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A Process Analysis Framework to Adopt Intelligent Robotic Process Automation (IRPA) in Supply Chains

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Abstract: Intelligent Robotic Process Automation (IRPA) combines Artificial Intelligence (AI) and Robotic Process Automation (RPA) to automate complex unstructured tasks, improve decision-making, and cope with changing scenarios. A process analysis framework for IRPA adoption was developed by identifying key factors through a literature review and semi-structured expert opinion survey. The employed experts in the survey comprised RPA/IRPA consultants, RPA/IRPA initiative team leaders, and RPA/IRPA developers with three years or more experience. For the initial factor collection phase, there were a total of eighteen (18) responses, and for the factor evaluation phase, a total of twenty-six (26) experts were used to collect responses. Identified factors were shortlisted and evaluated using a Relative Importance Index (RII) analysis. The study's findings are presented through a Causal-Loop Diagram (CLD) to illustrate the relationships between factors. The framework provides practical guidance for organizations planning to adopt IRPA, informing decision-making, resource allocation, and strategy development. The final process analysis framework highlights the importance of accuracy, level of human involvement in a task, and standardization as the main three primary factors for successful IRPA adoption. Three major secondary factors were identified: digital data input, integration with existing systems, and the cost of adopting new technologies. This research contributes to the added value to existing knowledge and serves as a foundation for future research in IRPA adoption.

Keywords: robotic process automation; intelligent robotic process automation; process analysis framework; relative importance index; causal loop diagram

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1. Introduction

Digital transformation in businesses is driven by various factors, including the importance of innovation, globalization, changes in consumer behaviors, and industry 4.0-related technological contributions such as Artificial Intelligence (AI), cloud computing (CC), big data, the Internet of Things (IoT), and robots. The COVID-19 pandemic has also catalyzed digital disruption and further motivated industries to adopt digital transformation [1,2]. The primary reason behind technology adoption is to enhance productivity, reduce cost, improve service quality, reduce delivery time, automate corporate procedures, improve decision-making, and relieve staff of tedious and repetitive work [3].

Robotic Process Automation (RPA) is a widely used technology that automates processes using software bots, replacing rule-based, repetitive human tasks that work with structured data [4]. Automation with RPA can greatly benefit organizations, including lower processing time, reduced human errors, lower operations costs and increased Return on Investment (ROI), improved compliance levels, higher data accuracy, and increased integration flexibility with tools and systems [5–7]. Intelligent Robotic Process Automation (IRPA), which combines RPA with Artificial Intelligence (AI), offers even greater efficiency than traditional RPA [8]. Furthermore, IRPA has comparatively more advanced capabilities than RPA, including cognitive capabilities to analyze and understand unstructured data, decision-making and problem-solving capabilities, intelligent data handling, advanced analytics, exception handling and adaptation to changing scenarios, and natural language processing capabilities [4]. Moreover, IRPA also serves as a low-code automation option, allowing non-technical workers to develop their own robotic solutions for handling time-consuming repetitive tasks as well [9]. The supply chain is one of the complex sectors and encompasses the multifaceted and interrelated nature of diverse processes, entities, and elements inherent in the production, distribution, and delivery of goods and services, thereby presenting considerable difficulties in effectively managing and optimizing the entire network. Therefore, adopting IRPA in supply chains can revolutionize operations, drive cost savings, improve efficiency, and deliver enhanced customer experiences [10].

The benefits of IRPA are particularly relevant in today's fast-paced, data-driven business environment. The demand for automation is increasing, but traditional RPA falls short in handling complex and dynamic processes. IRPA addresses these challenges by leveraging AI to enable automation that is more intelligent, adaptable, and capable of processing both structured and unstructured data. The ability to enhance decision-making, reduce costs, and improve accuracy justifies its growing adoption [11]. Additionally, as businesses seek to scale operations and improve customer experiences, IRPA offers the flexibility and scalability needed to meet these goals while maintaining high levels of efficiency and productivity.

In summary, IRPA brings together the strengths of AI and RPA to deliver a powerful solution that improves operational efficiency, enhances decision-making, and offers scalability, making it a valuable tool for organizations looking to modernize and streamline their business processes.

Adopting IRPA to different supply chain processes can streamline order fulfillment, enhance inventory control, and provide accurate demand forecasts and simplifies supplier management, optimizes warehouse operations, and ensures product traceability [12–14]. Real-time visibility into inventory levels, improved demand forecasting, and optimized logistics planning result in cost savings and better customer service [6]. Moreover, IRPA enables supply chain professionals to make informed decisions by enabling efficient supplier management, product tracking, and data analytics [15].

However, recent research conducted by Ernst and Young (E and Y) highlights that 30–50% of RPA initiatives are failures. The study conducted by Malhotra [16] elaborates that the main reason behind those RPA failures is the wrong process selection. On the other hand, implementation of IRPA involves a high cost compared to RPA [15]. The two platforms can be distinguished as shown in Table 1.

These previous findings highlight the importance of having a process analysis framework to select the most appropriate process when implementing both RPA and IRPA.

Process analysis is a critical step in both RPA and IRPA implementations to identify and assess processes before automation. It involves analyzing the existing processes to determine their suitability for automation, defining automation requirements, and ensuring that the automation solution meets the desired objectives [17]. Organizations can identify existing bottlenecks, eliminate waste, and streamline operations by analyzing processes. This method improves resource allocation, reduces implementation costs, and increases customer satisfaction while reducing the chances of failures [18,19]. Moreover, process analysis ensures the RPA/IRPA implementation's alignment with business strategic goals and fosters a data-driven decision-making culture, ultimately driving organizational effectiveness and success [16,20].

However, analyzing processes requires a systematic framework to identify the most suitable process as well as to ensure a successful implementation [21]. Such a systematic framework contains several factors that must be considered when analyzing the process. Therefore, the identification of such process analysis factors is important for conducting a more comprehensive process analysis [21]. Although a considerable number of previous studies provide the process analysis frameworks to adopt RPA in supply chains, there is a lack of studies to provide the process analysis frameworks to adopt IRPA [22].

Table 1. Distinguishing the broader requirements for RPA and IRPA.

Requirement	RPA	IRPA
Data Requirements	Structured data only. Requires clean, well-organized, consistent data inputs.	Can process both structured and unstructured data. Requires AI technologies like NLP, OCR, and ML to handle diverse data.
Deployment and Maintenance	Faster and simpler deployment. Requires rule adjustments for updates.	More complex deployment due to AI integration. Requires continuous learning, model updates, and retraining.
Process Complexity	Suited for simple, repetitive, rule-based processes with clear decision trees.	Can automate simple to complex processes, including decision-making and cognitive tasks.
Cost and Investment	Lower initial costs and lower ongoing maintenance costs for rule adjustments.	Higher initial costs due to AI infrastructure and expertise. Long-term cost savings through adaptability and scalability.
Technology Requirements	Basic software for mimicking human actions. Predefined scripts and workflows.	Requires AI technologies (ML, NLP, OCR), AI model training, and advanced computing infrastructure.
Scalability	Limited scalability; requires manual reconfiguration for new processes.	Highly scalable. AI can generalize and adapt to new processes with minimal manual configuration.
Skill Requirements	Basic technical knowledge to configure and maintain rule-based automations.	Advanced AI expertise, data science, and experience with machine learning models. Multidisciplinary teams are needed.
Error Handling	Follows predefined rules for error handling; needs human intervention for unexpected issues.	Can handle errors dynamically using AI and make decisions based on context and past learning.
Infrastructure	Simple IT systems, legacy system integration, and minimal computing power required.	Requires cloud computing, AI platforms, big data environments, and significant processing power.

On the other hand, System Dynamics is a methodology used to model and analyze complex systems, especially those characterized by feedback loops and dynamic behavior over time [23]. At the core of the System Dynamics approach is the use of causal-loop diagrams, which are graphical representations that illustrate the cause-and-effect relationships among different variables within a system. These diagrams help to visualize the feedback loops and understand how changes in one variable can influence other elements of the system, facilitating the identification of key leverage points for improving system behavior and decision-making [24,25].

Hence, there is a research gap that prevails for a comprehensive study on process analysis factors for IRPA and the process analysis framework to adopt IRPA in supply chains. This study aims to achieve three Research Objectives (ROs) to fulfill the above-identified research gap.

RO1: Identify the process analysis factors that help to select the most suitable process for IRPA;
RO2: Evaluate the contribution of process analysis factors that help to select the most suitable process for IRPA;
RO3: Develop a suitable process analysis framework to adopt IRPA.

The implications of this research are significant for decision-makers in organizations, as it provides insights into the factors to consider when undertaking IRPA initiatives and offers a framework to facilitate IRPA adoption in supply chains. The study fills the research gap by providing a comprehensive process analysis framework for IRPA adoption. Additionally, the research contributes to the academic field by advancing knowledge in IRPA adoption frameworks.

The remainder of this paper is organized as follows. Section 2 includes a detailed literature review on RPA, IRPA, process analysis, and the process analysis factors considered to adopt RPA and IRPA. Section 3 provides an overview of the research methodology, including the research process, the use of a causal-loop diagram, data collection methods, and the details of the questionnaires. Section 4 presents the analysis of the collected data from literature reviews and expert surveys, along with the final results and their implications. Finally, Section 5 further discusses the research findings, research scope, and the significance of this research, its practical applications, and potential areas for future research.

2. Literature Review

2.1. Robotic Process Automation (RPA)

Robotic Process Automation (RPA) technology automates repetitive and tedious human tasks. Its popularity began to rise around the year 2012 [26]. RPA involves creating task instructions using screen recording techniques and structured, rule-based data inputs [1,23]. It serves as a process analysis approach, aiming to improve efficiency and effectiveness for process optimization [20].

RPA operates by manipulating software application user interfaces and automating mouse and keyboard actions to eliminate monotonous tasks and reduce human errors. It focuses on streamlining automation through a user interface automation layer rather than extensive involvement with underlying application or database layers [27].

Despite the benefits of RPA, there are challenges related to effective process mining, adapting to dynamic conditions, handling large data volumes, addressing inconsistency in decision-making, and limitations in handling judgment-based tasks [4]. These challenges allow Intelligent Robotic Process Automation (IRPA) to be introduced as a solution.

RPA Application in Supply Chain Processes

Robotic Process Automation (RPA) has emerged as a valuable tool in improving various supply chain processors, including procurement, logistics, warehouses, and manufacturing. Organizations are increasingly adopting RPA to enhance service delivery and operational efficiencies [4].

In the supply chain, RPA is applied to automate critical processes. For instance, email automation streamlines communication between suppliers, manufacturers, service providers, and customers. RPA can handle tasks such as opening and comprehending emails, accessing Enterprise Resource Planning (ERP) systems, and providing real-time updates to customers. Additionally, RPA plays a significant role in demand and supply planning by assisting in forecasting and data consolidation, replacing the manual and time-consuming tasks of gathering and organizing data [28].

Procurement processes also benefit from RPA. The automation of tasks related to managing supplier relations such as issuing purchase orders, invoice processing, and data gathering improves efficiency and accuracy [29]. RPA streamlines vendor selection, facilitating the entire process from quotation preparation to finalization [28].

In logistics, RPA simplifies monotonous and repetitive tasks, such as data entry and processing. It helps manage inventory levels by monitoring in real-time, generating reports, synchronizing data with other systems, and automating communication with suppliers [30]. RPA robots can automate delivery and sorting, order management, logistics information management, bidding, and transport management, contributing to streamlined logistics operations [31].

Within the warehouse sector, RPA is used for goods receiving and inspection. Robots compare shipments with purchase orders, verify product quality, and update inventory accordingly [32]. Integration with systems such as ERP and Warehouse Management Systems (WMSs) ensures seamless information flow and enables automated data synchronization [12,31,32].

RPA optimizes production processes in the manufacturing sector by automating production order transmission, reducing waste, and increasing plant capacity [4]. It is pivotal in creating and implementing intelligent manufacturing systems that exhibit enhanced performance, agility, integration, and collaboration [33].

2.2. Intelligent Robotic Process Automation (IRPA)

Intelligent Robotic Process Automation (IRPA) takes automation to the next level by incorporating AI capabilities, enabling the automation of complex tasks involving decision-making and judgment. IRPA goes beyond traditional RPA by incorporating technologies such as machine learning, deep learning, artificial vision, natural language processing (NLP), and mathematical programming [4].

Implementing IRPA offers several advantages over RPA. It allows organizations to work with unstructured data, gain insights, adapt to changing circumstances, and improve tasks that require judgment and decision-making [34]. As a result, IRPA provides deep process insights, enhances operational efficiency, improves accuracy, enables advanced data analysis, facilitates the development of new business models, and helps overcome challenges in complex processes [15].

While implementing IRPA may present challenges in identifying suitable processes and the associated cost, careful evaluation and understanding of organizational operations are crucial for successful implementation [35]. Furthermore, incorporating IRPAs into business operations presents potential risks, such as financial or reputational losses. A key concern is the manipulation, or unintended biases present in the training data, particularly related to race, gender, or ideology. Additionally, business users often exhibit caution and lack implicit trust in AI models [36]. While IRPAs primarily address non-routine tasks, more intricate tasks require the combination of multiple IRPAs and the establishment of effective collaboration and coordination among them. This complexity poses challenges when adopting IRPA, as it necessitates leveraging the specialized capabilities of each IRPA to handle complex tasks [15].

In the supply chain context, IRPA plays a significant role in various areas such as data entry, validation, demand forecasting, inventory management, order processing, supply chain visibility, and supplier management [37,38]. By leveraging AI and machine learning algorithms, IRPA robots can perform tasks such as extracting data from invoices, predicting demand, managing inventory levels, processing orders, and monitoring the supply chain in real-time [28,39].

The primary objective of implementing IRPA in the supply chain is to reduce errors, improve data quality, optimize inventory levels, make informed decisions, and enhance overall supply chain performance. It helps handle unforeseen demand surges and enables advanced demand and supply planning.

2.3. Process Analysis

Process analysis involves examining processes to determine the most suitable process candidate to implement RPA or IRPA within an organization. It breaks down processes into individual steps, evaluates their efficiency and effectiveness, and identifies areas for improvement [3]. Process analysis offers several benefits to organizations.

Firstly, it helps to improve efficiency by identifying and addressing bottlenecks and inefficiencies, streamlining operations, and optimizing resource allocation. Secondly, it enhances product or service quality by identifying flaws and defects, allowing for corrective measures to be implemented. Standardization and consistency are also promoted by establishing best practices, reducing errors, and ensuring uniform protocols [40].

Process analysis contributes to effective risk management by identifying vulnerabilities and enabling the implementation of controls and contingency plans. It supports informed decision-making by providing valuable insights and data on key performance indicators. Engaging employees in the process analysis frameworks empowers them to contribute ideas and fosters a culture of continuous improvement.

Moreover, process analysis enables organizations to adapt quickly to market changes and seize new opportunities. It enhances communication and collaboration across teams, promoting better alignment and coordination. Overall, the process analysis frameworks drive operational efficiency, quality enhancement, risk mitigation, informed decision-making, and a culture of continuous improvement, all contributing to the success of the organizations [18].

There are several factors that must be considered when conducting a process analysis. Those factors cover different aspects of a process such as automation potential, connectivity with other processes, cost and time savings, and change management [3,6,37].

2.3.1. Process Analysis Factors for RPA Implementations in Supply Chains

Several researchers have underlined the process analysis factors that are considered to be considered when selecting processes to implement RPA in supply chains. The process analysis factors noted during the literature review are summarized in Table 2.

Table 2. Process analysis factors considered to adopt RPA.

Process Analysis Factor	Description	Reference
Automation rate	The degree of automation within a process is considered high when there is minimal manual interaction with the software during the process. An excessive level of automation negatively influences the RPA's effectiveness.	[3,17,40–43]
Complexity	The length of time it takes one person to perform an activity is referred to as the "complexity of a task" in the literature. Therefore, more difficult tasks take longer to conclude.	[3,17,40–42,44,45]
Digital data input	In addition to RPA, technologies like optical character recognition and pictures recognition are being used to make RPA bots more intelligent. Digital data input still improves the stability of automation using RPA.	[40–42,45–47]
Stability and maturity	A process is considered stable and mature when it demonstrates minimal or gradual changes and when its results are foreseeable. A higher level of maturity and stability is useful for the stability of automation using RPA.	[3,17,40–47]
Standardization	Greater standardization has a beneficial impact on the appropriateness of RPA for automation purposes.	[3,17,40–47]
Structured data input	Structured data helps to increase accuracy while lowering the cost of processes. Data are referred to as structured when it is saved in a defined format. The input of structured data enhance the suitability of automation using RPA.	[40–42,45–47]
Volume	The volume of a task is an average amount of repetitions. This makes obvious sense because RPA is routinely used to automate repetitive tasks. Enhanced volume has a favorable influence on the viability of implementing RPA for automation purposes.	[3,17,40–42,44–47]

2.3.2. Process Analysis Factors for IRPA Implementations in Supply Chains

IRPA has found application in various organizational domains, including the supply chain, as organizations strive to enhance service and operational efficiency [1]. The implementation of IRPA follows a series of key steps to ensure successful deployment. These steps include creating an IRPA implementation roadmap, process discovery and mining, AI analysis and RPA estimation, defining a suitable solution architecture, and integrating an RPA design with AI capabilities [4].

In the context of process analysis, IRPA is still in its early stages, and there is a limited availability of literature which shows process analysis factors and process analysis frameworks. This research intends to fill this literature gap by developing a System Dynamics model that shows loop behaviors and the connectivity between process analysis factors.

3. Methodology and Analysis

This research employed a qualitative approach and focused on three research objectives to collect and analyze empirical data systematically. Figure 1 illustrates the objective-wise research methodology.

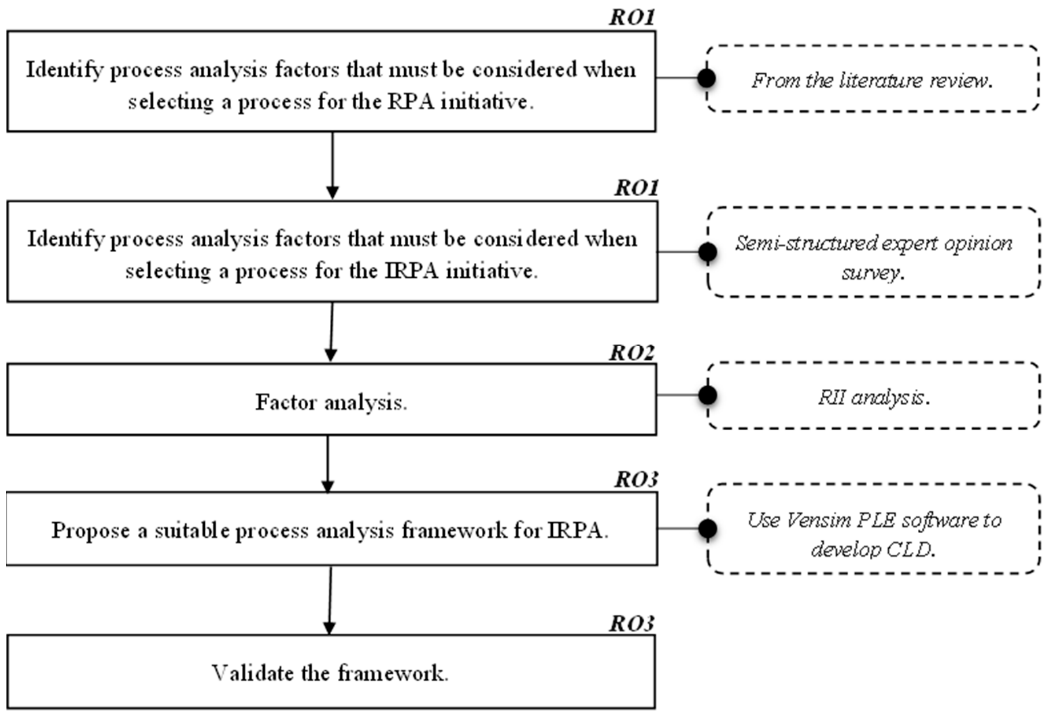

Figure 1. Research methodology.

3.1. Research Objective 1: Identify the Process Analysis Factors That Help to Select the Most Suitable Process for IRPA

The literature review identified seven process analysis factors essential for adopting RPA in supply chains. Subsequently, an expert opinion survey was conducted to identify the process analysis factors that must be specifically considered for selecting a process for IRPA implementation. Throughout the survey processes, the data were collected and we filtered the experts' opinions by their positions (e.g., head of supply chain, managers, senior RPA and IRPA analysts, project managers, senior RPA consultants, RPA business analysts, and senior RPA developers who had 5–10 years of experience in the industry). The questionnaire provided an option for respondents to offer further suggestions for the IRPA process analysis factors. The snowball sampling method was employed to identify highly experienced and suitable individuals; moreover, LinkedIn connections were used to further identify and contact experts. Hence, the questionnaire was initially distributed among three RPA and IRPA heads/consultants in two well-established multinational organizations and we asked them to distribute the questionnaire among their teams. Further, it was distributed among the LinkedIn connections. This survey questionnaire comprised two sections. In the first section, the seven factors identified from the literature review were further examined to find their relevance for IRPA implementations. Then, the second section of the questionnaire provided an option for respondents to provide further suggestions for the factors relevant to analyzing processes for IRPA implementations. They suggested 15 new process analysis factors that must be considered when selecting processes for IRPA. Altogether, 22 factors were identified from this initial survey. Those factors are accuracy, automation rate, change management, complexity, constraints, continuous improvement, cost, data management and analytics, decision-making, defined business rules, dependency, digital data input, exception handling, governance and risk management, integration with existing systems, level of human involvement in a task, reliability, stability and maturity, standardization, structured data input, time and speed, and volume. Though a total of 23 responses were received, 18 responses were selected after checking the validity of their responses by their years of experience in the domains of RPA or IRPA and their relevance to industrial applications. According to their responses, all seven process analysis factors relevant for RPA implementations are relevant for analyzing processes for IRPA implementations too.

Another survey was conducted aiming to identify the most relevant factors for IRPA adoption among the previously identified 22 factors. This questionnaire collected binary responses (Yes/No) for each factor. A total of six expert responses were collected for this questionnaire. Entirely new respondents were used to avoid the biasness for the factors and the questionnaire was distributed through LinkedIn connections. This survey helped to finalize 15 process analysis factors as the most relevant factors for the IRPA adoption. Those shortlisted factors were categorized into three distinct categories to consider the aspects of people, process, and technology, and those selected factors are shown in Table 3.

Table 3. Categorization and the meaning of shortlisted process analysis factors considered to adopt IRPA.

Process Analysis Factors for IRPA	Description	Category
Accuracy	The accuracy of a task or a process has a huge impact on the overall output of a system. Therefore, adopting IRPA should also give a 100% accurate output for a process.	Process
Automation rate	The degree of automation within a process is considered high when there is minimal manual interaction with the software during the process. An excessive level of automation negatively influences the IRPA's effectiveness.	Technology
Change management	Implementing IRPA involves significant changes in the way people work, including introducing new roles and responsibilities, new technologies, and new processes. Therefore, it is important to manage the change effectively to ensure that people are prepared and motivated to work with the new technology.	People
Complexity	The length of time it takes one person to perform an activity is referred to as the "complexity of a task" in the literature. Therefore, more difficult tasks take longer to conclude.	People
Cost	The cost of adopting new technologies or process improvements may be high due to the advancement of the technology. It is important to have a financially sustainable approach to adopting IRPA.	Technology
Dependency	When considering a particular process, look to see if that process has a relationship with any other processes.	Process

Table 3. *Cont.*

Process Analysis Factors for IRPA	Description	Category
Digital data input	In addition to RPA, technologies like optical character recognition and picture recognition are being used to make RPA bots more intelligent. Digital data input still improves the stability of automation using IRPA.	Technology
Integration with existing systems	IRPA needs to be integrated with existing systems and applications to ensure it can access the data and functionality needed to perform the tasks. This includes API (Application Programming Interface) integration, middleware development, and other technical considerations.	Process
Level of human involvement in a task	The level of human involvement in a task means that when more people are involved in a function, the function would be more likely to be automated.	People
Reliability	The process should be trustworthy to apply the IRPA, which means a particular process should have long-term usage and impact on the company. On the other hand, IRPA should provide the expected outputs for that process.	Process
Stability and maturity	A process is considered stable and mature when it demonstrates minimal or gradual changes and when its results are foreseeable. A higher level of maturity and stability is useful for the stability of automation using IRPA.	Process
Standardization	Greater standardization has a beneficial impact on the appropriateness of IRPA for automation purposes.	Process
Structured data input	Structured data helps to increase accuracy while lowering the cost of processes. Data are referred to as structured when it is saved in a defined format. The input of structured data enhance the suitability of automation using IRPA.	Process
Time and Speed	When a process takes a long time to be completed by a human, it is more appropriate and beneficial to adopt IRPA. That will increase the efficiency of the process and reduce the time to complete the process.	Process
Volume	The volume of a task is an average amount of repetitions. This makes obvious sense because IRPA is routinely used to automate repetitive tasks. Enhanced volume has a favorable influence on the viability of implementing IRPA for automation purposes.	Process

3.2. Research Objective 2: Evaluate the Contribution of Process Analysis Factors That Help to Select the Most Suitable Processes for IRPA

The fifteen shortlisted factors underwent a detailed examination to determine their relative importance and contribution. It was conducted by utilizing the Relative Importance Index (RII) analysis technique. The Relative Importance Index (RII) facilitates the identification of key factors and allows for their prioritization based on their relative contributions, which are enhanced by the comparative analysis of factors by assigning numerical values to their importance [48]. It provides a structured and systematic approach to evaluate and rank the relative importance of different factors in qualitative analysis. It allows for a consistent and standardized method of assessing the significance of factors [49,50].

The RII utilizes a Likert scale, where the points assigned to each factor correspond to the weighting (W) attributed to them by the respondents. The RII is computed using the following equation.

The equation for the Relative Importance Index (RII):

$$\text{Relative Importance Index (RII)} = (\textstyle\sum \text{W})/(\text{A} \times \text{N}), \tag{1}$$

where W is the weighting given to each factor by the respondent, A is the highest weight in the research, and N is the total number of respondents.

The respondents in the study were asked to rate factors on a five-point Likert scale, where "H" represented the highest rating of five. A total of 26 responses were collected from industry experts, indicating a sample size of 26 (referred to as "N").

The shortlisted factors obtained from Questionnaire 2 were used to create Questionnaire 3. Data were collected using Questionnaire 3 to assess the relative importance of the factors.

The RII analysis was conducted on the process analysis factors using Equation (1). The analysis results are presented in Table 4. Based on this analysis, we categorized the factors as the primary and secondary process analysis factors that are crucial for adopting IRPA in supply chains by considering the mean value of the RII obtained for each factor as the threshold point for the categorization [51]. The mean value is equal to 0.8503.

Table 4. Results of the RII analysis.

Factor No.	Process Analysis Factor	RII	Factor Type
1	Accuracy	0.9308	Primary
2	Level of human involvement in a task	0.9154	Primary
3	Standardization	0.9077	Primary
4	Stability and maturity	0.9000	Primary
5	Structured data input	0.8769	Primary
6	Reliability	0.8769	Primary
7	Time and Speed	0.8769	Primary
8	Volume	0.8615	Primary
9	Dependency	0.8538	Primary
10	Digital data input	0.8462	Secondary
11	Integration with existing systems	0.8385	Secondary
12	Cost	0.8231	Secondary
13	Complexity	0.7846	Secondary
14	Change management	0.7462	Secondary
15	Automation rate	0.7154	Secondary

The division into primary and secondary factors helps prioritize critical elements for decision-making in complex projects like IRPA implementation. Primary factors are essential for success and require immediate attention, while secondary factors are important but can be addressed later. This approach enhances clarity, optimizes resource allocation, mitigates risks, simplifies complexity, and allows for strategic flexibility as the project progresses. It ensures that the most impactful issues are handled first, improving efficiency and reducing the likelihood of major setbacks.

3.3. Research Objective 3: Develop a Suitable Process Analysis Framework to Adopt IRPA

The process analysis framework was developed by utilizing the identified process analysis factors. To conceptualize the factors and their interrelationships, the earlier discussions employed Causal-Loop Diagrams (CLDs). The CLD which is a part of the System Dynamics (SD) methodology serves as a visual tool that shows the dynamic and dependent behavior between different elements/factors [24]. Therefore, this research developed the process analysis framework as a Causal-Loop Diagram (CLD) and Vensim PLE software (Version: 9.3.5) was used for the framework designing purpose. The variables within the CLD were derived from the factors identified during the data collection stages. The developed CLD provides a clear understanding of the relationships and interactions among the factors, supporting decision-making and strategic planning in implementing IRPA initiatives. The framework contributes to enhancing the effectiveness and success of IRPA adoption efforts in supply chains by providing organizations with insights into the key elements and their interdependencies.

The CLD was completed (Figure 2) by defining reinforcement and balancing loops with the presented relationships and the impact of the nine primary factors and the six secondary factors identified on the adoption of IRPA in supply chains.

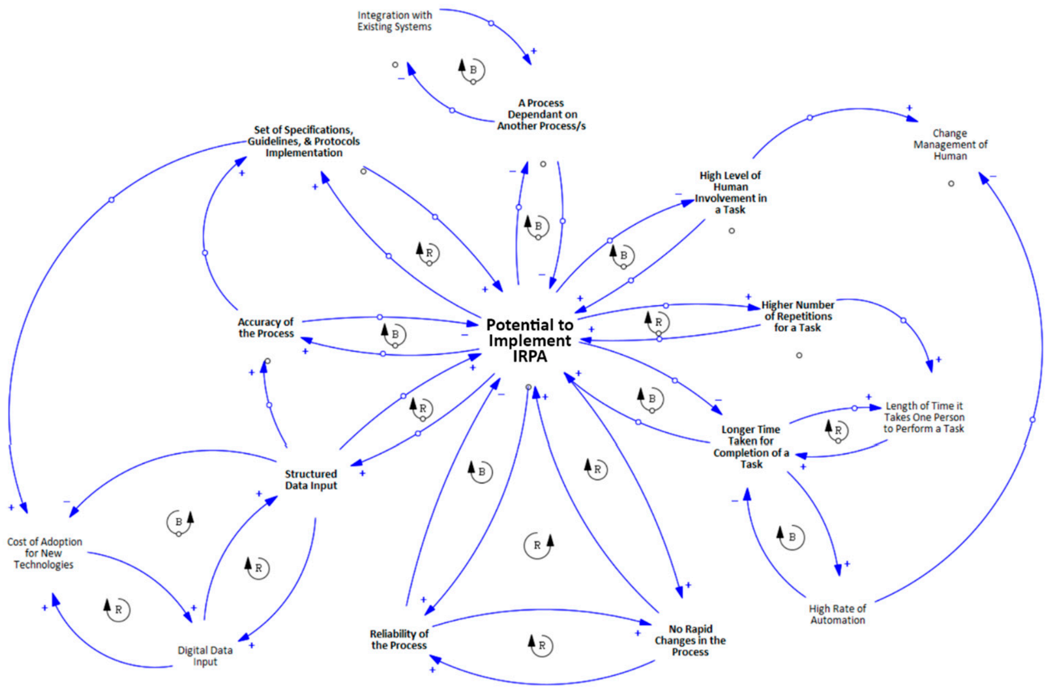

Figure 2. Causal-loop diagram with loop polarity.

The identified process analysis factors are defined in the CLD as mentioned here. The accuracy of the process; standardization as implementation of a set of specifications, guidelines, and protocols; stability and maturity as no rapid changes in the process; reliability as reliability of the process; time and speed as longer time taken completion of a task; volume as higher number of repetitions for a task; dependency as a process depends on another process/s; cost as cost of adoption for new technologies; complexity as length of time it takes one person to perform a task; change management as change management of human; automation rate as high rate of automation; high level of human involvement in a task; structured data input; digital data input; and integration with existing systems.

The process analysis factors impacting the adoption of IRPA in supply chains have been discussed. In summary, a detailed CLD has been included to illustrate how these factors affect the adoptability of IRPA as a framework.

Basically, there are two types of loops in a CLD: reinforcing loops (R) and balancing loops (B). A reinforcing loop is observed when a modification in one variable initiates a self-reinforcing cycle. It is essential to examine loops where the direction of the arrows signifies a positive or reinforcing relationship. In a reinforcing loop, a change in one variable triggers an amplification or growth effect in the same direction. On the other hand, a balancing loop is observed when a modification in one variable stimulates a corrective or balancing response in another variable, opposing the initial change. It is important to identify loops where the direction of the arrows signifies a negative or balancing relationship. In a balancing loop, a change in one variable prompts a counteracting effect that stabilizes or restricts the change [52]. Further, (+) sign indicates a positive relationship between the considering factors and the (−) sign indicates a negative relationship between the considering factors in both sides of an arrow.

The loops relating to the highest three ranking factors of the RII analysis are described as follows.

- Accuracy—When an already existing process has a higher level of accuracy, that specifically does not need to adopt IRPA. Therefore, that relationship has a negative impact. On the other hand, when there is a high potential to adopt IRPA, that helps to increase the accuracy of the processes. Therefore, that relationship has a positive impact, as represented in Figure 3.

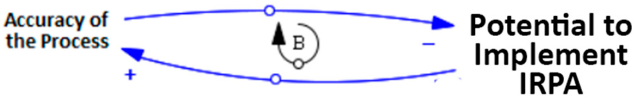

Figure 3. Loop for accuracy of the process.

- Level of human involvement—When automating a process with a high level of human involvement, it requires to have decision-making capabilities, adopt to changing conditions, and it should reduce human errors; then, there is a higher potential to implement IRPA. Therefore, that relationship has a positive impact. On the other hand, implementing IRPA reduces human involvement in a process, since that relationship has a negative impact, as represented in Figure 4.

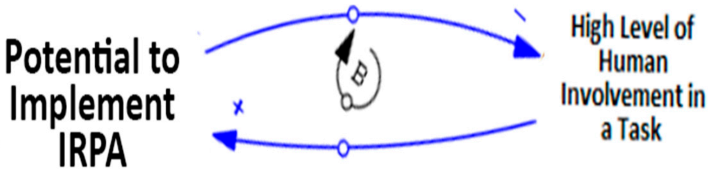

Figure 4. Loop for the level of human involvement.

- Standardization—Standardization means the implementation of a set of specifications, guidelines, and protocols. If a process already has standardization, that increases the potential to implement IRPA and vice versa, so that both relationships have a positive impact, as represented in Figure 5.

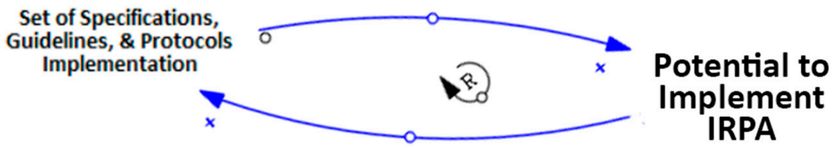

Figure 5. Loop for standardization.

There are nine reinforcement loops and eight balancing loops in the CLD framework.

Finally, the CLD underwent a verification process based on the opinions of five experts using a validation survey. To validate the CLD, inputs from the six experts were collected through another questionnaire. A 5-point Likert scale was utilized to collect responses. Entirely new respondents were used to avoid bias.

4. Findings and Discussion

This research intended to develop a process analysis framework for IRPA adaptation given that there is a lack of research on process analysis frameworks for IRPA. This research used a System Dynamics-based CLD diagram to develop the framework. Causal-Loop Diagrams (CLDs) are powerful tools for illustrating the feedback structure inherent in a system that enables one to construct conceptual models that effectively showcase the dynamic aspects of a given problem or situation [53,54]. In a CLD, variables are interconnected, and the arrows symbolize the causal relationships between them [55,56].

According to the findings of this research, there are two important loops between the process analysis factors. The first loop connects two factors with the adaptation of IRPA in supply chains. Those two factors are reliability of the process and no rapid changes in the process.

When considering the loop behavior of the CLD, there is a major reinforcing loop, as shown in Figure 6, with the two primary factors that directly impact the adoption of IRPA in supply chains. The factors, no rapid changes in the process (stability and maturity) and reliability of process, create a reinforcing loop within the system. If a process is reliable and trustworthy, it indicates a process does not have rapid changes, which helps in adopting IRPA. After adopting IRPA, the process reliability will increase. The behavior of this loop can be further validated from the findings of the study conducted by I. E. Nielsen et al. in 2022 [20]. According to their findings, having an immutable process or a process with no rapid changes is a critical factor for a RPA implementation. This can be further validated with the study conducted by Nema K. and Sonwaney V. [57]. They highlight that automation of already complex processes that face rapid changes over time would further increase the current inefficiencies in processes.

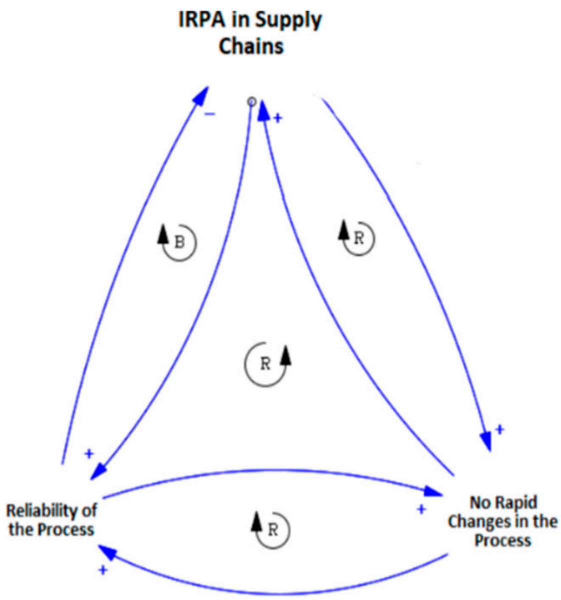

Figure 6. Reinforcement loop between primary factors.

There was a valuable balancing loop that has been identified in the CLD shown in Figure 7. The factors structured data input, digital data input, and cost of adoption for new technologies are contributing to this loop. Utilizing digital data and structured data in processes can provide significant benefits and serve as a wise investment. When a process involves digital data input, the information received is typically well-structured. This structured nature of input data offers advantages in terms of implementing new technologies, as it eliminates the need for extensive data cleansing or restructuring efforts. By leveraging existing structured data, organizations can avoid additional costs associated with data preparation and streamline the implementation process.

Adopting technologies that can effectively utilize digital data and structured data leads to improved efficiency, accuracy, and effectiveness. These technologies can readily process and analyze structured data, enabling organizations to make informed decisions and gain valuable insights. Moreover, digital data can be easily stored, accessed, and shared, facilitating collaboration and information exchange within the organization.

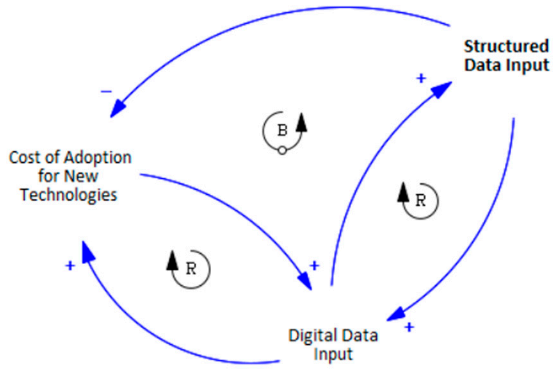

Figure 7. Balancing loop between primary and secondary factors.

The utilization of digital data and structured data prove to be a significantly valuable decision due to the inherent advantages it offers. By leveraging the structured nature of the data and the usage of digital data, organizations can optimize processes, reduce implementation costs, and enhance decision-making capabilities.

Finally, the proposed process analysis framework for Intelligent Robotic Process Automation (IRPA) presents notable improvements over traditional Robotic Process Automation (RPA) frameworks, especially in handling complexity, adaptability, and scalability. While RPA focuses on automating repetitive tasks using structured data and rule-based systems, it struggles with unstructured data and complex decision-making. IRPA, on the other hand, integrates Artificial Intelligence (AI) technologies such as Machine Learning (ML), Natural Language Processing (NLP), and Optical Character Recognition (OCR). This allows it to manage both structured and unstructured data, make more complex decisions, and learn from outcomes over time. Unlike conventional RPA, which depends on fixed workflows and rule-driven process discovery, IRPA leverages AI to dynamically adapt and optimize processes, making it suitable for more sophisticated tasks. Its cognitive abilities improve error handling and decision-making by learning from past performance and refining operations autonomously. Moreover, IRPA is highly scalable, easily integrating with emerging technologies like IoT and blockchain, thanks to its AI foundation. Ultimately, IRPA frameworks offer greater flexibility, continuous improvement, and enhanced decision-making, making them more robust and future-proof compared to traditional RPA frameworks.

Further, the IRPA process analysis framework can help address some of the challenges associated with IRPA implementation by providing a clear structure for managing its complexities. One of the main difficulties in implementing IRPA is the complexity involved in setting up intelligent systems and dealing with unstructured data. The framework helps overcome this by using AI-driven process discovery and analysis, making it easier to identify tasks that are ideal for automation and optimizing them efficiently. Additionally, the framework supports continuous learning and adaptability, allowing IRPA systems to improve over time and reducing the need for constant manual intervention. With built-in intelligent error handling and decision-making, the framework also helps to manage exceptions effectively, minimizing potential disruptions. This structured approach simplifies implementation and helps ensure IRPA solutions are scalable and easier to maintain.

5. Conclusions

In conclusion, this research aimed to provide practical implications through a process analysis framework for adopting Intelligent Robotic Process Automation (IRPA) in supply chains. The developed framework can be used to improve supply chain operations across logistics, procurement, warehousing, and supply and demand planning. Data collected from these sectors validates the framework's applicability and effectiveness in diverse supply chain functions, such as order processing, inventory management, demand planning, supplier management, warehouse optimization, track and trace, and data analytics. The framework streamlines order fulfillment, enhances inventory control, provides accurate demand forecasts, simplifies supplier management, and optimizes warehouse operations, ultimately ensuring product traceability and generating actionable insights. These capabilities support real-time visibility into inventory, better demand forecasting, and optimized logistics planning, which result in cost savings and improved customer service. The integration of track-and-trace functionality, efficient supplier management, and data analytics empowers supply chain professionals to make informed decisions, driving continuous improvement and enabling data-driven, efficient operations. Through this framework, intelligent RPA has the potential to revolutionize supply chains, making them more resilient, responsive, and efficient.

To achieve this objective, the study focused on three research goals: identify the process analysis factors that help to select the most suitable process for IRPA, evaluate the contribution of those process analysis factors, and develop a suitable process analysis framework to adopt IRPA. In the evaluation stage, fifteen shortlisted factors were categorized into primary and secondary factors using the mean of RII values as the threshold point. The "accuracy" factor was identified as the most important factor, followed by the "level of human involvement in a task" and the "standardization". Furthermore, the study showcased the most important factors that should be considered by the organizations when adopting IRPA from the identified loops in the CLD. The identified loops include one reinforcement loop and from that the "reliability" and the "stability and maturity" factors were identified as they provide a positive impact on the IRPA adoption. In the balancing loop, "digital data input" and the "structured data input" help to optimize the processes and subsequently help to reduce the "implementation costs".

By leveraging this research, organizations can develop their frameworks considering the impact and significance of these primary and secondary process analysis factors. Further, organizations can gain valuable insights into effectively implementing IRPA in supply chain operations and enhance the overall success of their automation initiatives. The proposed IRPA process analysis framework enhances the success rate of IRPA implementations by helping select the most suitable processes for automation. It uses AI-driven discovery and analysis to assess processes based on factors such as complexity, data type, and decision-making needs. By analyzing tasks that involve both structured and unstructured data, the framework identifies the processes that would benefit most from IRPA's advanced capabilities. It focuses on processes that require dynamic decision-making or deal with high data variability—areas where traditional RPA may not be effective. This targeted approach ensures that the chosen processes align well with IRPA's strengths, increasing the chances of successful automation.

In the future, this research can explore the identification of specific supply chain processes that can derive the greatest benefits from the adoption of IRPA. Employing a System Dynamics approach, researchers can integrate a stock flow diagram as a step towards cause-and-effect analysis and feedback loop structures to establish practical business scenarios for implementing the IRPA framework in real-world contexts. This methodology would enable a comprehensive understanding of the dynamic relationships involved in IRPA implementation, thereby enhancing the decision-making process.

By utilizing a System Dynamics approach, researchers can model and simulate the complex interactions and dependencies within the supply chain, considering factors such as process optimization, resource allocation, and performance evaluation. Such studies can provide valuable insights into the potential impacts of IRPA on supply chain processes, including cost reduction, increased efficiency, improved quality, and enhanced customer satisfaction.

Moreover, future research can delve into the challenges and barriers that organizations may encounter during the implementation of IRPA in supply chain processes. By examining these issues, researchers can develop strategies, best practices, and guidelines to overcome hurdles and ensure the successful integration of IRPA within the supply chain domain.

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