinpoint bottlenecks and deviations, which helps select the most impactful automation processes (Geyer-Klingeberg *et al.*, 2018).

Additionally, process mining plays a crucial role in bot discovery by identifying repetitive, rule-based, and voluminous tasks through detailed event data analysis, making these tasks ideal candidates for RPA. Once these tasks are identified, RPA automates them based on the insights gained from process mining, with detailed process models guiding the bots to ensure alignment with actual process needs. Finally, after implementation, process mining continues to provide ongoing monitoring and analysis of RPA bot performance by examining the event logs they generate. This continuous evaluation allows for fine-tuning bots, addressing emerging issues, and quantitatively assessing their impact.

The literature on the combined use of process mining and RPA has identified several research gaps (Sallet, 2021). These include the lack of standardised frameworks for task discovery, limited support for initial task suitability assessment, insufficient focus on automation objectives, lack of data-driven task selection, restricted use of event logs, need for clear criteria for automation, and limited research on cognitive RPA (El-Gharib & Amyot 2023).

The literature also highlights the need for standardised, data-driven, and comprehensive frameworks that leverage process mining to effectively identify and select appropriate tasks for automation. More research is also needed into how process mining can support the more advanced applications of RPA, such as cognitive RPA (van der Aalst, 2021).

Currently, many RPA methods rely on manual processes for task selection, and there is a lack of evidence on assessing task suitability using process mining before task selection. Additionally, there are no clear criteria for analysing process suitability for RPA, and there is a lack of research on combining process mining and Natural Language Processing (NLP) to enable RPA (El-Gharib & Amyot 2023).

Hence, while process mining is a valuable tool for enhancing RPA initiatives, more standardised, data-driven, and comprehensive frameworks that leverage process mining to identify and select appropriate tasks for automation effectively are needed.

To have a structured view of the interplay between PM and RPA, we present a class diagram that summarises the organisation of this interplay (see Fig 6). The diagram describes process mining as follows: Process mining is a domain that uses an EventLog as input to discover, analyse, and enhance process models. It produces a Process Model as output and has discovery, conformance checking, and enhancement methods.

Robotic Process Automation is a domain that includes robots performing automated actions and Automation Rules. The Event Log is a core component for process mining, containing information about process execution, such as case ID, activity, time stamp, resource information, and other attributes. Tasks are categorised by category and can be automated by Robotic Process Automation.
Relationships between process mining and robotic process automation include using EventLog as input, identifying suitable tasks for RPA implementation, and generating EventLog events. Process mining can also be used for RPA configuration, creating models that define workflows to be automated with RPA and enhancing cognitive RPA by providing insights on variant tasks. This diagram illustrates the core classes and relationships in integrating process mining and robotic process automation.

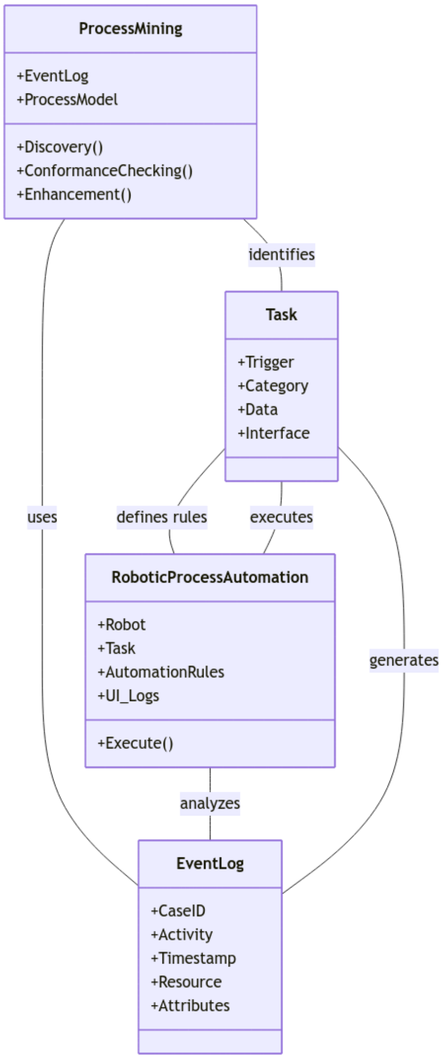

Fig. 6. PM and RPA interplay class diagram.

To visually represent the challenges and solutions in integrating RPA and PM, we present a mind map in Fig. 7. It is divided into two main sections: Challenges and Solutions. Challenges include RPA implementation, process mining, and integration challenges. Solutions focus on process mining as a key enabler, framework development, process standardisation, AI and machine learning integration, continuous monitoring and improvement, and tool development. The map provides a structured overview of the information, focusing on the main points of each challenge and solution. The map aims to understand the integration process and its potential benefits comprehensively.
Process mining is a valuable tool for RPA initiatives, providing a visual and fact-based approach to identifying automation opportunities and prioritising activities. It helps assess RPA potential and monitor the performance of robots to ensure sustainable benefits. Key performance indicators (KPIs) considered when using process mining and RPA include automation rate, process maturity, throughput time, cost savings, ROI, process performance KPIs, accuracy and consistency, process efficiency, deviation detection, task frequency and complexity. Process mining also helps benchmark, prioritise activities, identify root causes, and ensure process transparency. By using these KPIs, organisations can make informed decisions about automation, training robots, and monitoring performance, leading to more effective RPA implementation and greater return on investment. By identifying and addressing these KPIs, RPA initiatives can lead to more effective implementation and greater return on investment. Table 5 describes these KPIs.

Fig. 7. PM and RPA integration challenges and solutions

Table 5: KPIs for the joint application of RPA and process mining.

KPI	**Description**	**How Process Mining and RPA work together**
Automation Rate	The ratio of cases where a robot executes an activity is divided by the total instances of that activity.	Process mining identifies areas with high or low automation potential and can measure automation's impact on task completion rates.
Process Maturity	The level to which a process is scalable, repetitive, and standardised indicates its suitability for RPA.	Process mining helps assess process maturity and identifies areas that need standardisation before RPA implementation. **Standardisation should occur before automation**.
Throughput Time	The time it takes to complete a process.	Process mining can show changes in throughput time as automation rates increase, highlighting the impact of RPA on process efficiency.
Cost Savings	Reduction in expenses as a result of RPA implementation.	Process mining identifies where cost savings can be achieved by showing the change in performance indicators when automation rates increase.
Return on Investment (ROI)	Measures the profitability of RPA initiatives.	Process mining helps track the impact of RPA initiatives and their ROI. **Prioritising tasks with a higher ROI is important for successful RPA selection**.
Process Performance KPIs	Measures of how well a process performs, such as throughput time.	Process mining provides insights into RPA's impact on performance KPIs, such as throughput times.
Accuracy and Consistency	Measures how correct and consistent process execution is.	RPA ensures accuracy and consistency; process mining can be used to monitor error rates and identify areas for improvement.
Process Efficiency	The overall effectiveness of a process, including resource use, time, and quality.	Process mining identifies bottlenecks and compliance issues, which can be addressed through process standardisation to improve efficiency.
Identification of Deviations	Ability to detect when a process changes and how robots need to adapt.	Process mining helps identify process evolution and how robots must adapt to changes in the business environment.
Task Frequency and Complexity	How often a task occurs, and how intricate the process is.	Ideal processes for automation are both complex and frequent. Process mining can help identify these tasks.
Process Transparency	Level to which a process is visible and understandable.	Process mining provides transparency by mapping processes to identify which parts are suitable for automation.
Identification of Root Causes	Ability to trace problems to their origin.	Process mining provides insights into the root causes of process complexity to standardise processes before implementing RPA.
Benchmarking	Comparing the performance of different robots and non-robotic supported processes.	Process mining can compare the performance of different robots and non-robotic supported processes to identify the most effective RPA implementation.
Prioritisation of Activities	Identifying which activities to automate first.	Process mining helps to prioritise activities with the highest potential for automation.

CONCLUSIONS

Process mining and Robotic Process Automationare synergistic technologies that optimise business processes. They aid process discovery by analysing event logs during RPA bot activities, enabling organisations to identify inefficiencies and prioritise automation efforts. Process mining enhances processes by evaluating logs to pinpoint bottlenecks and deviations, helping select the most impactful automation processes. It plays a crucial role in bot discovery by identifying repetitive, rule-based, and voluminous tasks through detailed event data analysis. Once identified, RPA automates them based on the insights gained from process mining, with detailed process models guiding the bots to ensure alignment with actual process needs.

Key performance indicators (KPIs) considered when using process mining and RPA include automation rate, process maturity, throughput time, cost savings, ROI, process performance KPIs, accuracy and consistency, process efficiency, deviation detection, task frequency and complexity.

However, the literature on the combined use of process mining and RPA has identified several research gaps, such as the lack of standardised frameworks for task discovery, limited support for initial task suitability assessment, insufficient focus on automation objectives, lack of data-driven task selection, restricted use of event logs, need for clear criteria for automation, and limited research on cognitive RPA. More research is required to develop more standardised, data-driven, and comprehensive frameworks that leverage process mining to effectively identify and select appropriate tasks for automation.

FUTURE SCOPE

Future research should focus on developing standardised frameworks for task discovery, assessing task suitability, defining automation objectives, utilising data-driven task selection, integrating process mining and RPA tools, real-time monitoring and adaptation, anomaly detection, and exploring cognitive RPA frameworks. Enhancing process mining techniques for RPA and integrating RPA tools is also necessary. Future work should include framework evolution, automated monitoring, task-level automation, process standardisation, AI integration, automation of RPA construction, testing automation, and multi-perspective analysis.

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