

Original Article

Evolution of Automation to Hyperautomation: Leveraging RPA, AI ML, NLP for Optimal Operational Efficiency

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Abstract - Automation has emerged as a crucial factor in gaining a competitive edge in the constantly evolving business environment we find ourselves in today. Its significance goes beyond just improving efficiency. The fusion of Robotic Process Automation (RPA), Artificial Intelligence (AI), Machine Learning (ML), Process Mining, and Natural Language Processing (NLP) has given rise to what is now referred to as hyperautomation. This cutting-edge approach amalgamates these technologies' strengths to optimize operational processes and enable organizations to make real-time data-driven decisions. The transition from traditional automation to hyperautomation represents a major change in how businesses tackle operational workflows. Leveraging RPA, AI, ML, OCR, and NLP in unison empowers enterprises to streamline complex tasks, enhance predictive analytics, and fundamentally revolutionize how data is utilized. Businesses find integrating these technologies essential for gaining a competitive advantage. This paper seeks to investigate the various stages underlying the evolution of automation to hyperautomation, outline the conceptual hyperautomation architecture, and offer insights into how organizations can harness the power of Robotic Process Automation (RPA), Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) to achieve optimal operational efficiency. Through measurable KPIs and benefits, the paper aims to underscore the profound impact of hyperautomation, shedding light on the transformative potential of this paradigm shift in automation. Overall, the paper serves as a valuable resource for understanding the stages and architecture of hyperautomation, shedding light on its potential implications for organizations seeking to achieve operational excellence.

Keywords - Artificial Intelligence, Hyperautomation, Intelligent Automation, Process Mining, Robotic Process Automation (RPA).

1. Introduction

The concept of hyperautomation has revolutionized the way businesses operate in today's dynamic environment. By integrating Robotic Process Automation (RPA), Artificial Intelligence, Machine Learning, and Natural Language Processing (NLP), organizations can now achieve unprecedented levels of operational efficiency and agility [5]. This introduction will explore the fundamental principles of hyperautomation and its transformative potential, outlining how these technologies are reshaping the future of work and decision-making processes in businesses across various industry sectors. The emerging technologies of RPA, machine learning, and artificial intelligence are driving the evolution of automation toward hyperautomation [2]. As companies focus on digital innovation, RPA has attracted widespread attention in many industries [1]. RPA utilizes software robots, sometimes called "bots," to automate

repetitive activities, minimize human error and enhance productivity [2].

2. Understanding Hyperautomation and its Components

Hyperautomation is the next stage in the evolution of automation, combining robotic process automation with artificial intelligence, machine learning, and natural language processing. This synergy of technologies enables organizations to automate repetitive tasks and complex decision-making processes and analysis. This leads to increased operational efficiency, reduced costs, and improved productivity [5].

2.1. Robotic Process Automation (RPA)

Robotic Process Automation (RPA) utilizes software bots to automate repetitive processes based on rules [8].



These bots interact with IT systems like people. These automated systems perform a range of functions, including inputting data and generating reports, improving corporate processes' effectiveness and precision. RPA's versatility enables its application in various fields, such as finance and customer service, facilitating straightforward and intricate operations. RPA enhances operational efficiency by following predetermined rules and implementing data validation, minimizing human error. In addition, RPA establishes the foundation for hyperautomation, enabling the integration of AI, ML, and NLP technologies to cultivate a sophisticated automation ecosystem for enhanced operational efficiency and well-informed decision-making.

2.2. Artificial Intelligence Machine Learning (AI) in Automated Systems

Artificial Intelligence (AI) and Machine Learning (ML) play a crucial role in driving the shift toward hyperautomation [9]. AI involves simulating human intelligence processes, while machine learning focuses on creating algorithms and statistical models that allow systems to complete tasks without direct programming. When integrated into hyperautomation, AI and ML enable organizations to automate cognitive tasks, predictive analytics, and decision-making processes. AI and ML algorithms can analyze large volumes of data to identify patterns, make predictions, and continuously improve decision-making processes. For instance, in the finance sector, AI and ML can be leveraged for fraud detection, risk assessment, and personalized customer experiences. Furthermore, AI and ML enhance operational efficiency by automating complex processes, enabling proactive problem-solving, and supporting data-driven decision-making.

2.2.1. Natural Language Processing (NLP)

Natural Language Processing [NLP] is a field of artificial intelligence that centers around the interaction between computers and human language [10]. The area covers a broad spectrum of applications, including automatic speech recognition, machine translation, sentiment analysis, and text generation [10]. One of the fundamental concepts in NLP is the processing of unstructured human language data, which involves tokenization, part-of-speech tagging, syntactic analysis, and semantic understanding. These techniques enable machines to extract meaningful information from text data and make sense of human language. In recent years, there have been notable advancements in NLP, especially due to the emergence of deep learning models like recurrent neural networks and transformers. These models have significantly enhanced the accuracy and capabilities of NLP systems. Additionally, the availability of large-scale pre-trained language models, such as BERT and GPT-3, has further propelled progress in natural language understanding and generation [11].

Natural Language Processing (NLP) is another integral component of hyperautomation. NLP is centered on the interaction between computers and human language, allowing systems to comprehend, interpret, and produce human language [9]. Organizations can automate tasks such as language translation, sentiment analysis, and text classification by integrating NLP into automation processes. This capability is particularly valuable in customer service, content analysis, and information retrieval applications.

The evolution from traditional automation to hyperautomation is driven by the strategic integration of Robotic Process Automation (RPA), Artificial Intelligence, Machine Learning, and Natural Language Processing. This combination enables firms to reach peak operational efficiency, base decisions on data, and greatly improve their competitive edge in the fast-changing business environment.

2.3. Process Mining

Process Mining technology involves the use of specialized algorithms to analyze event data recorded by information systems such as ERP, CRM, and workflow management systems [12]. By examining these event logs, process mining technology can reconstruct the actual processes, identify bottlenecks or inefficiencies, and provide insights for process optimization and automation. This results in automatically constructing process models from event data. This allows organizations to gain a clear understanding of their existing processes without the need for manual documentation. Process mining also includes conformance checking, which involves comparing the actual execution of a process with the prescribed or ideal process model. Any deviations or non-conformities can be identified, enabling organizations to take corrective actions.

Furthermore, process mining technology offers enhanced visualization capabilities, allowing stakeholders to gain a comprehensive view of the processes and their performance. This includes various types of process maps, such as flowcharts, Petri nets, and Gantt charts that provide different perspectives on process behavior.

2.4. Intelligent Document Processing (IDP)

Intelligent Document Processing (IDP) is a technology that involves the integration of Optical Character Recognition (OCR), Natural Language Processing (NLP), and machine learning to extract and analyze data from documents in an automated manner [13]. This technology can intelligently process various documents, such as invoices, contracts, and forms, to extract relevant information and perform tasks like data entry and classification, improving overall operational efficiency.

IDP utilizes OCR to convert different types of documents into machine-readable text, enabling the extraction of relevant information [13]. NLP techniques are

then applied to comprehend the context and meaning of the extracted text, allowing for deeper analysis and interpretation of the document content. Machine learning techniques help the system to consistently learn and enhance its accuracy in extracting and categorizing data, therefore improving the efficiency of document processing.

By automating the extraction of data from documents, IDP not only minimizes manual intervention but also significantly improves the accuracy and efficiency of document-intensive processes. Additionally, the integration of IDP into organizational workflows facilitates streamlined and error-free data entry and retrieval, leading to enhanced productivity and cost savings across various business functions.

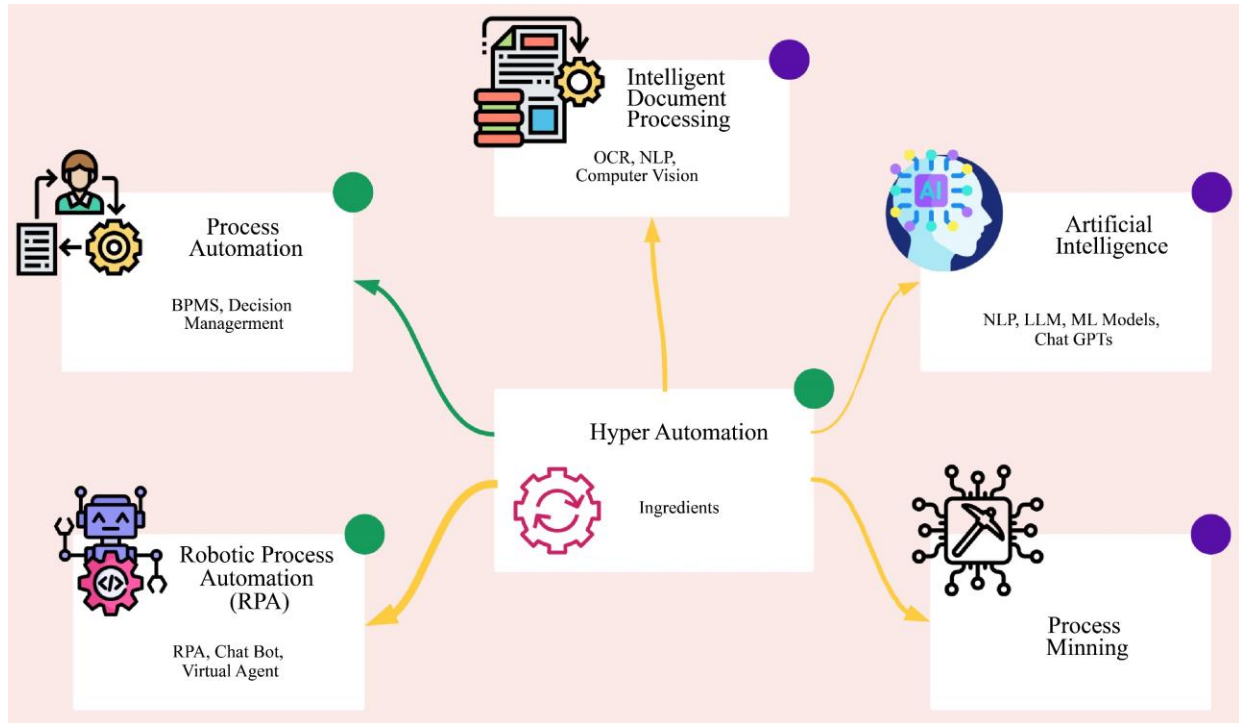


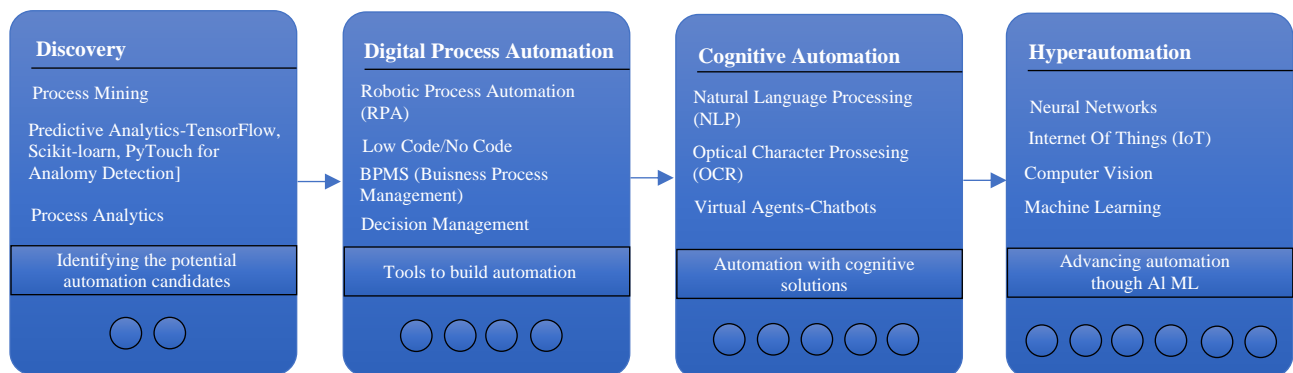
Fig. 1 This represented the various components of Hyperautomation

3. Stages of Hyperautomation

The journey of hyperautomation can be divided into several stages, each representing a progression toward higher levels of automation, integration, and optimization. These stages are essential for organizations to advance their automation capabilities systematically and derive maximum

value from hyperautomation technologies [4] [9]. The various stages have been illustrated in Fig.2 of the journal.

The detailed diagram has been illustrated in Figure 2 of the journal.



Note: This diagram was demonstrated by Swaroop Raj in 2024. This illustrates the various stages of Automation and the corresponding technologies alligned with each stage

Fig. 2 The various stages of Hyperautomation and the technologies alligned for each stage

3.1. Discovery

The discovery phase involves identifying and analyzing existing processes and workflows within an organization. The objectives of this phase include understanding the current state of operations, identifying bottlenecks and inefficiencies, and uncovering opportunities for automation [14]. The outcomes of this phase are crucial as they provide the foundation for further stages of hyperautomation implementation. The discovery stage involves the use of Process Mining, Predictive Analytics, and Process Analytics.

Process Mining enables organizations to analyze event logs and extract data-driven insights to gain a comprehensive understanding of their existing business processes [12].

Predictive Analytics leverages historical data and statistical algorithms to forecast future trends, identify potential issues, and optimize decision-making.

Process Analytics provides real-time visibility into process performance, enabling continuous monitoring and improvement [15].

Together, these components play a pivotal role in identifying automation opportunities, streamlining workflows, and laying the foundation for successful implementation of hyperautomation. Automation technologies like artificial intelligence and machine learning are used in the discovery phase of hyperautomation to examine event logs, predict future trends, and recognize patterns in process efficiency.

3.2. Digital Process Automation

In the Digital Process Automation stage of the hyperautomation journey, organizations focus on automating the processes and decisions identified during the discovery stage. This involves the use of technologies such as workflow automation, business rule management, and case management to streamline and optimize digital processes, driving efficiency and agility across the business. The use of digital process automation technologies enables organizations to eliminate manual and repetitive tasks, reduce errors, and improve overall operational efficiency.

Digital Process Automation encompasses a range of advanced technologies such as Robotic Process Automation (RPA), Low Code/No Code platforms, Business Process Management Systems (BPMS), and Business Rules Management Systems (BRMS).

Robotic Process Automation (RPA) automates repetitive, rule-based tasks by emulating human interactions with digital systems, leading to significant gains in operational efficiency and accuracy [8].

Low-code / No-code platforms empower business users to create applications and automate processes with minimal coding, accelerating the development and deployment of automation solutions [16].

Business Process Management Systems (BPMS) provide a framework for modeling, executing, and optimizing business processes, enabling organizations to orchestrate complex workflows and integrate disparate systems seamlessly.

Business Rules Management Systems (BRMS) tools facilitate the automation of decision-making processes by leveraging data, business rules, and predictive analytics to drive intelligent, automated decisions at scale.

Together, these components form the foundation of Digital Process Automation, enabling organizations to achieve higher levels of agility, responsiveness, and productivity in their automated processes.

3.3. Cognitive Automation

Cognitive automation is an advanced stage in the hyperautomation journey that encompasses the use of sophisticated technologies such as Natural Language Processing (NLP), Optical Character Recognition (OCR), Chatbots, and Virtual Agents.

Natural Language Processing (NLP) allows systems to interpret and analyze human language, enabling them to understand, interpret, and respond to unstructured data in a natural and meaningful way. This capability is crucial for automating tasks that involve processing and understanding textual data, such as customer queries, feedback analysis, and document processing.

Optical Character Recognition (OCR) is crucial for automating tasks that require converting printed or handwritten text into machine-readable text, enabling the extraction and digitalization of important information from physical documents. This is particularly valuable in scenarios where large volumes of documents need to be processed and analyzed, such as in financial services, healthcare, and legal industries.

Chatbots and Virtual Agents leverage NLP and machine learning to interact with users and provide automated assistance. They are capable of handling a variety of queries, completing tasks, and starting processes based on user input. This greatly minimizes the necessity for human involvement in mundane tasks and improves customer service experiences.

Incorporating these advanced technologies in the Cognitive Automation stage significantly expands the scope of automation capabilities, enabling organizations to handle complex, unstructured data and interactions with greater efficiency and accuracy, ultimately driving higher levels of operational productivity and customer satisfaction.

3.4. Hyperautomation

In the final stage of hyperautomation, advanced and complex machine learning techniques are integrated to further enhance automation capabilities. This stage incorporates cutting-edge technologies such as neural networks, computer vision, and Internet Of Things (IoT) sensors to enable advanced levels of automation and decision-making.

Neural networks, a key component of artificial intelligence, are utilized to learn and adapt to complex patterns and data, enabling systems to make intelligent decisions and predictions autonomously.

Computer vision technologies enable machines to interpret and understand the visual world, allowing for automated analysis of images and videos, which is crucial in various industries such as manufacturing, healthcare, and security.

Internet Of Things (IoT) sensors play a critical role in gathering real-time data from physical assets and environments, which can be leveraged for automated monitoring, control, and optimization of processes. The integration of these advanced technologies in the final stage of hyperautomation empowers organizations to achieve unprecedented levels of process automation, operational efficiency, and strategic decision-making.

The stages of hyperautomation, from discovery to hyperautomation, encompass the use of advanced technologies discussed above to drive operational efficiency, agility, and productivity. These stages enable organizations to identify automation opportunities, streamline workflows, handle complex data, and achieve unprecedented levels of process automation, ultimately leading to enhanced decision-making and overall business success. This facilitates organizations to streamline their processes, reduce manual errors, and optimize resource allocation resulting in cost savings and improved productivity, ultimately leading to a more agile and competitive business operation. In general, striving for hyperautomation enables organizations to reach increased levels of efficiency, accuracy, and productivity.

4. Conceptual Architecture of Hyperautomation

The technical architecture of a hyperautomation project involves a detailed framework that enables the smooth integration and coordination of different automation

technologies and components. This architecture is essential for enabling organizations to achieve the full potential of hyperautomation and drive transformative changes in business processes and decision-making [4].

The abstract architecture diagram has been illustrated in Figure 3 of the journal.

4.1. Automation Orchestrator

At the heart of the hyperautomation architecture lies the automation orchestrator, which serves as a centralized platform for managing and orchestrating diverse automation technologies. The orchestrator provides capabilities for designing, deploying, and monitoring automated processes across the organization. It enables the coordination of RPA bots, AI/ML models, NLP engines, and other automation tools to work in concert, ensuring smooth execution and optimization of end-to-end business workflows [3].

4.2. Integration Framework

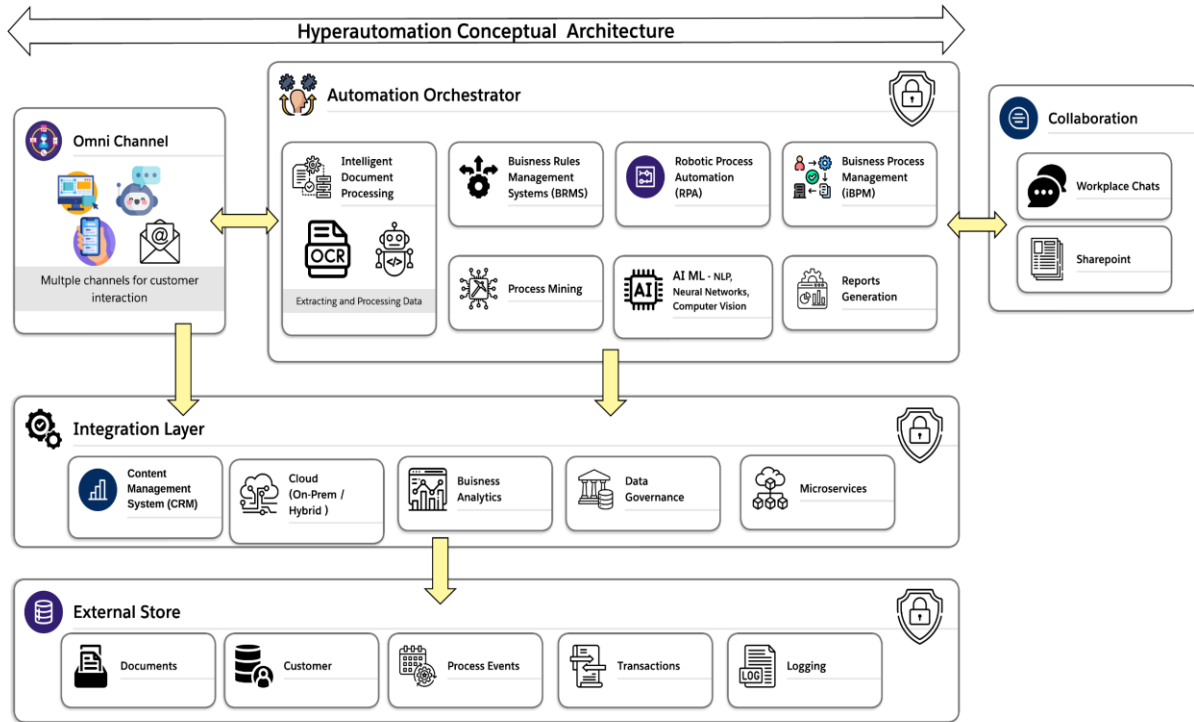
A robust integration framework forms the backbone of the hyperautomation architecture, enabling seamless connectivity and data exchange between disparate systems, applications, and data sources. This framework facilitates the integration of diverse technologies, ranging from legacy systems to modern cloud-based applications, to ensure a unified automation ecosystem. By establishing seamless integration, organizations can automate cross-system processes and leverage data from various sources to drive intelligent decision-making.

4.3. Cognitive Services Layer

The architecture incorporates a cognitive services layer that encompasses NLP engines, computer vision modules, and other cognitive technologies to enable advanced automation capabilities. This layer empowers automated systems to comprehend natural language, process visual information, and interact with users in a human-like manner. By leveraging cognitive services, organizations can automate tasks that require language understanding, sentiment analysis, image recognition, and interpretation of unstructured data, thereby enhancing the scope and intelligence of automated processes.

4.4. Data Management and Analytics

Effective hyperautomation architecture includes robust data management and analytics capabilities to support data-driven automation and decision-making. This part includes tools for data storage, processing, and analytics that help organizations utilize data to optimize processes, identify patterns, and gain insights. By leveraging advanced analytics, organizations can continuously improve automated workflows and drive innovation through data-driven optimization.



Note: This is a conceptual architecture diagram for Hyperautomation demonstrated by Swaroop Raj on the journal published at 2024

Fig. 3 Abstract Diagram of a Hyperautomation setup

4.5. Security and Compliance Framework

Ensuring the protection of sensitive data and adherence to regulatory requirements is a crucial component of the hyperautomation architecture. This framework encompasses robust security measures, access controls, encryption mechanisms, and compliance monitoring tools to safeguard automated processes and maintain data integrity. By embedding security and compliance measures within the architecture, organizations can mitigate risks and build trust among customers and stakeholders.

4.6. Scalability and Flexibility

The architecture of a hyperautomation project should be designed with scalability and flexibility in mind to accommodate evolving business needs and technological advancements. Scalable architecture allows organizations to expand their automation capabilities seamlessly, adapting to increasing workloads and diverse business requirements. Moreover, flexibility in the architecture enables the incorporation of new automation technologies and adjustments to meet changing organizational needs and industry trends.

4.7. Continuous Monitoring and Feedback

In line with the earlier strategies, the technical architecture of hyperautomation should establish mechanisms for continuous monitoring of automated processes. This involves implementing monitoring tools,

performance dashboards, and analytics capabilities to track the efficiency, accuracy, and utilization of automated workflows. Additionally, gathering feedback from end-users and stakeholders is crucial for identifying areas of improvement and aligning automation with organizational objectives. By integrating continuous monitoring and feedback mechanisms within the architecture, organizations can drive iterative improvements and optimization of automated systems, ensuring their sustained alignment with business goals.

5. Measuring the impact of Hyperautomation on Operational Efficiency

When considering the impact of hyperautomation on operational efficiency, it's essential to measure Key Performance Indicators (KPIs) to assess the tangible benefits. KPIs such as cost savings, reduction in processing time, error rates, and resource utilization can provide valuable insights into the effectiveness of hyperautomation implementation. Additionally, organizations should also consider qualitative factors such as improved decision-making, enhanced customer experience, and employee satisfaction. By establishing a comprehensive framework for measuring the impact of hyperautomation, organizations can effectively evaluate the success of their automation initiatives and make informed decisions for continuous improvement and optimization. The below table outlines some of the Key Performance Indicators (KPIs) that could be used to measure.

Table 1. KPIs for measuring operational efficiency

| Key Performance Indicators (KPIs) | Definition | Evaluation Method |
|--|---|---|
| Labor Cost Savings | Reduction in expenses related to employee wages and benefits. | Financial analysis |
| Processing Time Savings | Decrease in the amount of time required to complete a process. | Time tracking, Process mapping |
| Resource Allocation Efficiency | Improvement in the use of assets and resources for optimal output. | Efficiency metrics, Resource utilization analysis |
| Error Rate Reduction | Reduction in the percentage of errors encountered during process execution. | Error tracking, Quality control metrics |
| Process Cycle Time | Time required to complete a process from start to finish. | Time tracking, Process analysis |
| Process Accuracy | Increase in the precision and correctness of process outcomes. | Quality assurance tests, Accuracy metrics |
| Customer Satisfaction | Degree of customer contentment with services or products. | Surveys, Feedback scores |
| Employee Satisfaction | Level of workforce contentment and morale. | Surveys, Turnover rates, Engagement metrics |
| Decision-Making Speed | Reduction in the time required to make and implement decisions. | Decision time tracking, Case studies |
| Compliance Adherence | Ability to comply with directives, regulations, and security requirements. | Compliance audits, Regulatory review |
| Revenue Growth | Increase in the company's sales and income over time. | Financial performance analysis |
| Adoption Rate | The rate at which employees take up a new technology or process. | Usage metrics, Adoption surveys |

6. Conclusion

In conclusion, the evolution of automation to hyperautomation represents a significant advancement in leveraging Process Mining, RPA, AI, ML, IDP, OCR, BPM, BRMS, IoTs, and NLP for optimal operational efficiency. The integration of these advanced technologies, scalable architecture, and robust governance frameworks enables organizations to orchestrate a cohesive and intelligent automation ecosystem that drives strategic decision-making and operational excellence.

Hyperautomation is optimal for operational efficiency due to its comprehensive framework that encompasses seamless integration of disparate systems, cognitive services for advanced automation capabilities, robust data management and analytics, a security and compliance framework, scalability and flexibility, as well as continuous monitoring and feedback mechanisms. Integrating different technologies and systems allows firms to automate activities across platforms and utilize data from several sources, resulting in informed decision-making. The inclusion of a cognitive services layer empowers automated systems to comprehend natural language, process visual information, and interact with users in a human-like manner, thereby enhancing the scope and intelligence of automated processes.

Moreover, the robust data management and analytics capabilities support data-driven automation and decision-making, allowing organizations to continuously improve workflows and drive innovation through data-driven optimization. The integration of a security and compliance framework ensures the protection of sensitive data and adherence to regulatory requirements, mitigating risks and building trust among customers and stakeholders.

Scalability and flexibility in the architecture accommodate evolving business needs and technological advancements, allowing organizations to expand their automation capabilities seamlessly and incorporate new automation technologies. Furthermore, the establishment of mechanisms for continuous monitoring and feedback enables organizations to drive iterative improvements and optimization of automated systems, ensuring their sustained alignment with business goals. By measuring the impact of hyperautomation on operational efficiency through KPIs such as cost savings, reduction in processing time, error rates, resource utilization, and qualitative factors like improved decision-making and customer and employee satisfaction, organizations can effectively evaluate the success of their automation initiatives and make informed decisions for continuous improvement and optimization.

In summary, hyper automation's holistic approach to automation, incorporating advanced technologies, data-driven insights, security measures, scalability, and continuous improvement mechanisms, makes it optimal for achieving operational efficiency and driving successful digital transformation within organizations.

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