AI-Powered Procurement Architecture: Streamlined UX, Scalable ML Pipelines, and Enterprise Efficiency

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Abstract
Manufacturing firms had difficulty in providing their supplies during monsoons due to two major reasons first, traditional methods of procuring supplies were problematic because they rely heavily on manual processes and are normally time consuming due to delays and waiting on approvals from various parties (vendors); second, companies with fragmented suppliers have difficulty getting what they need in a timely manner, which drives up costs for them and causes longer cycle times in temporary supply interruptions. To solve these problems, an architectural solution for improved procurement management was proposed that utilized AI-based technology including the use of recommendation systems; machine learning pipelines; and natural language processing. Possible solutions include predictive demand forecasting; use of real-time dashboard displays; vendor personalization; and automating all phases of contract management, thereby reducing the number of manual transactions (interactions). The case study presented by AutoComp provided concrete evidence of their success in achieving significant reductions in costs, shorter cycle times than previously experienced, compliance with all contract terms by all vendors, and a very high return on investment. The architectural portion of the proposal also includes implementation of governance and scale through fairness checks. The paper also provides exemplary blueprints for practitioners implementing AI solutions into an overall compliant and effective procurement transformation that is integrated with Dynamics 365 covering aspects like supply chain planning processes; supplier selection; and process of implementing the procurement program.

Keywords: Procuring Supplies, Fragmented Suppliers, Machine Learning Pipelines, Natural Language Processing

Introduction

Advanced technologies are transforming how organizations procure and sell goods by enabling data-driven analysis and analysis of large sets of data such as sales and invoices, as well as inventory and trends. Organizations can leverage predictive analytics provided by the latest technologies to help them determine future demand and to facilitate automation of procurement processes and supplier evaluation leading to an overall increase in efficiency. Another positive outcome from AI-driven procurement is that the employee engagement required to track and buy products will decrease because of the use of more efficient way of tracking products using real-time tracking and purchasing technology, such as the use of online purchasing methods. On-going performance assessment will also assist organizations with their operational decision making resulting in increased efficiency, decreased cost and decreased risk and aligning all purchasing departments to optimize their ability to compete within an increasingly complicated and competitive supply chain environment.

Material procurement and supplier relationship management are two important parts of the entire procurement process. Ivalua provides the framework for managing both supplier relationships and procurement transactions. By utilizing a multi-tenant cloud-based architecture, Ivalua allows each of its tenant's databases to remain completely separate from all the other tenants in the Ivalua repository, so that database contamination does not take place. In this manner, client databases are established in separate zones on different networks that have limited outside exposure while still supporting strong security protections like TLS when transmitting data and AES 256 when storing purchased items in the system. The Ivalua cloud repository architecture additionally provides strong tenant separation, meaning that there is no cross-tenant visibility within the Ivalua repository and securely stores all inactive data, which helps organizations maintain the confidentiality and security of their data. As a consequence, Ivalua continues to maintain a competitive advantage by delivering all of its customers with an enterprise-level multi-instance SaaS solution through a strong emphasis on securing the privacy of its customer's data, thereby realizing greater flexibility for its clients. [1]

Procurement solutions that utilize AI technology to support the procurement process provide finance executives with the tools needed to effectively manage the financial operations of an organization by eliminating inventory management and purchase order processing; therefore resulting in a decrease in overall costs and an increase in their efficiency. A pharmaceutical company with annual sales exceeding $30 billion has achieved significant dollar savings and reduced procurement cycle time from utilizing AI technology for automation of procurement functions. Other organizations such as Scribd and Landsec have also acquired benefits from using AI technology in their procurement processes through improved accuracy in their accounts payable processes and automation of their compliance activities, which has freed their employees to devote more of their time to value-added functions.AI also assists with expense classification, risk assessment and supplier compliance which will improve efficiencies and help to enhance financial stability.

CSCS has improved their procurement process by moving away from an Ivalua on-premise system to a cloud-based solution, thereby removing the requirement for an external middleware integrator and allowing for data to be consolidated and managed in a single database. By moving to the cloud based solution, CSCS can respond to requests more quickly and manage procurement, risk and data more efficiently, resulting in significant savings on an annual basis. Cloud based platform´s capabilities to integrate with other systems provide the ability for rapid, reliable and secure transfer of data that will help to automate compliance and improve operational efficiency. Overall, the use of AI and Cloud technology has provided CSCS and its stakeholders with a more intelligent, effective and stream-lined procurement process; saving time, money and providing for easier future improvements [2].

In today´s fast ending and quickly changing environments such as manufacturing and retail, the traditional method of procurement is being negatively impacted by time consuming manual processes. This is demonstrated in a case study for an automotive parts supplier where there was a market shortage of raw material due to logistical issues associated with COVID-19. All of the procurement work has been performed by manual processes; and procurement teams have been forced to rely on cumbersome methods to manage approvals via e-mail and conduct vendor comparisons in Excel creating a time consumption of over 40% of their entire workday. Manual processes introduce the potential for human error to add costly duplicate payments and delay the timeliness of order deliveries by an average of 10 to 15 days which could resultInefficiencies of this nature are estimated to add 20 to 30 percent to company operating expenses and create the potential for an error rate as high as 15 percent.

There is an issue regarding the fragmentation of supplier data between incompatible SAP systems, particularly in when working with local vendors to secure reliable suppliers and to build inventory in preparation for Diwali. Because of this issue of vendor fragmentation, there is currently substantial inconsistency between different organizations, which impacts how they can make accurate assessments regarding performance and how rapidly they can select vendors, ultimately creating issues with product and quality and representing a waste of 15% to 25% each year across all company procurement activity due to inefficiencies. As a result of the inability to see full supplier data at one time, organizations are further exposing themselves to supply chain risks through ineffective management of those risks, especially in volatile market areas; having real-time supplier visibility can prevent major disruptions.

Integrating Intelligent Recommendation Engines and AI-powered Advanced Analytics platforms can ultimately enhance Procurement Management by providing personalized supplier recommendations and predictive analysis, improving the user experience and the operational efficiency of the organization, thus allowing for proactive decision-making with shorter Procurement cycles and compliance with established regulations. This article provides technical leaders with an AI-based Procurement Transformation Framework which provides common pain points, leading-edge AI-based solution, technical implementation recommendations, use cases and governance. Technical Leaders can use these resources to successfully implement processes resulting in lower Procurement Cycle times and expenses and provide a foundation for ethical use of AI within an organization.

Traditional Procurement processes are inefficient due to delays that occur because of disconnected processes and multi-level email approvals. Delays take between 7 to 14 days depending upon the criticality of the delay, for example, after the monsoon season, supply shortages affect the manufacturing hub, thus, reactive buying tremendously increases costs and loss of discounts. Additionally, the purchasing cycle time can be increased by as much as 30%-50% from industry averages. Procurement organizations also lack visibility due to the fragmentation of data across unmapped silos and thus making it difficult to make informed decisions and resulting in unrecognized vendor delays, leading to increased downtime costs that occur during peak demand periods. In a complex governance environment, this level of fragmentation results in a higher risk of compliance risk, where organizations that employ manual processes do not comply with an established system of checks, leaving them exposed to potential monetary penalties as well as regulatory exposure. All of these factors create overall inefficiencies, resulting in increased cycle times and a manual process that incurs excessive cost overrun. Many studies suggest that integrated AI-based procurement solutions would have a dramatic positive impact on the financial performance of companies [3].

Japan's earthquake and tsunami disaster caused supply chain disruptions at Toyota in 2011 due to its reliance on the "Just in Time" (JIT) model and ultimately led to a halt of production and billions in financial loss for the company. Boeing also experienced major delays in the 787 Dreamliner program caused by extensive outsourcing issues resulting in defects and late delivery of 60 percent of the necessary components leading to massive cost overruns. Procurements through manual processes at Rasico negatively impacted the company's bottom line and it was only after converting to digital procurement processes that improved profitability. A mid-size biotech company also has been impacted by procurement inefficiencies from an inability to manage vendors effectively resulting in increased costs and increased administrative workload. Similarly, global manufacturers have seen increased production costs and unfulfilled orders as a result of late shipments and lack of communication with suppliers resulting in long delays due to customs and incorrectly specified products [4].

Literature Review

The increasing sophistication of procurement processes has resulted in increased dependence on cloud-based solutions which enable enhanced workflow by providing automated processes and improved, more streamlined, communications between supplier networks and enterprises resource planning systems (ERP). Companies like Honeywell and Credit Agricole serve as examples of how digital technologies, (such as Ivalua), can optimize expense management (including invoice management). Digitalization's impact on both the future of the public sector and private sector will come primarily from the use of cloud-first technologies in combination with artificial intelligence, since finance and procurement will be automated in their tasks. Specifically, AI will enable finance and procurement to save time and money by automating the processes of risk assessment and financial forecasting, while using the flexibility and rule capabilities of AI to improve supplier risk management in procurement and continuously improve on procurement processes thus requiring flexible integration frameworks to manage connected ecosystems. [5]

Ivalua enables organizations to move from on-premise applications onto cloud platforms to successfully manage their purchasing process by providing an open ecosystem. Also introduced is the concept of Predictive Procurement Orchestration (PPO), which is intended to increase the effectiveness of procurement processes by introducing automation, simulation and evaluation of results by providing real-time data, while providing ease of use to end users. The evolution of technology from simple web-services to complex orchestration frameworks is demonstrated in how PPO will help organizations to enhance their supplier efficiency and experience lower costs by embedding the desired results into their procurement process. [6]

Strategically managing suppliers with performance, governance, risk and sustainability built into the method of supplier management is critical for high performing organizations. This demonstrates the evolution of supplier management from fragmented “best of breed” to autonomous purchasing with real-time analytics. Many recent research studies reveal the important role of AI, automation and collaboration in delivering value at every point in time throughout the source-to-pay cycle; furthermore, as many researchers are indicating, innovation purchasing transcends solely resource efficiency and resource integration. Schmelzle and Tate's work examined the correlation between procurement orchestration and innovation performance, while Laari's research examined how supply-demand imbalances create challenges for those who procure, serving as the theory for resource orchestration theory, and thus providing future direction for research in procurement orchestration. [7][8]

Proposed Framework

The procurement process is undergoing dramatic changes through AI-powered solutions like natural language processing (NLP), machine learning, and recommendation systems. These AI-based solutions use collaborative filtering and content-based approaches to dynamically match vendors to fulfill procurement requirements with more than 90% relevancy using performance metrics, historical purchase information, urgency and sustainability requirements, and other contextual information. AI will also be used within the machine-learning model to predict expenditures, automate the entire process from data ingestion to delivery, and utilize corporate data lakes for feature engineering.

Returning to NLP, there will be much improvement to how procurement processes currently handle RFPs. In fact, with strong NLP solutions, procurement users will be able to quickly scan unstructured texts and identify pricing discrepancies significantly reducing the amount of time required to manually review RFPs. Furthermore, the user experience will be significantly enhanced with the use of rich user interfaces including intuitive dashboards that provide real-time visualizations of spend analytics, supplier health scores and the ability to create customized views for procurement stakeholders and drill down into specific data. Finally, personalization through user behavior profiles can increase the rate of adoption of AI-based solutions significantly. Additionally, Finance approvers will be able to benefit from risk assessment forecasts, while Category Managers will be able to receive actionable insights.

Lastly, predictive sourcing (predicting future demand and proactively identifying potential suppliers) will be the primary focus of AI automation. Predictive analytics models will evaluate time-series data to automate the majority of routine purchase orders and create alert notifications based on market conditions, while also automating compliance checks through robotic process automation (RPA) to dramatically reduce cycle times on invoice matching.Various components of the architecture for these AI solutions. Various components are connected to different data sources, which include things like: supplier APIs, market feeds, recommendation systems within the AI layer, pipelines used for machine learning, and NLP processors, an end-user experience layer (which delivers dashboards, automated actions or insights about customers), assist in generating accurate reports/alerts/purchase orders, etc.

The overall workflow describes a complete process from when a requisition is submitted by the end-user to when it reaches a completed state. Each of the AI components has been integrated into a business process in order to make efficient use of the business's resources, particularly Dynamics 365 customers. The request process starts at the user level, by creating requisitions on either mobile devices or via the Internet, and the NLP system changes any free-form text requistion(s) to structure data. Once the data has been transferred, AI systems predict future usage based on historical sales data. Risk assessment is accomplished by using an isolation forest for IRR (isolation/regression/return-to-regression). Other data sources also allow the AI algorithms to provide predictive analytics for product volume/timeliness and suggest potential buffers/substitutions of product(s) that users are requesting.

Recommendation systems link users to suppliers (based on specifications/criteria and historical purchase information) and provide a score for each supplier based on cost, dependability, environmental/social/governance (ESG), and fitness criteria. Suppliers are automatically assessed based on predetermined criteria for qualification as suppliers under the request and ensure that bias is removed from the request process before entering into the proposal process. The proposal process is generated via NLP for the suppliers that are on the shortlist (based on qualification) and are invited to submit one or more proposals for fulfilling the user's request. The evaluation of bids takes place on a real-time bidding system, with responses being submitted from each supplier; AI can validate each proposal for irregularities and produce an executed contract. The approval process/acceptance of bids is facilitated through Dynamics 365 with predictive warning indicators identifying bottlenecks leading to the issuing of purchase orders (POs) via electronic signatures.

Order processing is done through RPA, and real-time delivery is tracked by using IoT and API data inputs. Pro-actively future orders/purchases will have data from dashboard monitoring; payment is primarily automated. AI is able to match invoices to POs and detect anomalies (matching to POs) to prevent the payment of excessive or duplicate invoices. Metrics for compliance/audit are generated for all transactions, and knowledge gained from post-execution reviews is used to continuously refine AI models for future execution time improvement. Overall, the document details a multi-layered data architecture which incorporates Dynamics 365 CRM as the base architecture and subsequently builds additional layers of functionality. The core architecture components is shown in below Figure 1:

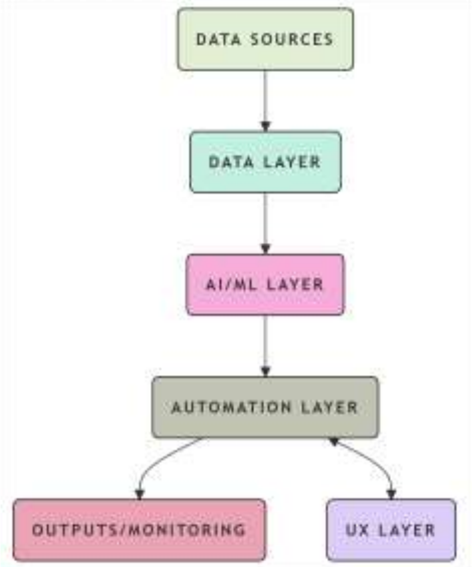

Figure 1: AI-driven procurement Architecture

- The Data Architecture's Data Sources, Using Dynamics 365 CRM as an Example: Dynamics 365 CRM is a Primary Source of Data within the Data Architecture's Data Layer, Using the AI / ML Layer for Support. Dynamics 365 CRM will feed into the Data Layer of the Data Architecture, which consists of the Data Storage and Processing Components. Components that are within the Data Layer for the Data Architecture include: Snowflake Lake for Processing DataFrame; ERP / Supplier APIs, to import Data; HRSys Models to Support Employee Management Requirements; and use of Data Analytics Methods including

✓ Long Short Term Memory (LSTM) Forecasting; and

✓ Spark ETL Pipelines.

In addition, External Data Sources will also be utilized to capture Market Data; Kafka Streams; Natural Language Processing (NLP) using BERT; and RFPs.

- Managing Your Machine Learning Workflows with MLflow Experiments in Datatastic - A Demonstration of Using MLflow Experiments to Handle Machine Learning Workflows in Data Architecture.

- Importance of Automation Layer and UX Layer as Value-Added Data Architecture Components: The Automation Layer and the UX Layer are key Components of the Data Architecture because they support use cases through Automation and User Experience by means of: Power BI dashboards and Robotic Process Automation (RPA) for Managing Purchase Order and Contract Management Process Automations.

- Output and Performance Monitoring Layers of Data Architecture: The Output and Performance Monitoring Layers of the Data Architecture contains Workflows designed to support Management of Approval Processes (e-Signature Capabilities), Mobile Access via Progressive Web Application (PWA), KPIs / Dashboards, and Role-Based Points of View (POV) for Performance Analysis. The Data Architecture is also capable of supporting functions to detect anomalies and maintain records for Compliance.

Evaluation will be performed on the Data Architecture by conducting an Audit of the current Systems used in the Enterprise Procurement Process. The Audit will be approachately structured to measure the level of Maturity of Current Data Architecture and Systems. Current Technologies such as Great Expectations, will be used to Automate the Profiling of Data and Identify issues with Quality and Gaps of Integration with the Current Systems of Records (e.g.,This study is based on five stages of maturity, with great focus on critical components such as raw materials used for production, and plans for data readiness will be measured by an 80% accomplishment target within four to six weeks through gap analysis and repair strategy.

A scalable pipeline using either python/sql will be established as a part of the snowflake/aggregate spark platform to develop models using ai (i.e., forecasting and recommending systems) and then model-containerization for orchestration, models will also utilize spark for distributed training of the ai models with input from the etl pipeline into snowflake. The real-time inference will provide supplier matching at lower latencies using mlflow for versioning and deployment of models. User training to properly navigate and use the ai-based dashboard will occur using tried and true training methods (i.e., role-based training, elearning, and seminars).

Dyn365 integration will provide bi-directional synchronization along with receiving approvals from ai created shortlists. A pilot program with 50 users will be used as the basis for high acceptance levels and feedback. KPIs will measure performance through. Data pipeline maintenance and health will monitor continuously and provide iterative (quarterly) updates for retraining and user experience improvement based on user feedback. Major deliverables from this project are proof of concept data pipeline, operationalized models, high levels of user acceptance, continued KPI tracking for enterprise success.

AutoComp Industries in Vjayawada is a mid-sized auto parts manufacturer who has had difficulty obtaining parts through regional issues due to broken supply chains. The supply chain problems have contributed to inefficiencies in the processing of approximately 5,000 requisitions per quarter through the use of disjunction systems, and the manual processing of requisitions has resulted in delays causing loss of money to AutoComp and in extreme conditions, as demonstrated during monsoons when a critical requisition for steel coils needed 52 days to complete much to the detriment of their ability to remain operational and continue relationships with suppliers.

To address the above issues AutoComp decided to develop an ai model through the creation of a model development framework through three phases: first phase focused on consolidating/re-evaluating their current datasets for the purpose of developing a good foundation for further developing datasets. The second phase had them design/implement a hybrid recommendation system that utilized machine learning to optimize the selection of suppliers based on multiple factors. The third phase was focused on developing/enhancing user experience and automating the procurement process through the use of ai.

The systematic decrease of the steel coil procurement cycle from 52 days down to a 5 day procurement cycle between diwali 2025 to the new model implementation is proof of the new development framework. Every KPI measure that demonstrated significant (56%) reductions of holding fee costs; 36% ovr savings on total procurement; improved compliance and timely delivery by suppliers was achieved within the framework. The first year return on investment was established through this project as being a 5.9 return on investment; additionally the implementation will scale to all other manufacturing categories. The successful implementation will demonstrate to all other manufacturers throughout India that an ai developed solution for solving logistical problems can be executed, and that a solid data management strategy, user driven development and local vendor involvement will play major roles in solving logistics production. Please refer to table 1 below:

Metric	Before AI	After AI	Improvement
Cycle Time	45 days (avg)	20 days (avg)	56%
Cost per Order	$5K (₹4.2L)	$3.2K (₹2.7L)	36%
Compliance Rate	82%	98%	20%
Supplier OTIF	72%	94%	31%
Manual Effort	15 steps/user	4 steps/user	73%

Table 1: Hypothetical Enterprise Deployment

Challenges and Mitigation's

Through the use of AI technologies in procurement, organizations can realize significant savings through increases in efficiency driven by automation, optimization and the reduction of order costs per requisition by between 20-36%. Automating the procurement process also allows for a significant reduction in cycle time for the procurement function, resulting in annual savings of between 15- 25% of total spend. AI also improves scalability through its effective management of massive amounts of data, and the ability to integrate with existing systems, allowing organizations to significantly grow without performance issues. AI will ultimately improve compliance and governance in the procurement function by automating the regulatory processes, resulting in increased compliance rates and the elimination of fines, while ensuring that Indian businesses maintain data sovereignty. Ethics are an important issue and concern surrounding AI recommendation systems, along with trust, fairness and transparency, for users of these types of platforms. Based on projections for ROI, we anticipate total savings in the first year totalling approximately ₹45 million with three years cumulative savings of approximately ₹240 million, which represents significant financial benefit to AutoComp and other companies. [9][10].

The hindrance to effective AI training and gaining real-time insights into supply chain events is primarily due to the existence of data silos among numerous disparate procurement systems which result in significant predictive problems and delays in decision-making when a shortage occurs in supply through the lack of foundation to accurately determine or predict demand through the use of statistical methodologies. In order to address these challenges, a unified data lake would be created through using Snowflakes centralized environment for both storing the company's data and standardizing the organization's approach for ingesting data into the lake. On top of enhancing data quality, this will also improve the ability to perform federated queries. Since procurement has not accepted automation, the implementation rollout has been prolonged and therefore a phased approach will be used to develop trust and also include targeted training within this phased implementation. In addition, the initial set of AI solutions produced will not have the same level of accuracy as if the historical data had been there supporting them (this is due to how quickly supplier performance is changing). To combat this lack of confidence with AI solutions, trust will be developed between the suppliers and AI. Also, the lack of accurate training data will be mitigated by sharing knowledge through transfer learning and by regularly retraining the model in order to improve model accuracy. Integration to develop the data lake will also experience complications such as there being no native endpoints within Dynamics 365. These integration issues will be resolved through the development of secure APIs and event-driven design standards to achieve seamless updates. Finally, moving the infrastructure and services into the cloud will eliminate the current infrastructure limitation that exists and also allow for better scaling and performance. All of these efforts will occur over a structured 12-week methodology with a focus on eliminating challenges along the way while creating value along the way to be delivered.

The purpose of this analysis is to study advanced enterprise-scale procurement AI systems and determine areas of need for more effective mitigation strategies, practical large-scale implementation strategies and developing long-term sustainable practices for enterprise organizations to use for implementing their procurement AI systems. Areas of primary concern include data quality (for example, the presence of corrupted training data will result in the absence of valid recommendations in which to receive large penalties for non-compliance) and regulatory compliance risks (failure to follow compliance regulations will expose businesses to potentially very large penalties). The real-world implications of these issues can be felt by implementation of AI procurement systems and there is very little evidence that AI procurement systems can be relied upon since bad vendor recommendations have created suspicion towards using AI procurement systems. Through these activities, there is also a potential for legal complications related to fairness. To solve the data quality issue, data enrichment pipelines and schema evolution strategies will be used to create data of high accuracy and quality data within eight weeks. To assist with compliance, audit logging and fairness monitoring will be integrated so as to ensure MSMEs can participate in procurement. Lastly, Change Management must occur, as many AI initiatives will fail due to internal conflict (following the completion of an initiative). Solutions include creating executive level dashboards, and establishing cross-functional teams for collaboration.

Vendor integration is complicated by the fact that there are no API endpoints for SMEs, resulting in delays in communications. Proposed solutions include establishing a multi-channel gateway for bidders, and by incentivizing digital participation by vendors. Cost management will also be a main concern, with measures in place to control cloud expenses and provide financial oversight. The first-year estimates for the total cost of investment are ₹97L, and savings from the second year are estimated to be ₹4.8 crore, providing a high return on investment. This integrated strategy will provide sustainable procurement solutions to meet several needs associated with adopting enterprise-wide Artificial Intelligence.

Aerial visualizations created using Matplotlib and Pandas provide data on challenge metrics associated with AI procurement. The data defines challenges, the percentage of impact from those challenges, the length of time (in weeks) required to mitigate each challenge, and the amount of investment needed (in lakhs rupees) to mitigate each challenge. These visualizations will include scatter plots and bar graphs demonstrating the relationship between the challenge's impact (y-axis) and mitigation length of time (x-axis); a Radar chart representing each challenge's success metrics; a Waterfall chart representing the total investment made; a Strategic Risk Matrix representing each challenge as a function of both its impact and execution risk; a line graph, representing the return on investment over time; and a comprehensive visual summary table demonstrating the total number of Challenges and total investment, projected return on investment, and average time to mitigate each challenge. Each visual will be saved as an image file.

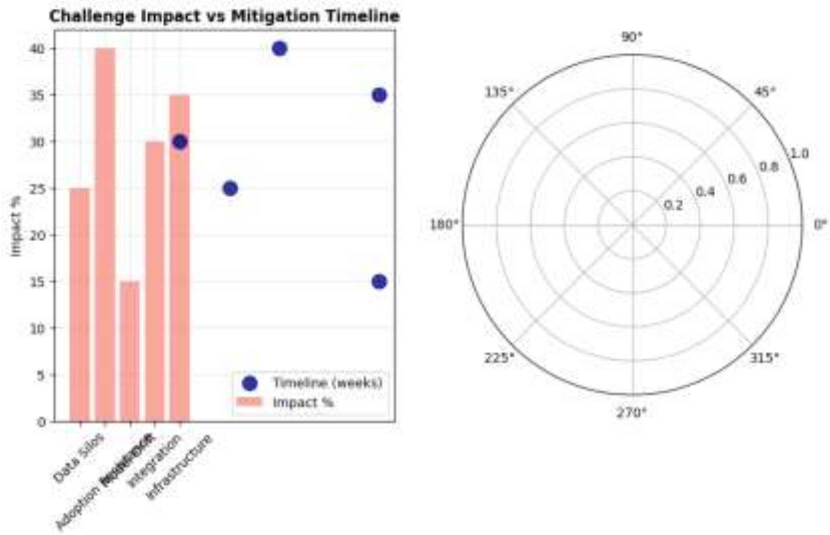

Figure 2: AI Procurement Challenges: Metrics & Risk Visualization

Conclusion

Manufacturers are facing an array of difficulties with the traditional procurement process. This includes lengthy delays for the approval of a new supplier, the need to piece together disparate supply chain operations as a result of vendor data not being integrated, as well as having to navigate through problematic and labor-intensive manual procurement processes. As these issues have created substantial costs to manufacturers and increased their compliance risk, manufacturers are therefore required to adopt a superior methodology for the acquisition of goods and services. To address the procurement concerns raised in the AutoComp Industries case study, the article presents an AI supported procurement framework as the best solution. Specifically, AutoComp benefited from enhanced compliance, cycle time, cost per order and return on investment as a result of implementing machine learning and real-time dashboards into its procurement processes, thus realizing substantial savings. In this article, the author describes the implementation of AutoComp's procurement transformation strategy, which was phased, to allow for the removal of impediments to integration, enhance data governance and scale up while ensuring that ethical governance conditions were present during the procurement transformation process. Lastly, the author highlights the strategic advantages that AutoComp has derived from its procurement transformation in terms of financial and operational efficiency, as well as its ability to leverage areas of weakness into competitive advantage. The author encourages all procurement executives to take immediate action in terms of measuring waste in their procure-to-pay process, establishing pilot projects, and engaging in continuous improvement initiatives with machine learning and to clearly demonstrate that achieving exceptional results within the procurement process is possible now, more than ever before, for all businesses.

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