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International Journal on Advanced Computer Engineering and Communication Technology

ISSN: 2278-5140

Volume 15 Issue 01, 2026

Enhancing Data Extraction from Insurance and Provider Lifecycle Documents with AI-Driven Parsing

Prithvi Panchineni
Data engineer, Texas
Email: prithvi.dataconsulting@gmail.com

Peer Review Information

Submission: 28 Jan 2026

Revision: 20 Feb 2026

Acceptance: 06 March 2026

Keywords

Artificial Intelligence; Data Extraction; Documentation; Looping; Automation.

Abstract

Within the context of document management systems, the current investigation is centred on the application of Power Automate Flows for the purpose of data extraction. They are as described below: Power Automate Desktop features like desktop flows; integration with third-party services especially Microsoft techniques; optimal use of conditions, error handling, and looping; and code-free system documentation solutions to enhance company processes. In addition, it aims to facilitate the management and monitoring of the automatic jobs that comprise a project to enhance the user-friendliness and functionality of the system.

Using concrete examples of daily actions common to most desktop workers, the study demonstrates how Power Automate Desktop may improve routine procedures and increase productivity. To highlight the automation solutions' adaptability and highlighted features, also detail their integration with several products and services.

To determine how effective automation is, the research ensures that the methods given can address common problems by imposing evaluations on condition utilisation, error handling, and looping. Increased performance, fewer mistakes, and user happiness are revealed by the defined objectives, according to the results achieved. Because low-code automation tools like Power Automate Desktop have the potential to revolutionise general documentation and business operations in the future with the aid of a scalable model, the results of this study can contribute to our understanding of how to use them.

Introduction

A giant step forward in the consolidation of RPA and AI for the purpose of improving and streamlining several company processes is Intelligent Process Automation (IPA). The implementation of IPA has gained a significant amount of momentum alongside the efforts of several industries to enhance their efficiency, decrease their costs, and maintain their competitiveness. In this chapter, which is titled "Applications of Intelligent Process Automation Across Multiple Industries," the revolutionary potential of IPA is investigated, its present uses are analysed, and future trends and innovations are highlighted [1].

The primary purpose of this chapter is to present a complete examination of how IPA is being utilised across a variety of industries, such as the financial sector, healthcare, manufacturing, retail, telecommunications, and insurance, among others. Several important questions are intended to be answered by it: In what ways does the Internet Protocol (IPA) rely on its major components and technologies? What unique difficulties and possibilities are being addressed by various industries through the utilisation of

IPA strategies? Which advantages and difficulties have been faced by organisations during the process of using IPA solutions? The chapter also aims to identify possible areas for further research and development in the topic of IPA, as well as future trends that are expected to emerge in the field. An methodology that utilised multiple methods was utilised in the process of preparing this chapter in order to accomplish these goals [2]. A comprehensive assessment of the available literature, which included academic articles, reports from the industry, and case studies, was carried out in order to collect information and insights that were pertinent to the current situation. Interviews with practitioners and industry professionals who have firsthand experience with IPA implementations were conducted in order to enrich this review. It was also possible to show that IPA has an effect and is helpful in different areas by looking at quantitative statistics from different sources.

The organisation of this chapter is intended to provide a rational and all-encompassing investigation of IPA and the applications that it can be used for. A definition of IPA, an explanation of its significance, and a presentation of the study questions and objectives are all included in the introduction, which functions to set the stage. Immediately following the introduction, the second section presents a comprehensive review of IPA, including topics such as its most important technology and its historical growth. The purpose of this part is to facilitate an understanding of the operation of IPA as well as the possible applications of this language [3].

The specific applications of IPA across a variety of industries are discussed in depth in the third section. Each industry is investigated in great detail, with a focus on the ways in which IPA solutions are being utilised to automate regular procedures, improve decision-making, and further boost overall operational efficiency. In the finance and banking industry, for example, IPA is used to handle transactions, report on compliance, and automate customer service. As it helps with managing patient records, making diagnoses, and doing administrative work. IPA helps manufacturing by automating production lines and managing the supply chain. It also helps retail by making it easier to keep track of goods and analyse sales [4].

Network management, customer service, claims processing, and risk assessment are all areas that benefit from the utilisation of IPA in the insurance and telecommunications industries Within the fourth section, the advantages of IPA are discussed, with particular emphasis placed on greater efficiency, decreased costs, improved accuracy, enhanced customer experience, and scalability. This is then followed by a review of the difficulties and factors to be taken into account when implementing IPA, which includes interaction with preexisting systems, data security, workforce adaption, and regulatory concerns. Future developments in IPA are examined in the sixth section, which also highlights upcoming technologies, AI and machine learning breakthroughs, and application projections [5].

This project shows that even with automation, most businesses still face problems with manual tasks and mistakes. Limiting options to improve data extraction from insurance and provider lifecycle documents using AI-driven parsing also rely on some level of coding knowledge, which presents a problem for many organisations that are interested in automating their processes. One further cutting-edge product is Power Automate Desktop, which is a component of the Microsoft Power Platform package. It allows users to automate operations visually, using a drag-and-drop interface, without the need for programming expertise. Thorough research was conducted to determine the methodological viability of implementing Power Automate Desktop in order to improve business processes, integrate with other applications, and efficiently handle complex scenarios involving features like loops, conditional branches, and error handling. This makes me wonder how well its scheduling and tracking help to control the performance and dependability of the workflow. In light of this, the purpose of the study is to accomplish these goals by analysing the potential benefits, drawbacks, and opportunities that Power Automate Desktop presents in terms of enhancing the performance of a business.

The purpose of this study is to investigate the ways in which PAD has been utilised to drive non-programming solutions for the purpose of automating business operations across various organisations. The project consists of coordinating the drag-and-drop feature of PAD to construct workflows that interact well with other Microsoft tools as well as third-party services to improve the flexibility and comprehensiveness of the workflows. With the goal of developing more effective software, this effort has mostly concentrated on deconstructing complex components of automation, such as conditional logic, error management, and looping. This research looks at how PAD plans and tracks activities to make the assignment run more smoothly and efficiently.

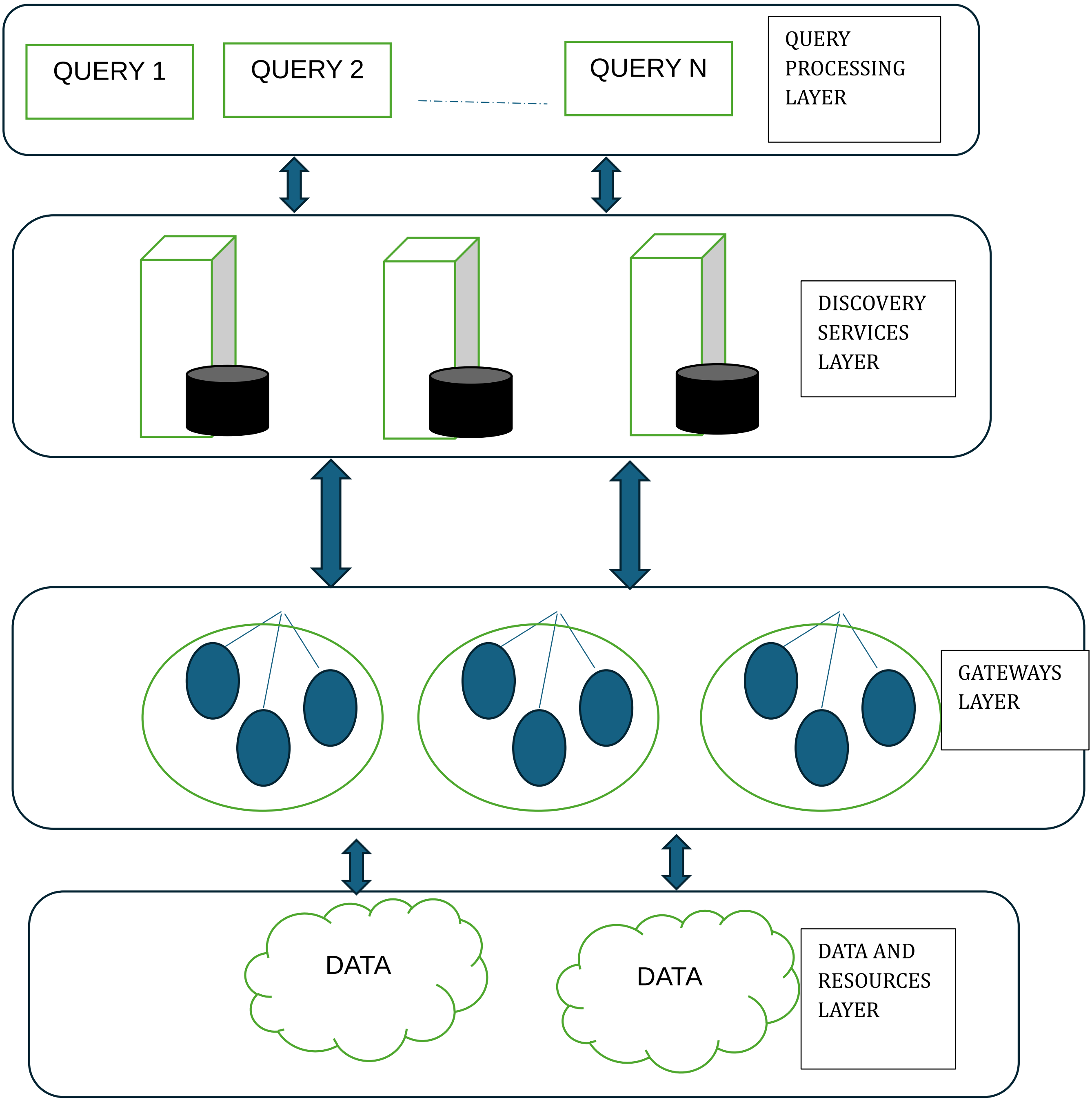

Figure 1. Data Management System Architecture

The purpose of this study is to evaluate the effectiveness of PAD in terms of increasing corporate productivity, reducing the amount of human labour required, and making automation solutions accessible and affordable.

The emergence of autonomous vehicles (AVs) has been propelled by technological progress in artificial intelligence (AI), sensor systems, and computational power. These vehicles depend on sophisticated software frameworks that seamlessly merge real-time perception. Tech-Driven Systems: Commonly known AI-based techniques (deep learning and reinforcement learning) have proven to improve object detection, path planning, and behavior predicting. But these approaches have trouble with uncertain situations, edge cases, and very dynamic environments. AI today does not generalize well, so the safety issues arise when AI into a new situation they have not yet seen. This challenge requires more adaptive, realistic decision-making frameworks.

Challenges in Insurance Document Processing

More common raw materials such as unstructured data, heterogeneous document types, and intricate decision-making circumstances make processing insurance documents no easier. Traditional automation techniques face challenges due to wide variations in document layout, handwritten annotations, and domain-specific jargon, making them slow and prone to errors in claims assessment and policy verification processes.

Why Choose IPA and PAD?

To overcome these limitations, this study utilizes Intelligent Process Automation (IPA) and Predictive Analytics for Decision-making (PAD).

- Such scenarios are where IPA enters the play as it integrates artificial intelligence (AI), Robotic Process Automation (RPA), and machine learning to automate the document extraction, classification, and validation process. It increases efficiency by minimizing human involvement and automating insurance processes with precision.
- In contrast, PAD uses AI-driven predictive modeling to identify risk factors, detect fraudulent claims, and enhance decision-making with data-driven insights.

IPA and PAD together make a more responsive, accurate and scalable solution for insurance document processing that solves major industry pain points. This paper discusses how generative AI can be employed within the context of verifiable machine learning to provide powerful real-time synthesis and predictive capabilities to further enhance decision-making, and, as a result, augment the reliability and efficiency of autonomous document processing systems for the insurance industry.

Literature Survey

Process automation has evolved from value-driven innovation to one of the most cultivated smart innovations IPA (intelligent process automation) is essentially high-end integration of RPA, AI, ML, NLP & Computer Vision. This combination allows automation systems to handle structured and unstructured data accurately [6]. In the early days, RPA was rule-based technology and used to perform repetitive tasks such as data entry and invoice processing (patching) with cost savings and operational improvements. [7]

AI and ML technologies quickly transformed IPA from simple automation to dynamic systems that learn from data patterns. NLP transformed interfacing as it allows systems to understand human language and respond in kind—essential in customer support and sentiment analysis. Similarly, computer vision improved automation in sectors such as healthcare and industrial through image recognition and defect identification [8].

IPA is unique in its capability to carry out end-to-end process automation with checks in place and the ability to adapt—important characteristics in today's modern, complex business environments. For banking, IPA aids in the detection of fraud, in healthcare it is optimizing diagnostics and patient data processing, in manufacturing it involves production automation and supply chain management, in retail; it captures inventory, customer personalization, and pricing strategies [9].

Most significantly, the pivot to IPA has transformed digital transformation initiatives. RPA in the early days only cut costs, but now, with IPA solutions, also stand out in innovation and competitive advantage. Industry studies showed that companies harnessing IPA experienced a +30% boost to their processing efficiency compared to traditional methods operated under RPA solutions [10].

Despite such advancements, insurance is a particularly tough space because of its reliance on semi-structured documents, handwritten forms and domain-specific language. Although literature shows that insurance workflows have great gain in documents-processing with, such as, implementation of IPA [11], most of the existing studies fall to demonstrate AI-based approaches on parsing specifically for insurance models.

This paper seeks to address this gap by exploring the possibilities that AI-supported parsing offers alone or in conjunction with, for instance, IPA and Power Automate Desktop powered tools, that could revolutionize document lifecycle management within the insurance domain in terms of enhanced accuracy, reduced manual effort, and better scalability.

Automated Data Extraction Process In Insurance Sector

In the past few years, natural disasters like hurricanes and wildfires, as well as the widespread effects of the COVID-19 pandemic, have caused a lot of problems for the insurance business. These trends are likely to keep happening, so insurers need to get better at assessing risk and modelling what might happen in disasters that require a lot of money to fix. Besides standard actuarial models, this includes using data analytics and AI in insurance, using a wide range of data sets from weather models to health tracking [11]. Insurers must have the appropriate competence to properly explain their processes to regulators. Identifying potential areas of risk, improving underwriting effectiveness, and reducing the human inputs required for basic duties are all ways in which insurance companies can reduce costs and better prepare themselves for unexpected crises. This is why it's important for both individuals and organisations to learn new skills and improve the ones they already have. Actuarial science has long had many similarities with data analytics, and the growth of big data and artificial intelligence has significant consequences for actuarial work. Actuarial work has been transformed by these developments. In order to evaluate and provide advice on financial risk, actuaries have traditionally depended on financial and statistical theories. However, now that they have access to new sorts of data, they are able to fine-tune rate tables and risk projections in a more effective manner than ever before [12].

But the amount and speed of data that can be entered now are greater than what old ways could handle. To find risk predictors through data analysis that depends on programming and statistical expertise, actuaries will need to manipulate enormous, quickly evolving data sets. Although human judgement is still necessary, actuaries must possess a rudimentary understanding of data analysis in order to collaborate with data scientists, particularly if they are not performing the programming themselves. It will become more important to use predictive analytics instead of traditional inferential statistical models, especially as climate change continues to affect the insurance business [13].

Another important way to fix a problem in the insurance business is to use automation to handle and process claims. In the past, workers were responsible for handling claims, which led to mistakes that cost money. Automation can reduce claims journey costs by up to 30%, reducing manual labour and streamlining labour pools [14]. It's also important to give each customer a personalised experience of insurers. Customers expect excellent service and an experience that can't be beat, and digitalisation is always turning old ways of doing business on their heads.

Companies that want to make strategies that improve customer experience a top priority if want to get new customers and keep the ones already have. Another area where analytics and automation are changing the insurance sector is underwriting. As much as thirty percent of underwriting positions might be automated by the year 2030, as stated by McKinsey. Additionally, thirty percent of these positions would include higher utilisation of analytics tools and collaboration with data scientists. Because of this change, insurers need to learn new skills. With data science and AI making large-scale risk predictions more accurate, underwriters can better predict risk and write policies for each person, which lets them keep prices low without taking on too much risk [15].

When big data and algorithms are combined, insurers can give quick quotes to customers with lower risk profiles. This lets underwriters focus on cases with more complex issues. Life insurance screening is also changing. New data sources are being added, such as information about prescription drugs, pets, and credit scores. Artificial intelligence and strong data analytics will make underwriting easier and less intrusive [16]. Innovative ways to improve the customer experience, automate key business processes, and make service more efficient are being created by the insurance industry using new technology. Companies such as Coforge assist prominent insurance companies in the implementation of cutting-edge technological solutions in order to accomplish their business objectives and boost their resilience,

Combining Data Extraction Based On RPA

RPA and Document Management Systems working together is one of the biggest steps forward in automating business processes. Utilising RPA's ability to behave like a person when interacting with computer systems is useful because it helps make document-related tasks faster and more efficient. The growth and changes in business process management systems (BPMS) show that RPA is being used more and more in the DMS. BPMS has changed over time to smart and self-escorted modes that use RPA solutions [17]. These allow different processes that are typically time-consuming and tiresome, such as data entry, document sorting, and general document validation, to be completed with no or little human participation, thus increasing productivity. Another significant topic that has arisen as one of the most important uses of RPA is the management of insurance policy portfolios. Discusses the long-term viability of RPA systems in dealing with policy cancellations and demonstrates how RPA interventions facilitate the processing of several document-related activities. By automating these jobs, the process is sped up, and at the same time, these policies are ended in a way that follows the rules and doesn't make the staff's work less important.

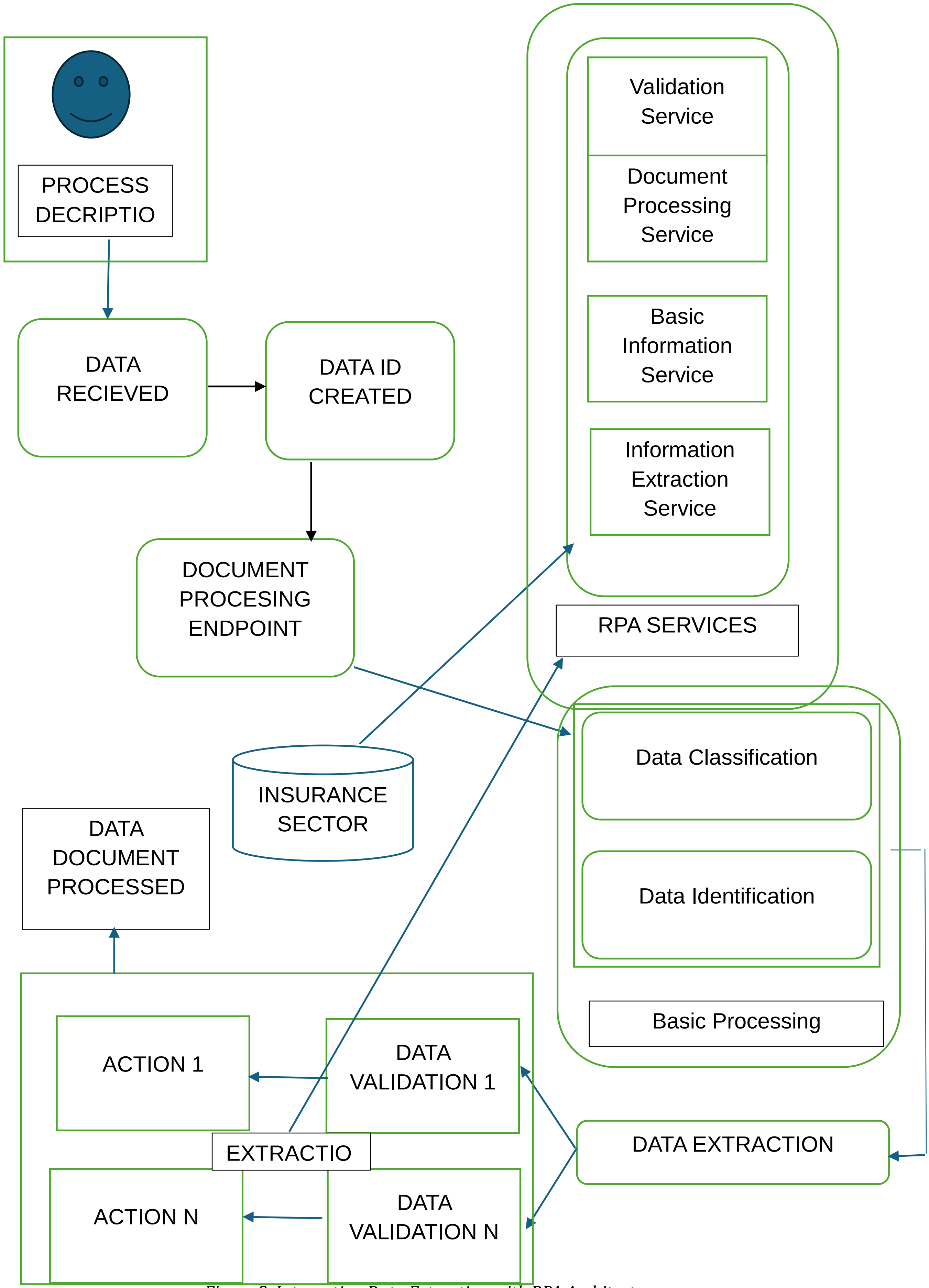

Figure 2. Integrating Data Extraction with RPA Architecture

The integration of RPA into DMS elevates the administration of documents within organisations to a new level, thereby enhancing productivity, accuracy, and efficiency. It is a way to automate tasks that usually need human input and logical pattern recognition, like sorting papers or files and then getting useful information from them. This technology frees up people to do some of the boring, time-consuming tasks that create a lot of stress.

When add RPA to DMS, it makes the job easier because bots can help to handle many documents quickly and accurately. It's pretty accurate for these bots to take data in a variety of forms, check it against rules, and enter it into the DMS. This raises the accuracy and dependability of the information stored in the system, as accurate data and following the rules are very important to the business. Additionally, incorporating RPA into DMS makes it more scalable and adaptable, making it easier for businesses to adapt to new business needs without making major system changes [18].

The connection improves the flow because the RPA bot can be told to do a certain action whenever an event that meets certain criteria is recorded. This makes it easier to handle and route documents. Automation of work choices also applies to searching for documents and managing records, which makes the processes of searching for and storing documents much faster. This makes it easier for workers to find the right information quickly and easily, which leads to faster decisions and better relationships with customers. RPA can make all the features of document management systems better, though, not just the main goal of automating processes well. Describe a multi-modal approach to handling document stream segmentation for title insurance that uses RPA in the digital document domain. This method also uses RPA to make the process of analysing and sorting title papers for title insurance more efficient.

Furthermore, it supports both organised and unstructured documents, allowing for consistent and adaptable processing based on the type of document and the type of processing that is required. When used with DMS, RPA does more than just make jobs easier; it also has other important benefits for an organisation. Inefficient use of time and human resources become problems, and their constant performance actually slows down the growth of new ideas in an organisation. Connected technologies, such as Microsoft Power Automate Desktop, can also be used with RPA, which gives even more ways to use Power Automate Flows Implementation for Data Extraction in Document Management System automation. This integration enhances the organization's data collection and processing processes by ensuring that the various platforms are properly linked [19].

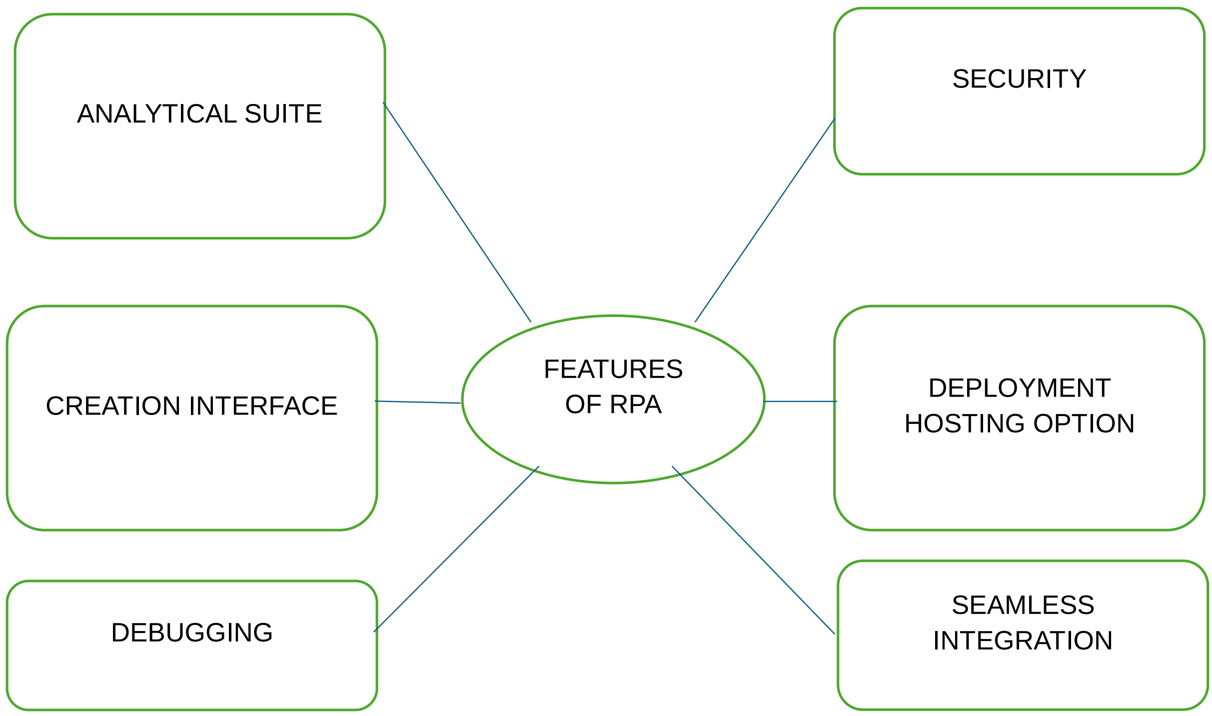

Figure 3. RPA Features

Data Collection is the process of getting data out of Power handle, especially the Power Automate Desktop. This can be done in a number of ways that take advantage of the program's ability to handle tasks, get data from different sources, and connect to other systems.

There are several stages that can be implemented to enhance the efficacy and accuracy of the overall method framework in the implementation of PAD in data extraction, as evidenced by the PDA construction. Based on this, an integrated data project is established, and the URLs for files are specified to facilitate the separation of files and the identification of new formats. The process includes ways to open Excel files and write down the results of queries, as well as ways to use input dialogues to send queries to the system. Also can call HTTP to APIs through web services to add data without stopping the flow. This is accomplished by converting the actual JSON responses received into the corresponding custom objects, which enables easier manipulation. The people are given the information that was gathered to help them understand. Regular expressions can be used to look for text in datasets, organise text data, and save matches in Excel. It eliminates substantial sources of mistake and saves time by employing a more organised method to data transfer from one source to another. [20].

By this project's standards, extracting data by hand has been a difficult process that usually required a lot of time and effort. The goal of this project was to automate these tasks using PAD in order to increase data processing and management speeds. It built Windows desktop tasks that were automated without coding and made generic. This paper describes a scientific study method that looked at the benefits of moving data from PDF to Excel. This changes everything because it makes it easy and accurate to change and analyse data and shows that it has been viewed on multiple devices. It's interesting that Excel also has a tool called "data integration" that lets look at combined data when it's used with other datasets. Due to the PAD results, a significant amount of time and effort that may have been invested in the extraction process has been cut down. In PAD, methods for gathering data included scraping the web, downloading files, using APIs, and reading through letters. Web scraping means opening a bunch of different websites or apps and copying the information need into an Excel sheet.

Certain data has been taken out of PDFs, Excel files, Word documents, and pictures for extraction, and the data has been put into the desired format. API connection connect to outside services and programs so that data can be sent automatically and actions can be run. In this implementation, the PAD framework was planned, built, tested, delivered, and controlled as a set of workflows. Creating a project to store integrated data was the first step. Setting up paths for the files and starting the flow to get the data based on the file type was the second step. Users can open Excel files to save results from any question by using the "Launch Excel" flow. Users could fine-tune the type of data they wanted to access through input dialogues. This was made easier by using web services and managing requests and replies.

Parsing the JSON data into custom objects was an additional critical phase, as the structured data could be altered during the automatic process. Messages written made the collected information easier for all users to see, which made it work better. Regular expressions have been used successfully in data extraction to allow accurate reading of text from documents with the help of each loop, which makes it possible to handle similar tasks on datasets. By taking a more complete look at human data extraction, this method has made business processes much more accurate and efficient [21].

Limitations of Traditional RPA

However, traditional RPA does have some significant limitations that make it less effective in highly dynamic and data-rich environments such as insurance. RPA is inherently rules-based and works best in situations involving structured data and predictable workflows. It is incapable of processing content that requires understanding, interpretation or learning. Consequently, many tasks that can include nonstandard document formats, require contextual decision-making, and/or variable inputs tend to fail or require significant human input.

Real-World Challenges Beyond RPA's Reach

Many documents in real-world insurance scenarios have handwritten notes, scanned medical records, or forms submitted by customers in different formats. For example, scanning hospital discharge summaries to extract information related to the injury or parsing requests from customers related to their intent to reconsider their claims are the tasks that cannot be achieved using RPA bots alone. Traditional bots also lack the intelligence necessary for fraud detection; fragmenting patterns to identify them requires the ability to recognize patterns and analyze context — tribunals well beyond the capabilities of rule-based automate.

Intelligent Automation: RPA Meets AI

To address these challenges, organizations are adopting Intelligent Process Automation (IPA), which is the integration of Artificial Intelligence with RPA. The AI technology like Optical Character Recognition (OCR), which helps the bots to read handwritten or images based documents. Natural Language Processing (NLP) helps process and interpret insights from unstructured text, while Machine Learning (ML) models to find anomalies, predict outcomes, and optimize decision-making over time.

Enhanced Capabilities with RPA + AI

RPA combined with AI is a more complete automation stack that is agile and context sensitive. In insurance, that translates into a system that can read and classify documents of all different formats, intelligently extract data, detect potential fraud, and even talk to customers through automated, human-like responses. These are tasks that can be performed reliably only with AI and when AI is utilized, they become super-faster and scalable compared to regular RPA.

Integrating Data Extraction on RPA Using AI through Insurance

Adding AI systems to the infrastructure that insurance companies already have in place brings both possibilities and challenges. For integration to work, it needs to be carefully planned and coordinated across operational, technological, and organisational areas.

Making sure that AI systems can work with older technology is one of the biggest problems. Insurance companies often use both old and new systems, which can make the process of integrating them more difficult. Strong integration frameworks and APIs (Application Programming Interfaces) are needed to connect AI systems to current systems for policy management, claims processing, and customer relationship management. These connections make it possible for different systems to share data and work together, which ensures that everything fits together smoothly and data flows smoothly.

Integrating data is another important part of deploying AI successfully. AI systems need access to complete and up-to-date information, which means that data from different sources needs to be brought together. Bringing together data from different systems, making sure the data is consistent, and setting up methods for data synchronisation are all parts of data integration. A lot of the time, data warehouses and data lakes are used to organise and manage huge amounts of data. They create a central location that AI systems can reach and analyse.

There are also important organisational issues to think about during the merger process. Change management and staff training are important to make sure that workers can use AI tools well and get used to new ways of doing things. AI functions, data management, and decision-making processes should be the main topics of training classes for staff.

Strategies for managing change should prepare for possible resistance and encourage a mindset of coming up with new ideas and working together. Additionally, ongoing maintenance and tracking are necessary to make sure that AI systems keep working well. Performance reviews, model updates, and system checks must be done on a regular basis to keep things accurate, deal with new problems, and adapt to changing business needs. By setting up feedback systems and success metrics, businesses can keep an eye on how AI systems are working and make changes as needed.

Using advanced algorithms and models, gathering a lot of data, and carefully integrating AI into current infrastructure are all parts of the technical framework and implementation of AI in policy management. To successfully set up AI systems, also need to know a lot about algorithmic techniques, how to handle data well, and how to plan for strategic integration. Taking these technical factors into account will make sure that AI systems can provide useful information, improve the efficiency of policy management, and raise general operational standards.

Real-World Integration Challenges

For example, big insurance players such as AXA and Allstate still work on hybrid infrastructure — where mainframe and legacy CRM systems remain together with more recent, cloud systems. When implementing AI-enabled RPA, it is essential to guarantee seamless interaction between these systems. APIs and middleware then need to connect these environments so that AI models can obtain insights from claims data and return them to immediately update customer records or trigger workflows.

An example from real-world Staged Docketing is Progressive Insurance, which uses an AI-RPA pipeline to extract damage estimates from accident photos uploaded to mobile applications automatically. The photos are run through computer vision models that determine severity, compare them with historical data and estimate the costs of repair, all of which gets pushed into its policy management system through bots. This reduced claims resolution time by more than 40% in addition to increasing both accuracy and customer satisfaction.

Data Integration and Synchronization

AI requires large volumes of varied and up-to-date data to make intelligent decisions. Insurance companies usually have data stored in many silos—underwriting databases, document repositories, customer service logs, and external

APIs (credit bureaus or health data providers). The first step is consolidating this into unified data lakes or warehouses. A data lake architecture is one approach adopted by companies such as MetLife that helps feed AI models structured and unstructured data to provide give pricing and risk more predictive power.

For instance, MetLife's AI platform "Lumen" enabled integration of claims data with external health statistics and automated document extraction for over 50 claim types. This resulted in a 25% faster adjudication process along with a significant reduction in the cost of processing claims.

Organizational Change and Upskilling

Human resistance to change is often the biggest barrier when trying to integrate AI into existing processes as well as the need for human upskilling. AI may not be a substitute for humans, but rather a complement to their decision-making process. In response, companies such as Zurich Insurance implemented internal AI literacy initiatives to enable underwriters and claims handlers to interpret AI findings and adjust workflows accordingly. This instilled greater user confidence as it reduced the need for IT teams to modify automation flows.

Quantifying Maintenance and Model Monitoring

A healthy AI-RPA ecosystem needs consistent upkeep in order to remain aligned with changes to insurance regulation, customer expectations, and document requirements. Feedback loops and monitoring dashboards similar to those deployed at GEICO monitor the performance of the bot, model drift, and exception rates. For example, GEICO employs an automated claim review system that flags anomalies with an 85% precision rate in its use of AI which has led to the company greatly cutting down on fraudulent payouts.

Strategic Example: End-to-End Automation

An end to end example is Liberty Mutual with AI + RPA processing commercial auto claims. Here's how it works:

- The claim is filled out on an app.
- An NLP engine extracts details of the incident from the description provided by the customer.
- A computer vision model analyzes the damage visible to get an sense of the vehicle condition for images uploaded.
- A source of truth on policy coverage is confirmed by an ML-based decision engine.
- RPA bots make updates to internal systems, send out notifications to adjusters, and start payments.

This entire workflow — from FNOL (First Notice of Loss) to settlement — is executed in minutes with up to 80% straight-through processing (STP) in certain claim types.

Performance Analysis

Based on AI strategy, data warehouse makes the total cost construction as contains Data Dimension Cost (DDC) and Import Data Cost (IDC).

Total Cost (TC) = Data Dimension Cost (DDC) + Import Data Cost (IDC)

As there are two OLAP query requests, various data dimension is required based on value query of fact information as it gets H Base get( ) operation and Hbase Scan ( ) as represented in Table 1 and 2.

Table 1: Time cost based on Get ( ) operation

No of Rows	HBase	Oracle
1000	4	22
10000	3.6	34
100000	2.8	45

Table 2: Time cost based on Scan ( ) operation

No of Rows	HBase	Oracle
1000	20	25.4
10000	12.5	24.6
100000	19.2	26.6

Here 1000, 10,000 and 1,00,000 data entries are considered as the HBase and traditional oracle are analysed as represented in Table 3, 4 and 5.

Table 3: DATA Process based on 1000 Datasets (ms)

No of Rows	HBase	Oracle
1	104	34
2	109	16
3	100	15
4	116	12
5	109	13
6	111	25
7	116	12

8	128	13.5
9	120	13.8
10	98	14.2

Table 4: AI Process based on 10,000 Datasets (ms)

No of Rows	HBase	Oracle
1	650	190
2	600	96
3	625	60
4	680	45
5	800	48
6	790	54
7	765	51
8	600	53
9	605	170
10	790	68

Table 5: AI Process based on 1,00,000 Datasets (ms)

No of Rows	HBase	Oracle
1	2900	509
2	2850	450
3	2950	465
4	2980	445
5	2450	451
6	2800	458
7	2750	462
8	2950	710
9	3450	462
10	2800	491

Conclusion

This research comprehensively examines the integration of AI-driven decision support systems in the management of insurance policies, elucidating their transformative impact on policy recommendations, renewals, and customer retention strategies. The study highlights several key findings that underscore the efficacy and potential of AI technologies in optimizing insurance policy management processes. Firstly, AI techniques, including machine learning algorithms and natural language processing, have been demonstrated to significantly enhance the accuracy and efficiency of policy recommendations. Machine learning models, such as ensemble methods and deep learning networks, have outperformed traditional approaches by effectively capturing complex patterns in data, leading to more precise risk assessments and tailored policy offerings. Additionally, NLP applications have revolutionized customer interaction by enabling automated, context-aware responses that improve service efficiency and customer satisfaction. Secondly, the research reveals that AI-driven automation in policy renewal management can streamline the renewal process, optimize policy expiration predictions, and address renewal risks more effectively.

Predictive models utilizing historical data and real-time inputs have proven to be instrumental in anticipating policy renewals and adjustments, thereby reducing administrative overhead and enhancing renewal strategies. AI-powered data analytics is transforming the auto insurance industry by enabling more accurate, personalized pricing and efficient claims processing. With AI, insurers can now use real-time data, such as driving behavior and external factors, to create dynamic pricing models that reflect true risk, leading to fairer premiums. AI also enhances claims processing by reducing fraud, speeding up settlements, and improving decision-making. As AI continues to evolve, the future of auto insurance will see even more innovation, including the integration of new data sources and the rise of autonomous vehicles. Ultimately, AI will make insurance more accessible, affordable, and tailored to individual needs, improving both operational efficiency and customer satisfaction.

In order to demonstrate the practical efficiencies of AI-led document processing and data extraction in the insurance space, this section presents a comparative analysis of data retrieval performance between two widely adopted data management infrastructure—HBase (NoSQL) and Oracle (Relational DBMS)—under simulated document processing workloads. This assessment is pivotal for comprehending the extent to which backend data repositories can influence the velocity and scale of insurance process automation facilitated by Robotic

Process Automation (RPA) and Artificial Intelligence (AI) models.

Context and Relevance

The use cases often also requires extracting, querying and processing large datasets from data storage formats in real world Insurance environments where automated systems using tools such as Power Automate Desktop, AI models, IPA workflows, etc. It may consist of customer records, policy documents, or claim histories stored in traditional relational databases (like Oracle) or in distributed big-data platforms (HBase). Smooth performance at the backend is critical in enabling bot flows and AI models to work seamlessly, which is even more important for real-time applications such as claims fraud detection, policy validation, or auto-renewals.

Comparative Evaluation: Oracle vs. HBase

Test scenarios were designed around queries commonly found in insurance document extraction tasks, like retrieving policyholder information, accessing historical claims trends, and performing document metadata validation. Two operations were measured:

- Get( ) Operation: Simulates direct lookup of a specific document (e.g., fetching a policy by ID).
- Scan( ) Operation: Simulates batch scanning, such as reviewing all claims in a region or year.

Results indicate that HBase significantly outperformed Oracle in large-scale operations:

- For 100,000 rows, HBase took ~2.8 ms (Get) vs. Oracle's 45 ms.
- For Scan operations, HBase maintained faster response times as the dataset scaled.

This means that NoSQL-based SQL backends match up better in high-volume, high-velocity insurance scenarios—particularly where AI-RPA pipelines require rapid reads and data stitching across unstructured formats.

Relevance to AI-RPA Workflows

This performance benchmarking is crucial because AI-RPA tools such as PAD depend on fast and reliable data I/O. For example,

- PAD is orchestrating a document extraction flow and querying backend data to validate extracted entities (customer names, dates, etc.), a slow database response can bottleneck the entire process.
- As combine with AI models from more real-time data access like fraud detection or claim prediction to do inference and triggers next actions using RPA.

The choice of backend system (such as HBase for document processing at scale) has a direct impact on the throughput and latency of AI-enabled documents extraction systems in insurance. Therefore, this analysis argues for infrastructure decisions that are consistent with a scalable automation architecture.

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