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Convergence of GenAI and RPA: A Digital Heaven in Supply Chain Optimization Process

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Abstract: One of the most groundbreaking advances in the field of intelligent automation is the merging of Generative Artificial Intelligence (GenAI) and Robotic Process Automation (RPA). This combination unlocks previously unachievable capabilities in automation. RPA (software bots) improves speed and operational efficiency by automating rule-based tasks, Standard Operating Procedures (SOPs), and repetitive workflows. At the same time, it minimizes manual labor and human errors. While, GenAI's advanced proficiencies in Natural Language Processing (NLP) with context, content creation, and smart decision-making make it well suited or tasks that require flexibility and adaptability. Leveraging the fusion of the two can empower greater improvements in the supply chain world. Overall, in the supply chain management workflow, this convergence drives automation to new heights and delivers the precision, and adaptability across the end-to-end process. This integration enables real-time forecasting of multiple level items to each item/eaches, case quantities, pallet load, inventory management optimization, demand forecasting, customer service and communication, logistics and transportation management, anomaly detection, damage detection, etc. in the supply chain process. This paper explores in brief the future potential of supply chain automation using the fusion of GenAI and RPA, along with practical applications, challenges, and future directions.

Keywords: Intelligent Automation, GenAI, RPA, Software Bots, SOPs, NLP, Supply Chain Management, Inventory Management Optimization, Logistics

Introduction

Supply Chain Management (SCM) is a broad concept that has recently gone through a significant transformation, driven by the rapid advancement of technology (Garay-Rondero et al., 2019; Li and Zhao, 2024; Holloway, 2024). Using intelligent automation and various automation tools in the supply chain enables efficient and seamless business operations. During the COVID-19 pandemic, there was a major interruption in the supply chain due to reduced manual labor, which caused disruption and delays in supply chain operations (Mızrak, 2024; Shah et al., 2024). Most of the companies in COVID-19 era leveraged bot automation such as Robotic Process Automation (RPA) that enabled these organizations to automate rule-based and repetitive operations, reducing errors and processes efficiently in order to mitigate the effects of these interruptions (Lubis and Sembiring, 2023; Kavitha, 2023; Banerjee and Parkhi, 2021). There is a study showing that the use of RPA in Supply Chain Management (SCM) can reduce cost and increase the efficiency of the business operations (Venigandla et al., 2024; Rajagopal and Ramamoorthy, 2023). In this context, the use of RPA technology in the supply chain pipeline is very beneficial.

Robotic Process Automation (RPA) is a technology that employs software bots (i.e., bot technology) to automate repetitive tasks and processes. It improves efficiency, increases productivity, reduces manual labor work, reduces operational costs (Hofmann et al., 2020). The primary advantages of implementing RPA are the

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increased efficiency and efficacy of business operations in a variety of applications and improved data security through access restrictions (Rivera Picado et al., 2024; Pandy et al., 2024; Khankhoje, 2024). Popular software vendors, including Automation Anywhere (Mahey, 2020), Blue Prism (Mukherjee, 2021), and UiPath (Khan and Khan, 2023), offer RPA tools for the development of bots. These platforms allow users to develop software bots that are designed to perform tasks such as data processing, web scraping, and information transmission. In the supply chain world, bots (software bots) are automatically updating inventory, keeping track of packages in real time, and getting useful information from supplier data on the Web (Krishna et al., 2022). However, Robotic Process Automation (RPA) lacks a cognitive brain and the capacity to think through, learn, or make sophisticated judgments on its own (Herm et al., 2021). It is a rule-based technology that follows preset guidelines or workflows to automate repetitive and organized processes (Dalsaniya, 2022). Cognitive bots are integrated with existing process workflows for end-to-end development, which enables cognitive capabilities such as perception and decision-making abilities. However, cognitive bots lack the ability to process complex tasks and reduce performance in complex datasets (Baki et al., 2023; Gidey et al., 2023). To overcome problems with complex decision making and unstructured data, the integration of RPA with GenAI technology builds advanced bots that use Generative AI (GenAI) to help make better decisions (enhance the decision-making process), automate content generation and provide predictive insights (Richardson, 2020; Pranavi AM and Cholli, 2024; Ooi et al., 2025).

Fig. 1 has provided a high-level integration pattern overview between various bot methodologies such as RPA (Rule-based software bots), Cognitive Bot (AI augmented bots), and GenAI Bot (Generative AI bots). This integration capabilities enhances the intelligent decision-making cognitive capabilities by leveraging the cutting-edge AI driven Retrieval Augmented Generation (RAG) systems. These systems automate the various tasks and create different content generation outputs by leveraging content generation models GPT, LLaMA and others.

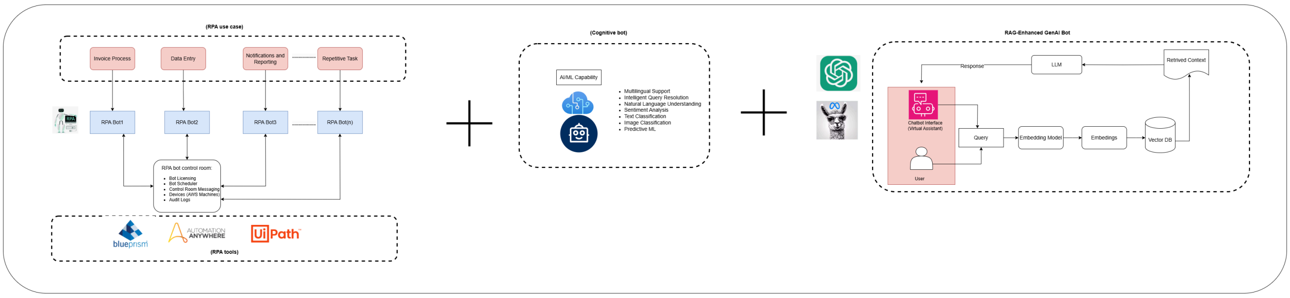

Fig. 1: Overview of RPA, Cognitive Bot, and GenAI Bot

As demonstrated in the Fig. 1, Cognitive Bots, Generative AI (GenAI) Bots, and Robotic Process Automation (RPA) bots can all work together in a single automation setting.

On the left side of the diagram, the RPA layer shows how repetitive tasks based on rules can be automated. These tasks include writing invoices, entering data, sending alerts, and other structured activities. Each of these tasks is performed by a separate RPA bot (like Bot1, Bot2, or Bot3), which is overseen by a control room. This control room manages important tasks like arranging bots, licensing them, managing devices (including virtual machines), letting bots talk to each other, and keeping audit logs. This layer is where the RPA top automation tool like Blue Prism, Automation Anywhere, and UiPath work well in this first layer.

Artificial intelligence and machine learning are built into Cognitive Bots in the main layer, making automation better. Smart question answering, Natural Language Understanding (NLU), sentiment analysis, text and picture classification, and predictive analytics are some of the advanced tasks that these bots can perform. Cognitive Bots process unstructured or semistructured data, which allows the system to deal with more complicated and changing inputs. This helps software to make smarter decisions and act in a way that is appropriate for the scenario based on the situation of the user.

In the upper right corner of the figure, there is a GenAI Bot that has been enhanced with Retrieval-Augmented Generation (RAG). This is the newest development in virtual helper technology using a LLM based model. People can talk to a chatbot system here. A vector embedding model takes the user's question and turns it into a vector representation. This representation is then compared with a vector database to get relevant contextual information. Then a Large Language Model (LLM), like those made by OpenAI or Meta (LLaMA), is given this information. The system comes up with an answer that is specific to the user's question. This method ensures that responses are natural and human-like and are based on correct data that is important to the situation.

RPA, Cognitive Bots, and GenAI Bots work together to create a strong automation framework. This framework allows companies to automate entire processes by mixing rule-based efficiency with AI intelligence and the flexibility, scalability, and adaptability of generative language models.

Generative Artificial Intelligence (GenAI) refers to various models and techniques which usually include strong Natural Language Processing (NLP) models like Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019; Sayeed et al., 2023; Miller, 2019) that are used in many fields to mainly perform various language related tasks. It performs better than other models on tasks such as answering questions, analyzing sentiments, and recognizing quotes. Generative Pre-trained Transformer (GPT) (Brown et al., 2020) is a deep learning neural network model that has become famous because it performs exceptionally well in interpreting the task of natural language, data augmentation, idea generation (Yenduri et al., 2024; Sufi, 2024).

GenAI systems are built on models such as Generative Adversarial Networks (GANs) and Large Language Models (LLMs). These models generally have two major components: Generator and Discriminator (or Encoder and Decoder). However, depending on the model architecture, only a subset may be present. The LLMs are often used in Retrieval Augmented Generation(RAG) systems to enhance its accuracy and effectiveness by pairing it with a vector database to retrieve relevant information and generate realistic outputs based on specific information (Wu et al., 2025; Sengar et al., 2024).

These characteristics of such models make them well suited to understanding contexts and generating responses and actions depending on the domain specific knowledge provided to it. This domain specific context can be fed to the model using a specialized dataset for fine tuning the selected LLM model. Fine tuning domain specific LLMs enables them to identify tasks and execute (based on the selected domain) the appropriate process depending on its context (Ismail et al., 2024; Cui et al., 2024). Multi-modal generative AI systems can understand and produce different kinds of information such as text, images, and videos. Also, These systems excel at tasks like converting text into images, editing images, and transforming text into videos (Wang et al., 2024; Jiang et al., 2024).

Generative AI has impacted many different industries. When integrated with RPA, it could help build enhanced automation systems with exceptional adaptability. In addition, various GenAI models can reinvent the supply chain optimization process in the future. As future market trends indicate the convergence of GenAI and RPA (Fig. 2), this has immense potential for the automation sector. Generative AI in the RPA market is expected to develop exponentially. The global generative AI market is expected to exceed \$800 million by 2025, demonstrating the high demand for AI-driven automation solutions in all industries (Gaul, 2023). Moreover, RPA vendors will offer to take advantage of GenAI-assisted automation according to the current market trend in RPA and GenAI world. In this work, we will explore some of the ways in which this integration can be accomplished as well as the challenges that will be faced in this pursuit and how they may be mitigated.

Generative AI (GenAI) and Robotic Process Automation (RPA) could work well together, but putting them into practice in the real world can be difficult. The high cost of deployment is one of the main problems (Chen et al., 2025). GenAI models need to spend a lot of money on computer infrastructure, cloud services, business software licenses, and staff training that are experts in their fields (Cacciari et al., 2010). These financial requirements can be especially hard for small and medium-sized businesses (SMEs), which may not have the money to pay for such large costs upfront.

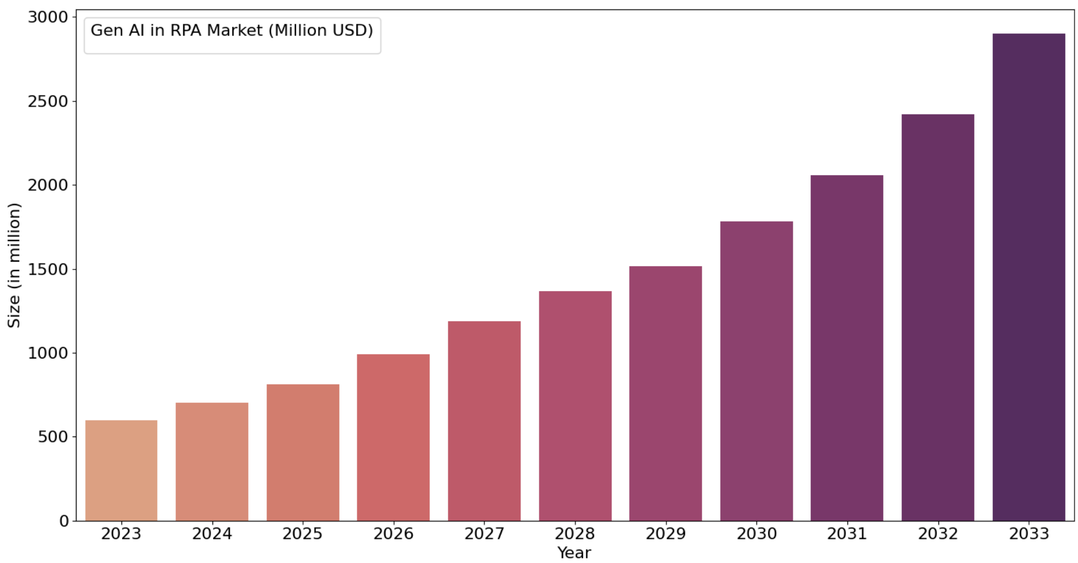

Fig. 2: GenAI and RPA Market Trend

Another big problem is that new systems have to work with old ones. This is especially true for large companies that use old systems and complicated, distributed structures. Concerns about data protection, the need to follow rules, and the lack of standard deployment frameworks all add to operational and reputational risks. Also, many companies are hesitant to use GenAI-enhanced RPA because they don't know the return on investment (ROI) and there are not many compelling, proven use cases that show worth to use this approach.

A lot of supply chain automation uses robotic process automation (RPA) to perform repetitive tasks and follow rules. But it has a lot of problems when it comes to being scalable, flexible, vendor contract inspection, response time based on historical order data, and handling unstructured data. When it is working with complicated vendor contracts, inventory records that change all the time, and logistics documents that are not standardized. These restrictions make it harder to make decisions in real time and slow down operations. This is especially true for global businesses, where cultural disparities and changing rules are frequently changes. Hence, to overcome these issues are fixed when GenAI and RPA work together because it enables rational understanding, context-aware automation, and the flexibility to make changes at any time. For example, a Retrieval-Augmented Generation (RAG) architecture can deal with unstructured files, adapt instantly to new rules in the supply chain with multiple languages, and make responses or reports based on need. These are things that regular RPA does not have. In this paper a new GenAI + RPA structure is proposed. It would leverage advanced features to fix the issues with current RPA-based supply chain systems.

This article makes several key contributions to the field of supply chain optimization through the integration of GenAI and RPA. Firstly, it provides an overview of how the convergence of these technologies can enhance automation capabilities, especially in the handling of unstructured data and complex decision-making processes. Secondly, the article proposes a conceptual framework for integrating GenAI and RPA within supply chain operations. Highlights potential improvements in areas such as inventory management, transportation efficiency, anomaly detection, and damage detection. In addition, it discusses the role of middleware in facilitating seamless data exchange between RPA and GenAI systems, ensuring efficient workflow automation. The article also addresses the ethical considerations, scalability challenges, and technical hurdles associated with this integration to offer guidelines for successful implementation. By exploring these aspects, the article aims to provide valuable insights and practical strategies to use the combined power of GenAI and RPA to drive innovation and efficiency in supply chain management.

Literature Review

Global supply chains have become far more intricate in today's interconnected environment. Effectively managing these networks, which involve complex financial, geopolitical, and resource-related considerations, requires more advanced systems than those used in the past (Riahi et al., 2021). The aftermath of the COVID-19 pandemic brought to the forefront the shortcomings of the existing SCM systems currently in use. In addition to their greater complexity, SCMs suffer from uncertainty and information asymmetry. These issues amplify the variability within the system and make it harder to make accurate predictions. This makes advanced machine learning systems a crucial tool in improving the performance of SCMs.

In this article, we will use the definition of supply chains by Mentzer et al. (2001), which describes a supply chain as "a supply chain is the network of organizations that are involved, through upstream and downstream linkages, in the different processes and activities that produce value in the form of products and services delivered to the ultimate consumer". SCM encompasses a broad range of tasks that require advanced analytical skills and decision-making expertise to effectively manage complex global supply chain operations. These tasks can be broadly categorized into several distinct sub-domain areas, each presenting its own distinctive set of complexities and challenges.

In particular, the following task categories are commonly found in SCM environments: demand forecasting, inventory optimization, supplier selection, route optimization, risk analysis and mitigation, warehouse management, logistics planning, and transportation coordination. Each of these tasks presents a unique set of analytical challenges that require specialized skills and expertise to resolve effectively (Soori et al., 2023; Mentzer et al., 2001; Pournader et al., 2021; Davuluri, 2023).

Demand forecasting is the process of estimating future demand for services or products in order to inform production planning, inventory management, and sales strategy decisions. This task requires the application of statistical models, machine learning algorithms, and data analytics techniques to forecast demand patterns and adjust production levels accordingly. Other factors such as market trends, competitor activity, and consumer preferences also need to be considered when making demand forecasting decisions.

Inventory optimization is another critical task in SCM that involves managing stock levels in order to reduce reduce lead times, inventory costs, and improve customer satisfaction. This task requires the application of optimization mechanisms like linear programming and genetic algorithms, to minimize waste and streamline inventory levels. Furthermore, supply chain managers must also consider other factors such as supplier reliability, logistics capacity, and market demand when making inventory optimization decisions.

Supplier selection is a critical task in SCM that involves recognizing and selecting reliable suppliers who can meet production demands at the lowest possible costs. This task requires the application of advanced analytical techniques, such as vendor selection models and supplier rating systems, to evaluate supplier performance and make informed decisions.

Route optimization is another important task in SCM that involves planning efficient transportation routes for goods or services between suppliers, manufacturers, and distribution centers. This task requires the application of advanced route-planning algorithms and data analytics techniques to maximize route efficiency, lessen transportation costs, and enhance delivery times. Accurate and timely availability of information from different sources is crucial for this task.

Warehouse management is a key task in SCM that involves managing storage facilities, inventory levels, and logistics operations to ensure efficient receipt, storage, and shipment of goods or services. This task requires the application of warehouse optimization models and supply chain simulation software, to optimize warehouse operations and minimize waste.

Each of these tasks is a challenge in itself but solving for feasible solutions for all of these without sacrificing the robustness of the chain is a exponentially more complex task. By utilizing advanced analytical algorithms, machine learning techniques, and data analytics tools, supply chain managers can improve their ability to handle all these tasks (Pournader et al., 2021; Tirkolaee et al., 2021; Davuluri, 2023).

In order to operate efficiently in a complex environment and accomplish all these tasks, SCM systems must be able to reasonably accurately forecast the market in a deterministic manner on both supply and demand sides and use these models to forecast sales and inventories and streamline the logistical operations based on these forecasts (Davuluri, 2023). A variety of methods have been used to accomplish this goal but machine learning methods are currently one of the most popular.

The primary advantages of using machine learning methods for SCM are their ability to model non-linear relationships in the SCM, and their ability to accommodate unstructured datasets (Ni et al., 2020). Machine learning techniques like neural networks (Leung, 1995; Aburto and Weber, 2007), support vector machines (Carbonneau et al., 2008; Guo et al., 2009), decision trees (Bala, 2010; Estelles-Lopez et al., 2017), etc. have been used in such applications for a while now. Many of these techniques have been used for SCM and have been evaluated to be better than traditional methods like moving averages, linear regression, exponential smoothing and auto-regressive models (Carbonneau et al., 2008; Soori et al., 2023). Recent progress in machine learning frameworks using deep neural networks variants like recurrent neural networks (RNN), convolutional neural networks (CNN), etc. have also been applied to SCM problems with a high degree of success (Hosseinnia Shavaki and Ebrahimi Ghahnavieh, 2023; Yu et al., 2024). However these require extensive data preprocessing which is only possible in case of time series data and a lot of unstructured data, especially multimodal data is not used for such models. With the advancement of large language models (LLMs) capable of processing unstructured data, their feasibility for various SCM tasks has been extensively evaluated (Li et al., 2023; Wang et al., 2024; Aguero and Nelson, 2024; Srivastava et al., 2024).

Another facet of SCM is the speed and efficiency of these systems. An accurate forecast is of no value if timely decisions can not be made based on those forecasts. The is where RPA traditionally comes in to improve efficiency of SCM (Wanner et al., 2019; Zhan et al., 2024; Mohamed and Frank, 2024). RPA is a system that performs repetitive tasks based on rules that usually involve structured data and deterministic outcomes (Aguirre and Rodriguez, 2017). However, due to their design, RPA systems are not very robust or adaptable to changes in the nature of the tasks despite their high efficiency and speed. This means that they are only effective on a static workflow and are poorly suited to more dynamic conditions (Balaguru, 2024).

The supply chain is one such application that is highly dynamic and requires constant monitoring. This is due to the frequent changes in prices as well as supply and demand conditions. Moreover, often unavoidable changes occur like changes in suppliers and distributors along with changes in their requirements, statuses and exceptions based on conditions. Tracking statuses and exceptions arising from these evolving conditions is also essential. RPA systems are useful to handle small parts of these complex webs but generally struggle to handle the broader context of such conditions by themselves (Nielsen et al., 2023; Mohamed and Frank, 2024). However, adding a cognitively capable system like GenAI can allow these systems to respond to changes in conditions like production schedules, inventory levels and demand and pricing fluctuations in near real time. This results in a system that can not only forecast trends and respond to such changes but is also able to proactively optimize the supply chain through strategic planning and resource allocations, which drives down costs, minimizes disruptions. These can produce small but significant advantages for the businesses utilizing such systems, giving them a competitive edge in the market (Yandrapalli, 2023). Multiple works have explored this integration between RPA and GenAI systems despite the relatively recent development of GenAI. Use of LLMs for RPA in supply chain optimizations problems have been studied and shown to be a promising future step to implement in the industry however there are still significant challenges to

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overcome due to the recency of these developments, especially in the areas of security, privacy and accuracy of information, all of which are active areas of research (Wang et al., 2024; Li et al., 2023; Balaguru, 2024; Jackson et al., 2024; Khlie et al., 2024; Jannelli et al., 2024; Liu and Meidani, 2024; Abdellatif et al., 2025; Ding et al., 2024; Zeng et al., 2023).

New Perspectives and Suggested Strategies in Supply Chain Technologies

Fig. 3 illustrates that the combination of RPA and GenAI enables intelligent decision-making and abilities in various process inside the SCM process. These processes include demand forecasting and planning, inventory optimization, logistics and transportation management, customer service and communication, data analytics and reporting, as well as handling customer returns and shipping exceptions such as overages, mispicks, or shortages in deliveries. Moreover, it supports inventory management (e.g., product availability alerts) and streamlines invoice and purchase order processing.

Fig. 3 depicts the combination of Generative AI (GenAI) and Robotic Process Automation (RPA) within a supply chain framework. It vividly highlights the interaction between various RPA components and an AI-driven Retrieval Augmented Generation(RAG) system, which uses vector database and generative model to enhance decision-making ability on unstructured data. Hence, by integrating GenAI and RPA on enterprise level, it will achieve the new level business automation process by leveraging the new cutting-edge technology of LLMs. In addition, to that process SOP, inventory records, unstructured data, customer support logs, vendor/supplier contracts, transportation and logistics documents, warehouse layout, and packaging data can be stored in a vector database for semantic search and automation that streamlines the supply chain operations.

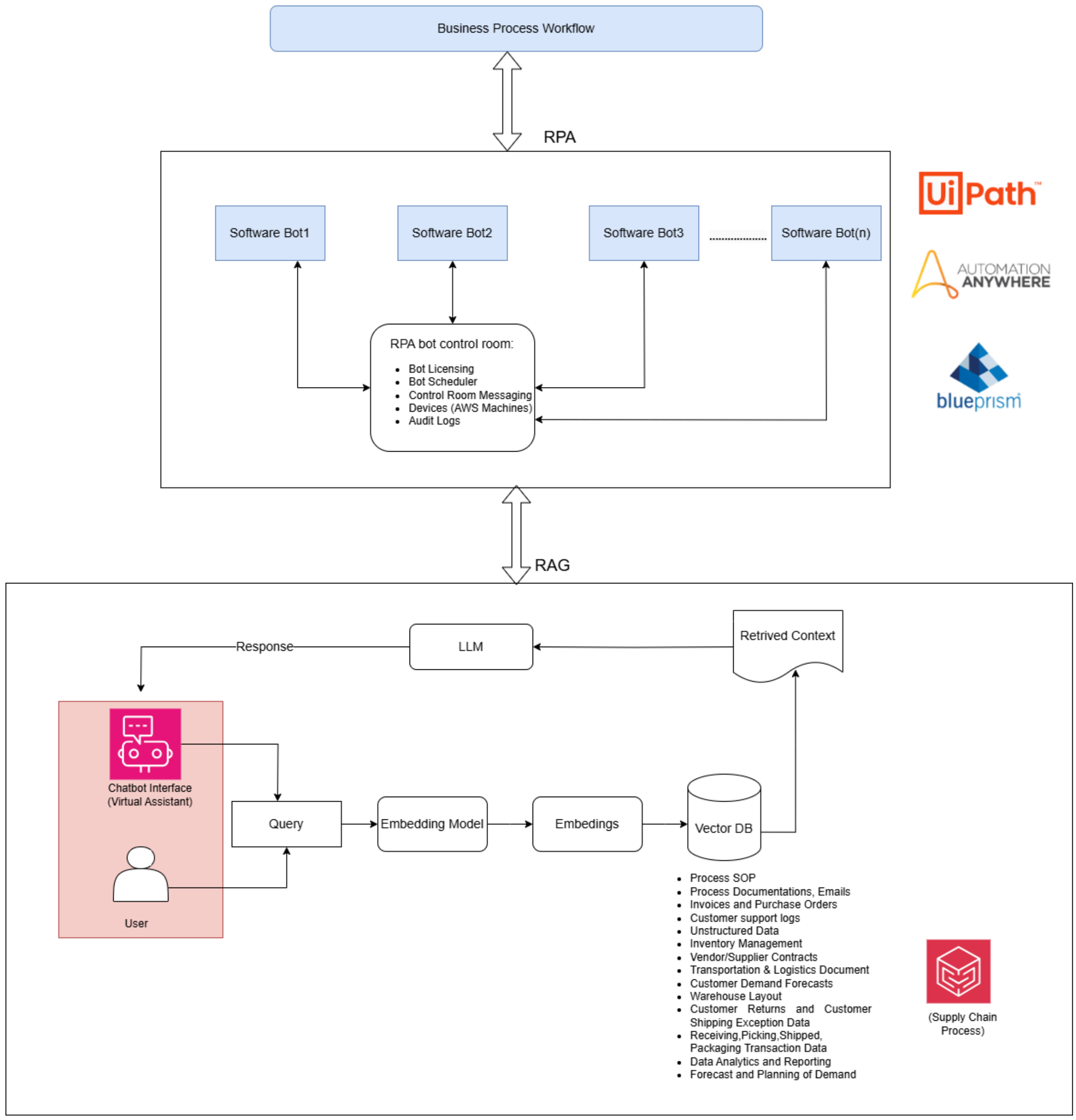

Fig. 3: Integration of RPA and RAG-Based GenAI in Supply Chain Management Process

Data Flow Architecture of RPA and RAG-based GenAI Integration

This section explores how data moves in a supply chain management system from robotic process automation (RPA) to retrieval-augmented generation (RAG)-based Generative AI (GenAI). Figure 3 shows how the architecture combines rule-based automation with smart, natural language user interfaces to make things run more smoothly (i.e., intelligent ability) and let users connect with the system better response to streamline the operations. The primary data flow patterns are outlined below and elaborated in detail.

- RPA bots are used to handle business tasks.
- Output from RPA to vector database.
- Query handling via embedding models.
- Context retrieval and LLM response.
- Final user interaction and feedback loop.

The process starts with a business workflow that includes repetitive structured tasks, such as processing invoices, updating purchase orders, and writing the process. These jobs are done by software bots in the RPA layer, such as Bot1, Bot2, Bot3, etc. These bots are controlled from a central location that handles licensing, scheduling, contact between virtual machines, and auditing. This layer can be used with well-known RPA systems such as Blue Prism, UiPath, and Automation Anywhere. The bots produce outputs that are both structured and semi-structured, such as reports, completed forms, transaction logs, and documentation.

These results are what the RAG-based GenAI system takes in. The RPA bots collect data, such as SOPs, invoices, customer interactions, logistics contracts, and support tickets. This data is then changed and stored in a vector database using an embedding model. This ensures that the GenAI system can get current full-text business data straight from operations.

The question is first turned into a vector embedding when a user sends it through the virtual helper (chatbot interface). This is checked against the vector database to find the content that is most semantically important. The original query and the context that was found are sent to a Large Language Model (LLM). The LLM then makes a natural language response that makes sense in this area. The chatbot gives the user this answer, which allows them to have smart talks that are aware of the situation.

Newly processed RPA data are put to the vector store one piece at a time by the system's continuous loop. This gives the GenAI helper the most up-to-date information on operations and transactions. With this kind of setup, the supply chain can handle many tasks, such as customer service, questions about returns and shipping, document analysis, and prediction analytics.

Basically, when businesses combine RPA with RAG-based GenAI, it can perform structured processes and handle queries instantly with AI power. This mixed method makes the system smarter, the user experience better, and makes it easier to change to changing supply chain environments.

Benchmarking Automation Strategies With Proposed RPA-GenAI Integration

It is important to see how the suggested combination of robotic process automation (RPA) with retrieval-augmented generation (RAG)-based Generative AI (GenAI) ranks compared to other cutting-edge automation methods already used in supply chain management. AI-enhanced Enterprise Resource Planning (ERP) systems, IBM Watson solutions, and blockchain-powered automation platforms, SAP S/4 HANA are additional possibilities with potential promise. The organization should be tested to see how well they work, how well they can be scaled, and how well they fit the situation.

AI-enhanced ERP systems, such as SAP S/4HANA (Prasetyo and Soliman, 2021) and Oracle Fusion Cloud (Kumar, 2022), integrate machine learning into the way businesses perform. With the help of predictive analytics, these systems are great at things like predicting demand, finding outliers, and optimizing supply. However, most of the time, their AI functions only work in structured data settings. To work with natural language or unstructured real-time data, they need to be highly customized. Additionally, these systems do not naturally allow conversational contact, which can make them less flexible in situations where decisions need to be made quickly.

Blockchain-based automation, on the other hand, ensures that supply lines with many parties are open and trustworthy. Distributed ledger technology is used by solutions such as IBM Food Trust (Kamath, 2018) and VeChain (Teoh, 2023) to track shipping events, make payments through smart contracts, and check where products come from. These platforms provide strong tracking and records that cannot be changed, but their business design depends on rules that cannot be changed. Because of this, they cannot handle language-driven queries or complex business logic by default, unless they are specifically programmed to do so.

To get a better idea of the benefits of combining robotic process automation (RPA) with generative AI based on the recovered generation (RAG) approach, it helps to examine how this method stacks up against other AI-powered supply chain options. Table 1 below shows the main ways in which the suggested model is the same as and different from popular platforms such as IBM Watson Supply Chain and SAP AI-driven logistics. This comparison shows how the combined RPA with the GenAI solution gives you more options, a better way to connect with users, and better ways to handle unstructured data, system intelligence, robust data intelligence interaction, and a suitable integration with RPA with other existing methodologies such as IBM Watson Supply Chain and SAP AI-driven Logistics.

Table 1: Benchmarking the Proposed RPA + GenAI Approach with Leading AI Supply Chain Solutions

Comparison Criteria	Proposed RPA + GenAI (RAG-based)	IBM Watson Supply Chain	SAP AI-driven Logistics	References
Integration with RPA	It works well with RPA systems like UiPath, Blue Prism and Automation Anywhere.	There isn't much native RPA involvement; most of the automation is built on the IBM Automation suite.	Requires custom methods or integration with external RPA tools (third party).	Tarihal et al. (2024); Yendluri et al. (2023); Sindhuja et al. (2024)
Natural Language Interaction	RPA and GenAI based powered chat tools that answer real-world questions immediately.	Expresses natural language communication through Watson assistant	Non-conversational AI that emphasizes dashboards and data analysis.	Sabharwal et al. (2020); Vaid and Sharma (2022)
Handling of Unstructured Data	RAG renders information from files, documents, and other places to give businesses the most up-to-date information.	Unstructured data can be processed with NLP and machine learning based approach.	Takes care of a lot of data that is structured but is unable to do much with unstructured data in real time.	Guan et al. (2024); Sim et al. (2023); Narne (2024)
Integration Complexity	Flexible API-based integration of GenAI models and RPA tools.	High level of difficulty; needs to integrate IBM Watson technology and work with IT teams.	Fully integrated into the SAP platform.	Putnoki and Orosz (2024); Sharma and Vaid (2022); Godse et al. (2018)
System Intelligence	High; it has levels for rule-based, cognitive, and generative layers.	Moderate; excellent at analytics but not very quick to pick up fresh/ cognitive tasks.	Moderate work; already-built machine learning models are set up and fine-tuned for specific tasks.	Hoyt et al. (2016); Pokala (2023)
Process Flexibility	High flexibility because of LLM prompt-tuning and retraining.	Changes to rules are made manually, with moderate complexity.	Low to moderate; depends on how ERP workflows are set up.	Ma et al. (2023); Khalil et al. (2021); Graves and Tomlin (2003); Lin et al. (2000)
Deployment Model	It was designed to be deployed in the cloud, but it can also be used in a hybrid or on-premise environment, based on how the LLM and RPA are hosted on instances.	Cloud-based by default, but hybrid deployment options are supported.	Mostly cloud and on-premise, based on how standard SAP S/4HANA is set up.	Vankayalapati (2025); Bhatia (2025); Kritikos and Skrzypek (2019)

Table 2, mainly illustrates the comparison table with a performance metric for the use case for inventory management based on various use case scenarios. It shows how the suggested GenAI and RPA integration framework can improve inventory record automation, vendor contracts interpretations, process adaptability, cost efficiency, scalability, and processing of unorganized data (ie, unstructured data in processing of logistic documents) and, on the other hand, a traditional RPA approach that works on its own does not help as much in these areas, especially when working with changing data and difficult decision-making jobs in the supply chain automation domain.

By integrating GenAI and RPA together in the supply chain domain, as illustrated in Fig. 4, there are several processes that can enhance supply chain optimization using the integration approach. In this work a conceptual framework for integration has been proposed, which showcases the potential improvements rather than the actual methods that have been implemented.

Enhancing Inventory Management for Real-Time Availability Alerts: There are proposed works on optimization technique for logistics and inventory management using advance use of machine learning techniques (Pasupuleti et al., 2024; Ola Al-Amin et al., 2024; Azari et al., 2024). However, here the approach is to leverage the GenAI to simulate different situations in the supply chain. This enables us to determine the best ways to monitor the inventory management flow, such as tracking product availability alerts (e.g., out of stock order, back orders, allocations, overfills, short dating or discontinuity of the product). By analyzing various data from each suppliers, GenAI can enhance the operation. Meanwhile, RPA automates the repetitive tasks like batch processing product orders based on supplier emails, tracking shipments of products from suppliers using tracking number, and updating products ETA details. These strategies are carried out smoothly on inventory website, so that customer can see the availability alert of the products.

Optimizing Transportation and Routing Efficiency: The research currently focuses on advanced analytical machine learning models, optimization algorithm, reinforcement learning to achieve the improvements (Zeng, 2024; Mollaoglu et al., 2023). In this context, we suggest an approach of utilizing GenAI that can play a vital role in transportation and routing optimization, which tends to save time and improve overall efficiency of supply chain logistics (e.g., avoiding the SLA breaches with customers). The GenAI model uses historical traffic data, along with other critical input parameters like vehicle condition, product load in the vehicle container, weather conditions, and the classification of products (refrigerated vs. non-refrigerated, controlled vs. non-controlled). These parameters are used for the optimization process to enhance the algorithm capabilities using GenAI. Moreover, RPA speeds up related tasks such as scheduling shipments in batch process, checking on delivery reports, and creating invoices automatically. The integration of GenAI and RPA significantly impacts optimization and smooths process within supply chain.

Table 2: Comparative Performance Metrics of Traditional RPA vs. RAG based (GenAI and RPA) in inventory Reconciliation: A Retail Case Study

Performance Metrics	Use Case Scenario	Traditional RPA	Proposed GenAI + RPA (RAG-based)	References
Response Time to Stock Request	(e.g., An improved fulfillment of vendor stock orders request by looking at past order data, vendor SLAs, and backorder optimization; it has also allows inventory management to make automatic restocking decisions based on sales trends.)	Moderate and depends on predefined processes	Making decisions quickly and dynamically by using sales data, seller SLAs (on various data points auto re-training of LLM models)	Mungla (2019); Zhu and Vuppalapati (2024); Venigandla et al. (2024)
Error Rate in Vendor Contract Interpretation	(e.g., By processing and inspecting huge Excel files with thousands of product lines against vendor contracts, especially when the language in the contracts isn't clear or consistent)	High error rate	Low error rate using semantic search technique in vector DB approach	Flechsig et al. (2022); Nielsen et al. (2023); Khlie et al. (2024); Dhara and Delgado Barba (2023)
Reduction in Manual Review Time	(e.g., Faster return claim processing from DC Ops team on customer returned products, quicker response on tracking data records like shipment details, validation of billing details)	Moderate improvement	Large-scale reduction by utilizing this methodology	Tayab and Li (2024); Nalgozhina and Uskenbayeva (2024); Wulf and Meierhofer (2024)
Handling of Unstructured Data	(e.g., Use of handwritten pdf files, audio recordings, scanned documents/images with embedded invoice, PO details)	Limited feasibility	Leverages RAG and Vector databases to assist	Kerutis and Calneryte (2022); Cutting and Cutting-Decelle (2021); Hikov and Murphy (2024); Khan et al. (2024)
Process Adaptability	(e.g., A policy/ work instruction changes, new vendor boarding or email template changes)	Low (difficult to handle the process with new enhancements)	Very high (through LLM retraining or prompt-tuning)	Gao et al. (2024); Gaddala (2023); Arslan and Cruz (2024); Stevens (2023)
Cost Efficiency	(e.g., To automate generation of custom report or reconciliation report for thousands of various customers and each customer has unique line item contract and price set up rules)	Low cost to set up but more expensive to maintain rules and complexity	Initial costs are higher, but they are lower in the long run as LLM models retrained that minimize less human work	Pahune and Rewatkar (2024); Arslan and Cruz (2024); Wang et al. (2025)
Scalability Feature	(e.g., Auto response needed from the warehouse operation team across the global customer bases in multiple languages and business context)	Limited scalability and maintenance needed	High scalability because of AI-driven flexibility and retraining approach	Palaniappan et al. (2024); Pahune et al. (2025); Kanka (2024); Smits (2024)

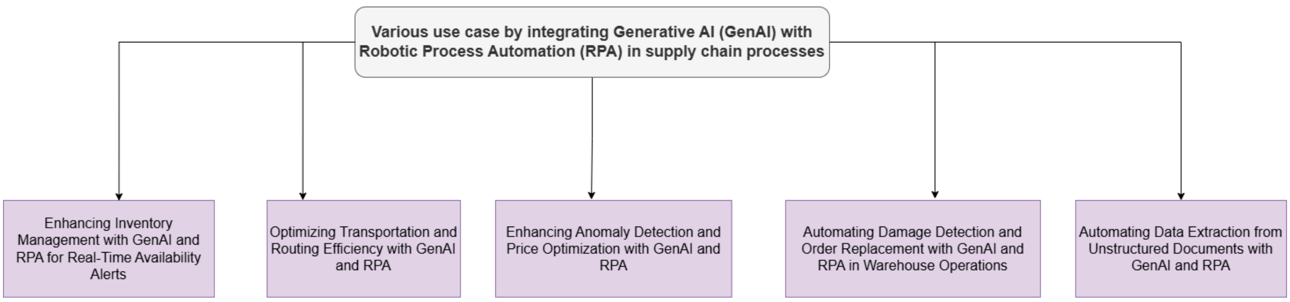

Fig. 4: Applications of GenAI and RPA Integration in Enhancing Supply Chain Operations

Enhancing Anomaly Detection and Price Optimization: A recent study explored an LSTM network-based approach for predicting multivariate time series data, and an LSTM autoencoder network-based approach combined with machine learning algorithm for detecting anomalies in sales (Nguyen et al., 2021). Moreover, it utilizes the various machine learning techniques for cost optimization process (Davuluri, 2023). In contrast, we propose a GenAI approach with the aim to identify the unusual pattern for anomaly detection such as supplier pricing changes all of sudden, demand of the product increases. GenAI can also analyze competitor pricing and optimize pricing strategies based on customer demand. While, RPA automates jobs like getting data from pricing feeds, keeping pricing systems up to date, and sending out real-time alerts to help people make quick decisions via emails, report generation, Splunk alerts, ServiceNow tickets. The overall integration of GenAI and RPA can lead to a smart decision-making process in supply chain workflow.

Automating Damage Detection and Order Replacement: The studies proposed for identifying damage detection use AI driven approach like neural networks and specialized models for recognizing the damage (Malyshev et al, 2021), along with the algorithm such as Fast-Solo algorithm (Wang et al., 2022). However, leveraging GenAI based model can enhance the computer vision monitoring of the packaging label in the warehouse operations. This includes recognizing critical details such as QR code, barcodes, product identifiers, iLPN (Inbound license plate number), SKU number, and Material Return Authorization (MRA) images from packaging labels. Also, GenAI can identify damaged boxes or container during warehouse operations like the pick, pack and shipping process. If damaged is detected, GenAI can process the images and videos from warehouse camera that will be a bird's eye to analyze the product. GenAI system can not only detect damaged boxes but also classify the severity of the damage. This capability can trigger automated alerts to the warehouse operations team, enabling prompt action. For example, through RPA integration, the system can automatically send emails to suppliers to request replacements for damaged goods, ensuring inventory is updated accordingly. This method streamlines the damage detection process, improves operational efficiency, and minimizes disruptions in warehouse workflows.

Automating Data Extraction from Unstructured Documents: As per the current trend, various techniques (e.g., OCR, autonomous RPA, cognitive automation, machine learning, computer vision methods) are available for information extraction (Baviskar et al., 2021; Kinra et al., 2020). Moreover, the combination of GenAI and RPA can be used to leverage enabling tasks like data extraction from unstructured documents. For instance, GenAI can be employed to interpret and extract text from handwritten invoices or unclear emails from various suppliers, converting them into readable formats. Then, RPA technology can be employed to input the extracted data into supply chain applications like Enterprise Resource Planning (ERP) system, Billing system, Warehouse Management System (WMS) system, Order Management System (OMS) system, Transportation Management System (TMS). This integration not only eliminates the need for manual data entry but also saves a substantial amount of time and effort, streamlining thereby the overall process.

Table 3 outlines the different characteristics of RPA, cognitive bots and GenAI bots. These systems are compared across various features, including automation type, learning capability, data handling, adaptability, use case, cost, and complexity. This comparison can help determine the appropriate environments and applications for the efficient deployment of each system.

Table 3: Comparison of RPA, Cognitive Bots, and GenAI Bots

Feature	RPA	Cognitive Bots	GenAI Bots	References
Automation Type	Automates repetitive tasks, Rule-based automation	AI driven technology, Decision-making processes	Content generation, Creativity and Optimize operations	Hofmann et al. (2020); Bédard et al. (2024); Sheth et al. (2019);
Learning Capability	NA (Not Available)	Limited and requires training with new data	Enhanced learning capacities and task-specific fine-tuning	Gao et al. (2025); Gómez Gandía et al. (2024); Soori et al. (2023)
Data Handling	Structured data only	Handling both structured and unstructured data	Mostly unstructured data (contextual comprehension and creative synthesis) as well as structured data	Pahune and Chandrasekharan (2023); Radke et al. (2020); de Haan et al. (2024)
Adaptability	Fixed process and workflows, repetitive task (Low flexibility)	Learns and adapts over time (Moderate flexibility)	Highly adaptive and creative due to high deep learning models (High flexibility)	Chauncey and McKenna (2024); Gausling (2023); Kunduru (2023)
Use Cases	Data entry, Payroll process, Purchase order process	Chatbots assistance, Intelligent document processing (Ex: OCR), Image identification	Content creation, Code generation, Complex customer interaction	Aguirre and Rodriguez (2017); Rao (2024); Chao et al. (2021)
Cost Efficiency	Low	Medium	Medium to High (Varies based on number of training parameters)	Deriu et al. (2020); Banerjee and Pahune (2023)
Automation Performance	High performance task for repetitive and rule-based tasks.	Moderate for tasks that use semi-structured data.	High adaptability, performance, and flexibility across a wide range of unstructured and changing tasks.	Bédard et al. (2024); Thota et al. (2022); Dalsaniya (2022); Xia et al. (2023)
Complexity	Low	Medium	High	Völker and Weske (2024); Feng et al. (2024)

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Middleware for Integration Patterns between RPA and GenAI

Middleware serves as a critical interface between sender and receiver, it effectively connects the integration pattern between RPA and GenAI to ensure smooth data exchange. It employs various mechanisms, such as APIs, cloud-based integration, middleware platforms, and custom integration, to ensure smooth workflow automation between RPA and GenAI components. This integration pattern, illustrated in Fig. 5, highlights the strategic role of middleware in bridging RPA and GenAI. By enabling efficient data exchange and connectivity, middleware enhances automation and optimization within supply chain operations, underscoring its importance in modern technological ecosystems.

Various middleware are available at the enterprise level to tune the connection between RPA and GenAI, such as Mulesoft, Dell Boomi, and Jitterbit. These middleware platforms are highly configurable based on the complexity of the workflow. Various API management tools, e.g., Apigee, Apache Kafka, Azure API , and AWS API gateway, are critical for enabling smooth data exchange in real time, batch processing, and near real time scenarios. These capabilities are essential in supply chain optimization process. The cloud-based enterprise-level middleware solution leverages integration pattern between RPA and GenAI, using platforms such as AWS Lambda, Microsoft's Azure logic apps, Google cloud platform. This approach impacts scalability and flexibility to manage complex integration using cloud computing. Moreover, there are several customer integration frameworks, including Node.js with express script, .js with GQL, Python frameworks such as Flask, and Djanago. These frameworks are widely used for high load performance API scenarios, where large volumes of data need to be processed efficiently. They are designed to handle high-load environments, enabling the transmission of millions of data points within a single payload while maintaining robust request and response structures without causing timeouts during processing.

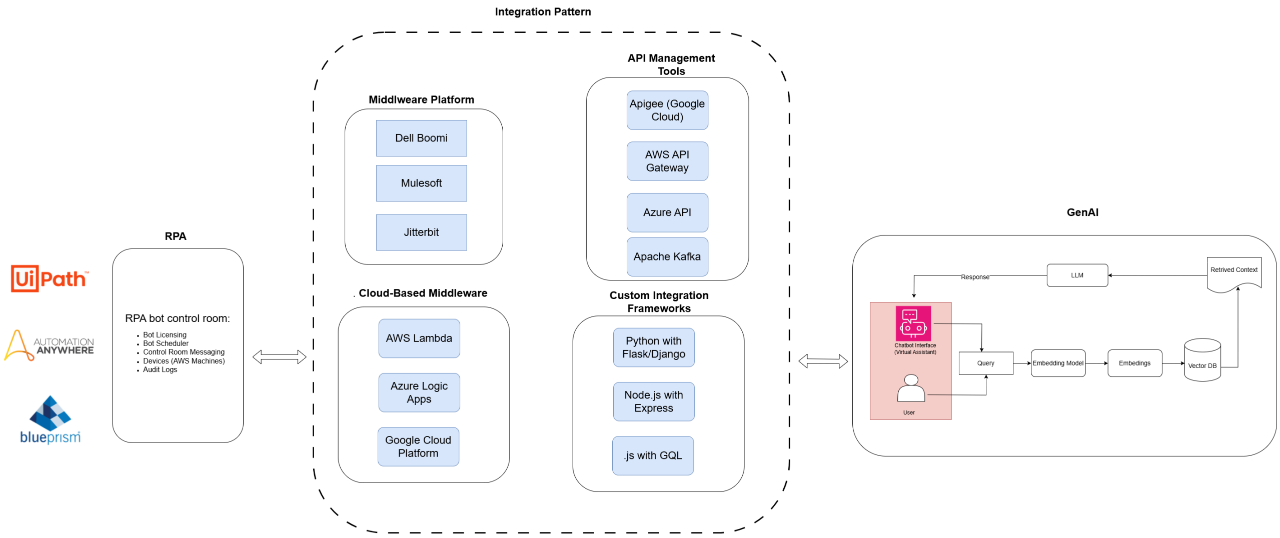

Fig. 5: Integration Patterns between RPA and GenAI

By utilizing the various middleware enterprise-based tools to work smoothly between RPA and RAG systems with GenAI platforms, it enhances smart decision-making capabilities. This integration pattern facilitates increased accuracy and continuous improvement in the automation process, delivering more accurate and unbiased responses as well as reducing the unfair outcomes with improved trustworthiness in the automated process. In addition, such tailored middleware can also enhance operational data security by using appropriate access controls, encryptions and data masking to secure data pipeline end-to-end. Hence, it will allow secure data integration, data mapping (through source-to-target mapping process), data translation, and data modeling logic, effectively mitigating data leakage risks. For example, it will ensure the secure storage of supplier contracts, SOPs, inventory records, product transaction data, customer support logs, supply chain data points, and other sensitive information.

There are still technical challenges to integrate RPA with GenAI on enterprise level due to the compatibility issues between two different frameworks and methodology. The load balancer and performance evaluation issue is concerning as it has a large amount of complex unstructured data related to the supply chain network which can slow down the processing outcomes. In addition, the high cost of implementation to integrate these two systems due to various factors, such as cloud expenses, multiple AWS virtual desktop costs, licensing fees, and infrastructure expenditures, can also pose a significant drawback. Furthermore, deploying Large Language Models (LLMs) to production and staging environments, particularly in the presence of RPA workflows, presents a considerable challenge. The use of

Language Model Operations (LLMOps) for deployment introduces additional complexities and potential obstacles, further complicating the integration of RPA and GenAI approaches.

Cost-Benefit Analysis of Traditional RPA and GenAI-Enhanced RPA

As per Table 4 several cost factors must be considered when choosing between traditional RPA and GenAI-Enhanced RPA. Since traditional RPA relies on rule-based scripting, it generally incurs lower initial implementation costs and can often leverage existing IT infrastructure without requiring significant upgrades (Tomar and Grover, 2024). In contrast, GenAI-Enhanced RPA demands a higher upfront investment due to the need for powerful hardware such as GPUs, cloud-based services, and licensing fees for large language models (LLMs) (Tang et al., 2023; Kachris, 2025). With Traditional RPA platforms, cost predictability is lower because expenses like licensing and maintenance tend to remain stable and easier to forecast (Axmann et al., 2021). However, GenAI-Enhanced RPA may experience more variable and potentially higher costs arising from pay-as-you-go cloud computing, frequent use of LLM APIs (i.e., OpenAI, AWS Bedrock), and ongoing model retraining or prompt tuning, which vary based on task complexity and usage volume (Liagkou et al., 2024). In contrast, GenAI-Enhanced RPA requires substantial cloud resources to manage large AI models and process unstructured data, resulting in increased operational expenses.

Maintenance costs also differs as traditional RPA requires periodic updates to bots to reflect process changes, which are generally manageable and predictable (Schuler and Gehring, 2018). Meanwhile, GenAI-Enhanced RPA demands continuous monitoring, model retraining, and performance optimization, contributing to higher ongoing maintenance costs (Balaguru, 2024). Integrating GenAI technologies often necessitates investments in new hardware and scalable cloud storage solutions, whereas traditional RPA typically does not require major infrastructure upgrades (Randhi and Bandarapu, 2024; Sudha Rani, 2024). At a basic level, the security and compliance costs are similar; however, these costs may increase for GenAI-Enhanced RPA due to the sensitive nature of the data handled by AI models and the enhanced security measures needed for cloud deployment (Hayagreevan and Khamaru, 2024; Mittal et al., 2025).

Licensing and subscription fees for traditional RPA platforms tend to be fixed and predictable, whereas GenAI-Enhanced RPA usually incurs higher and more variable fees based on LLM consumption and AI service subscriptions (Shekhar et al., 2024). Overall, RPA offers greater cost-effectiveness and predictability, while GenAI-Enhanced RPA involves higher initial and ongoing costs but excels at handling unstructured data and enhancing automation intelligence. Organizations must carefully evaluate these trade-offs in light of their automation objectives and budget constraints (Dalsaniya and Patel, 2022).

Table 4: Cost-Benefit Analysis: Traditional RPA vs. GenAI-Enhanced RPA

Aspect	Traditional RPA	GenAI-Enhanced RPA	References
Initial Implementation Cost	It costs less to get started and doesn't require big changes because it uses rule-based scripting and IT infrastructure that is already in place.	GPUs, cloud services, and LLM license fees will cost more up front.	Axmann et al. (2021); Smeets et al. (2021); Barker et al. (2025); Cheng et al. (2025); Liagkou et al. (2024)
Cost Predictability	It's easier to make budgets when licenses and maintenance costs are fixed.	Costs change based on how much you use the cloud, how you connect with the LLM API, and how many times you fine-tune the process.	Schuler and Gehring (2018); Xia et al. (2024); Chow et al. (2024)
Cloud Cost	Not much use of the cloud; usually runs on local computers or simple cloud setups.	A lot of cloud and computing power is needed to run big AI models and handle unstructured data.	Dai et al. (2024); Cheng et al. (2025); Ichnowski et al. (2020); Nayyar (2024)
Maintenance Cost	Regular updates that are easy to use help bots adapt to changes in the way things are done.	Costs keep going up because of constant tracking, retraining, and performance tuning.	Noppen et al. (2020); Ruha et al. (2023); Pahune and Akhtar (2025); Liagkou et al. (2024)
Infrastructure Upgrade Cost	Low start-up costs because it works with current systems and doesn't need extra storage.	Costs continue to go up because of constant tracking, retraining, and performance tuning.	Kehrer and Kaiser (2024); Macha (2020); Axmann et al. (2021)
Security and Compliance Costs	Most of the time, the initial prices of compliance and security are close to the same.	Costs for security and compliance have gone up because of the need to protect private data in the cloud.	Tol and Sunar (2023); Bollikonda and Bollikonda (2025); Murugappan and Sree Kala (2022); Bhamidipati (2022)
Licensing and Subscription Fees	Fixed fees that help with accurate cost planning.	Pricing that changes based on how much LLM is used and the AI service deals that go with it.	Janik (2024); Xu et al. (2024)

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Metrics for Evaluating the Impact of RPA and GenAI

By utilizing the combination of GenAI and RPA, a wide range of evaluation metrics can be used to assess performance. These include customer satisfaction metrics, continuous process improvement metrics, task enhancement and scalability metrics, cost savings metrics (ROI), process automation quality and improvement metrics, error reduction metrics, automation efficiency rates, and optimization success metrics. Numerous evaluation metrics have been proposed to measure the performance of RPA systems (Wellmann et al., 2020; Quille et al., 2023; Wanner et al., 2019; Teodorczuk, 2021). Key metrics from these studies are outlined below:

1. **Automation Efficiency Rate**
   Measures the percentage of tasks that are successfully automated compared to the total number of tasks attempted.
   $= \left(\frac{\text{Total Automated Tasks}}{\text{Total Tasks}}\right)$
   Purpose: Indicates the effectiveness of automation in handling workflows without failure.
2. **Task Error Rate**
   Tracks the percentage of errors encountered during automated tasks.
   $= \left(\frac{\text{Number of Errors}}{\text{Total Tasks Executed}}\right)$
   Purpose: A low error rate (e.g., <2%) reflects high-quality automation and system reliability.
3. **Process Completion Rate**
   Indicates the percentage of automated processes completed successfully within a specified timeframe.
   $= \left(\frac{\text{Completed Processes}}{\text{Total Processes Initiated}}\right)$
   Purpose: Ensures that automations are achieving their intended outcomes consistently.
4. **Automated Cycle Time**
   Measures the time taken by an RPA bot to complete a task from start to finish.
   $= \text{End Time} - \text{Start Time}$
   Purpose: Shorter cycle times indicate higher efficiency compared to manual execution.
5. **Return on Investment (ROI)**
   Evaluates the financial gains from RPA implementation relative to its costs.
   $= \frac{(\text{Net Automation Profit} - \text{Automation Costs})}{\text{Automation Costs}}$
   Purpose: Demonstrates the profitability and cost-effectiveness of RPA initiatives.
6. **Operational Cost Reduction**
   Quantifies the reduction in operational costs achieved through automation.
   $= \left(\frac{\text{Manual Process Cost} - \text{Automated Process Cost}}{\text{Manual Process Cost}}\right)$
   Purpose: Highlights direct financial savings from automating repetitive tasks.
7. **Gained Productivity (FTE Savings)**
   Measures how many Full-Time Equivalents (FTEs) were saved by automating a process.
   $= \left(\frac{\text{Manual Hours Saved}}{\text{Standard FTE Hours}}\right)$
   Example: If automation saves 160 hours per month and one FTE works 160 hours/month, then FTE savings = 1.
8. **Exception Rate**
   Tracks the percentage of cases where bots encounter errors or exceptions, such as missing data or system failures.
   $= \left(\frac{\text{Number of Exceptions}}{\text{Total Tasks Executed}}\right)$
   Purpose: Identifies process inefficiencies or areas requiring improvement. A good exception rate is typically <20%.
9. **Bot Utilization Rate**
   Measures how often bots are active versus idle during their available time.
   $= \left(\frac{\text{Active Bot Time}}{\text{Total Available Time}}\right)$
   Purpose: Ensures optimal use of bots and identifies underutilized resources.
10. **Value of Time Gains (VTG)**
    Compares the cost of manual processes with automated processes to quantify time-related savings.
    $= \frac{(\text{Employee Cost (EC)} - \text{Automation Cost (AC)})}{\text{Automation Cost (AC)}}$
    Where - EC includes wages, taxes, and office costs. - AC includes bot licenses, development, and maintenance costs.
11. **Business Value Lost in Downtime**
    Calculates the financial impact of bot downtime on expected business outcomes.
    $BV_{\text{Lost}} = BV_{\text{Expected}} - BV_{\text{Achieved}}$
    Where - BV_{Expected} is the projected business value over a given period. - BV_{Achieved} is the actual business value delivered during that period.

Challenges in Integrating GenAI with RPA Systems

Ethical Considerations

The integration of Generative AI into RPA systems has the potential to revolutionize automation across industries, improving efficiency, adaptability, and decision-making capabilities. However, this also raises significant concerns regarding the ethical implications of such a monumental change in the automation paradigm that will vary between fields such as healthcare, finance, education, and customer support. Some of these concerns are described below:

Truth and Accuracy: One of the main concerns with GenAI systems is the errors introduced in their results, often due to 'hallucinations' that may reduce the accuracy of the responses. In RPA systems, reliability is an important consideration and this issue is a major factor to be considered when introducing GenAIs into RPA systems. Although reduction and elimination of hallucinations is still an open challenge, many methods have been proposed so far to mitigate the negative effects of hallucinations, including better training methods and improved architectures with fact-checking for GenAI systems (Ferrara, 2023; Hadi et al., 2023; Liu et al., 2024).

Security and Data Privacy: RPA systems often handle sensitive data, e.g., personal information, financial and health records, etc. Ensuring that this data is properly handled without any lapses in privacy is of paramount importance both from a legal and ethical standpoint. There have been many instances where GenAI systems have inadvertently leaked training data and internal information due to specifically crafted prompts. There is also concern that using proprietary or operation critical data for fine-tuning such systems can result in information becoming accessible to outside entities without authorization to access such information to various extents. This, of course, depends on the model's reasoning abilities and resistance to prompt injection attacks, but currently there is no single method known to mitigate such risks. Therefore, a combination of such methods must be employed to ensure security and privacy. Some of the ways to mitigate these risks in the future include implementing robust encryption techniques, enforcing strict access controls, and conducting extensive testing of systems before deployment to reduce the likelihood of successful exploits (Liu et al., 2024; Cohen et al., 2024).

Bias and Fairness: RPA systems are expected to perform seamlessly to maximize the desired metrics, but use of GenAI systems trained on biased datasets may introduce unintended biases into the outcomes that can affect system performance. This issue can be minimized by the use of diverse sources of data for training and fine-tuning and by use of proper data processing and balancing techniques. Regular audit of such systems also helps to identify and correct any biases that might creep in due to other sources, such as user or administrator preferences (Jiao et al., 2024; Liu et al., 2024).

Scalability and Cost Implications

Traditional RPA systems are built to perform very limited and specific tasks with exceptional efficiency. However, they often struggle to adapt to tasks outside their predefined scope. GenAI has the potential to enhance such processes by enabling adaptability to new situations and contexts while maintaining high efficiency. Unlike traditional RPA that relies on rigid rule-based workflows, GenAI can generate new workflows autonomously in response to evolving conditions. This capability can significantly enhance the utility of such automation in different fields, particularly in supply chain management. Here, dynamic adaptability to new environments is achieved without the need for retraining the system. Such adaptability ensures uninterrupted automation, even in the face of fluctuating demands or process changes, thereby making the system more resilient and scalable. Moreover, it leads to substantial cost savings by reducing operating costs through minimized manual interventions and enabling faster, more efficient task completion (Liu and Meidani, 2024; Wang et al., 2024; Li et al., 2023).

Technical Hurdles in Integration With Existing Systems

RPA systems are traditionally designed for structured rule-based tasks, while GenAI models are based on unstructured data and dynamic input. Integrating these two technologies requires sophisticated middleware and tools to bridge their architectural differences between these two paradigms. This can be done by ensuring compatibility between RPA platforms and GenAI frameworks, which often use different programming languages and data formats. GenAI also requires a large amount of high quality data for training/fine-tuning purposes, which is not necessarily the case for RPA systems. This can result in an inefficient system if such discrepancies are not taken into account and sufficiently addressed. To mitigate this, suitable synthetic data should be generated or additional real-world data collected during the design of the integrated system. The integration of GenAI also introduces new attack vectors in the RPA system by malicious prompting and jailbreak attempts that require the implementation of additional security measures to mitigate such attempts (Balaguru, 2024; Aguirre and Rodriguez, 2017; Li et al., 2023; Wang et al., 2024).

Guidelines for Integrating GenAI and RPA in Supply Chain Processes

This section outlines best practices for seamlessly incorporating GenAI and RPA into supply chain workflows to ensure both innovation and reliability.

By using the GenAI and RPA approach to identify various use cases within supply chain processes (e.g., vendor invoicing, order and inventory management, and transportation and logistics records), it is necessary to fine-tune the LLMs to train on various tasks. This undertaking requires significant computing infrastructure like multiple high-performance GPUs, processors, and substantial storage capacity, as well as scalable and optimized communication and database software architectures to ensure efficient model training. This involves a substantial initial investment, and hence a thorough feasibility study must be undertaken for each use case prior to committing such resources.

Along with the computing resources required to fine-tune these systems, appropriate attention must also be paid to proper collection of vast amounts of high quality training data. Where necessary, the generation of synthetic training data should also be prioritized, ensuring it is as unbiased and balanced as possible to achieve optimal model performance. This data must be stored in an efficient database that is encrypted and secured against malicious breaches and are only available for access to authorized entities.

The interfaces used to access the model responses also need to be secured against attacks like prompt injection. Proper guardrails should be built into these interfaces to ensure the responses are free of any inadvertent or coaxed data leaks. These leaks could reveal sensitive internal data used for model training or stored in RAG systems.

The system architecture should be designed to ensure truthfulness and accuracy of the responses and actions. It should include guardrails to reduce hallucinations such as inclusion of robust fact checking subsystems. Moreover, the use of chain of thought models to ensure logical consistency in responses. Prioritizing responses with lower temperatures should also be implemented wherever information is available in the databases.

It is important to train business partners, including business stakeholders, operational team, as this integration is a new way of designing RPA and GenAI combination. Workshops and training sessions will be required to help people understand the integration structure, its capabilities, and provide an overview of the process. Additionally, writing down the Standard Operating Procedures (SOP's) will make sure that they are followed the process.

Selecting the appropriate middleware pattern between RPA and Generative AI is crucial, as it depends on the volume of data and the data exchange pattern (e.g., batch process, weekly basis process, real-time, cron/schedule jobs). Therefore, choosing the right middleware is a crucial process for seamless integration and scalability.

Maintaining end-to-end model life cycle management and deployment is a critical task for LLMs. Implementing an RPA and LLMs-based integration approach requires a robust LLM Operations (LLMOps) pipeline for successful deployment in production. This pipeline is essential to ensure that LLM model and RPA workflows operate efficiently.

Practical Mitigation Technique for Ethical and Privacy Risks in Supply Chain GenAI-RPA

Integrating GenAI and RPA together to handle processes in the supply chain creates big problems with privacy and ethics. Possible data leaks, biased decisions, and illusions (hallucinations) from large language models (LLMs) are all risks. To successfully handle these technical risks, hence it needs the both technical safeguards and procedural controls that are made to fit the way the supply chain process works.

Conclusion

The integration of GenAI and RPA brings about a transformative shift in supply chain optimization. This approach enhances flexibility and enables the effective handling of large volumes of unstructured data, such as invoice processing, vendor contracts, complex document retrieval, inventory management, intricate customer interactions, and adaptability. Also, it promotes continuous learning, thereby strengthening supply chain management systems. In this article, we explored some of the conceptual paradigms that may be used for such integration and also the advantages and guidelines for this approach. However, ethical concerns and performance evaluation issues arise when dealing with such data within the supply chain network. These challenges necessitate further research to ensure compatibility between RPA and GenAI, particularly in building secure middleware tools that enable their secure integration for seamless automation. Additionally, deployment challenges related to large language models (LLMs) within the RPA workflow, as well as the maintaining and securing extensive supply chain data, must be addressed as a part of future research in this field.

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Authors Contributions

Saurabh Pahune: Conceived the research idea, developed the core integration framework for GenAI and RPA, led the project, supervised data analysis, and drafted the manuscript.

Zahid Akhtar: Provided technical validation, assisted in data interpretation, and critically reviewed and revised the manuscript for intellectual content.

Manoj Chandrasekharan: Contributed to the conceptual framework design, performed benchmarking analysis, and assisted in compiling the literature review.

Shipra Shivkumar Yadav: Contributed to research design and methodology, performed data analysis, and participated in editing the publication.

Kamran Siddique: Conducted critical review and validation, helped structure the paper, and gave final approval for the submitted version.

Ethics

This manuscript is an original work. The corresponding author certifies that all co-authors have reviewed and approved the final version of the manuscript. No ethical concerns are associated with this submission.

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