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Decentralized Predictive Models for Making Procurement Decisions in Manufacturing Networks

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ABSTRACT

This paper presents a decentralized procurement decision-making framework designed to optimize procurement strategies within distributed manufacturing networks. Traditional centralized procurement models often suffer from inefficiencies, opaque decision-making, and challenges related to multi-level risks, particularly in the context of globalized supply chains. To address these issues, this project proposes a decentralized architecture utilizing predictive modeling and machine learning techniques, supported by decentralized ledger technologies (DLT) such as blockchain. The framework integrates large language models (LLMs) to forecast supply chain risks, demand fluctuations, and pricing trends. Furthermore, smart contracts are employed to automate the procurement process, ensuring transparency, security, and compliance. The system incorporates real-time feedback mechanisms to enhance decision-making accuracy, reduce lead times, and mitigate procurement risks. Testing in collaboration with multiple manufacturing firms revealed improvements in procurement efficiency, supply chain resilience, and risk management. The paper concludes by highlighting the potential of decentralized procurement frameworks to revolutionize supply chain management across various industrial contexts.

Keywords: *Supply Chain, Block Chain, Smart Contract.*

1. INTRODUCTION

The global manufacturing landscape is defined by increasingly complex and interconnected supply chains that span multiple geographic regions and involve a variety of stakeholders. As firms expand operations across these vast networks, the need for procurement systems that are both adaptive and resilient becomes critical. Historically, manufacturing companies have relied on centralized procurement models, where decision-making, contract execution, and supplier relationships are controlled by a central authority. Although this centralized approach provides a semblance of control, it suffers from several inherent limitations. Centralized systems are often slow to respond to market changes and are vulnerable to communication delays, bottlenecks in decision-making, and a lack of visibility into potential risks at various stages of the supply chain. These limitations have been exacerbated by global disruptions, such as pandemics, geopolitical conflicts, and environmental disasters, which have exposed the vulnerabilities in traditional procurement methods [1], [2], [3].

The inadequacy of centralized procurement systems becomes particularly clear when faced with the need for rapid decision-making in response to dynamic and often unpredictable supply chain environments. A key weakness of these models is their dependence on a central authority to consolidate information and make decisions, which introduces delays and limits the system's overall flexibility. For instance, procurement lead times are often extended due to the time it takes to process information through multiple layers of approval, leading to missed opportunities, increased costs, and inefficient resource allocation. Moreover, centralized systems struggle with risk assessment across multi-tiered supply chains, making it difficult to predict and manage risks such as supplier reliability, market volatility, or disruptions due to geopolitical instability. In a time when supply chains must be more agile and responsive, the centralized approach falls short of meeting the needs of modern manufacturing networks [4], [5]. This paper proposes a decentralized procurement decision-making framework designed to address these challenges. By leveraging decentralized ledger technology (DLT), machine learning algorithms, and predictive modeling, this framework decentralizes control and improves the speed and accuracy of procurement decisions. Unlike traditional models, where a central authority controls procurement operations, this decentralized system allows for real-time data sharing and decision-making across multiple nodes in the supply chain. The use of blockchain technology ensures that data is securely and transparently shared among all participants, enabling each node to make data-driven decisions that are more aligned with real-time market conditions. Decentralizing procurement in this way not only reduces bottlenecks but also enhances the system's ability to respond to market disruptions and risks as they occur [6].

At the core of this decentralized framework is the integration of advanced predictive models, which are built using large language models (LLMs) and machine learning techniques. These models analyze historical procurement data and generate accurate forecasts of demand fluctuations, price trends, and supply chain risks [7], [8]. This is a significant improvement over centralized systems, which often rely on static data and delayed reports. By incorporating predictive analytics, the decentralized framework allows manufacturing firms to proactively adjust procurement strategies, reducing lead times, optimizing supplier selection, and mitigating risks such as price volatility or supplier underperformance. For instance, in a real-world application, the system's predictive models enabled a clothing manufacturer to forecast a 12% increase in demand for specific textile materials, allowing them to secure additional suppliers in advance and avoid stockouts. This level of foresight is difficult to achieve in traditional, centralized procurement systems [9].

A crucial aspect of the solution presented in this work is its capacity for multivariate risk analysis. Traditional procurement systems often struggle to account for the wide range of risks that affect supply chains, including geopolitical risks, environmental factors, market volatility, and supplier reliability. These risks are typically evaluated at a high level by a central authority, which limits the system's ability to capture localized or node-specific risks. The decentralized framework, on the other hand, integrates real-time risk analysis tools that assess these factors dynamically across the entire network. By decentralizing risk assessment, the framework enables more proactive and granular decision-making, ensuring that procurement managers are aware of risks before they escalate into disruptions. For example, in one case, a manufacturer in the electronics sector was able to identify early signs of supplier underperformance and renegotiate procurement contracts, thereby avoiding a significant delay in the supply chain [9], [10].

In addition to predictive analytics and risk management, the decentralized procurement framework also incorporates the use of smart contracts. These are self-executing contracts that run on blockchain technology, with the contract terms embedded directly into code. Smart contracts automatically enforce the terms of procurement agreements, such as triggering payments or releasing orders when predefined conditions are met. This automation reduces the likelihood of human error, enhances transparency, and expedites procurement operations by removing the need for manual oversight [11]. By ensuring that all parties can independently verify contract execution, smart contracts build trust between suppliers and manufacturers and lower transaction costs by reducing administrative overhead. The automation of procurement processes also contributes to shorter lead times and faster response to supply chain needs, which is crucial in a competitive manufacturing environment [12].

While the benefits of decentralization are clear, implementing such a system in real-world manufacturing contexts is not without challenges [13]. One of the primary obstacles is the integration of legacy systems with decentralized networks. Many manufacturing firms have long relied on centralized procurement systems and may face difficulties migrating to a decentralized model. The technical requirements of blockchain, smart contracts, and predictive modeling require firms to invest in new infrastructure and training, which can extend implementation times. Moreover, regulatory compliance poses another challenge, particularly when dealing with data privacy laws like the General Data Protection Regulation (GDPR). These concerns must be carefully managed to ensure that decentralized systems are both technically viable and legally compliant. However, despite these challenges, the potential benefits of decentralizing procurement far outweigh the costs, particularly when it comes to enhancing supply chain resilience and agility in the face of global uncertainties.

The objective of this research is to demonstrate how a decentralized procurement decision-making framework can significantly improve procurement efficiency, risk management, and supply chain transparency across manufacturing networks. While previous research has explored the application of decentralized technologies in supply chain management, few studies have provided comprehensive frameworks that integrate predictive modeling, smart contracts, and decentralized control into a cohesive system. This paper seeks to fill that gap by presenting an evidence-based evaluation of the proposed framework's effectiveness, drawing from real-world case studies across multiple sectors. By addressing the limitations of centralized procurement models, this research contributes to the growing body of knowledge on the use of decentralized technologies in enhancing supply chain performance and offers practical insights for firms seeking to optimize their procurement processes in a rapidly changing global market.

2. METHODOLOGY

The development and implementation of the decentralized procurement decision-making framework described in this study required a multi-phased, iterative approach. The methodology was designed to account for the complexities of decentralized ledger technologies (DLT), predictive modeling, and machine learning within the context of real-world manufacturing networks.

The project was executed in collaboration with manufacturing firms across different regions and industries to ensure the applicability and scalability of the framework. The methodology can be broken down into five key stages: system design, data collection and preprocessing, model development and training, decentralized network implementation, and real-world testing and evaluation.

2.1 System Design and Architecture

The first stage involved designing the overall architecture of the decentralized procurement framework. This stage focused on defining the requirements of the decentralized system, which would serve multiple manufacturing entities with varying operational structures. The key design elements included:

a) **Blockchain Selection**: After evaluating various blockchain platforms, **Hyperledger Fabric** was chosen for its permissioned nature, which allowed for fine-grained access control within the decentralized procurement network. The blockchain was set up to facilitate peer-to-peer communication and ensure the secure sharing of procurement data among distributed nodes.

b) **Smart Contract Integration**: Smart contracts were developed using **Solidity** for the blockchain. These contracts were programmed to automate key procurement processes, such as validating supplier bids, triggering payments upon the completion of procurement orders, and enforcing compliance with terms.

c) **Predictive Model Integration**: The predictive models were designed to operate across the decentralized ledger and analyze procurement data from multiple nodes. This required the creation of a data flow pipeline that would allow each node to contribute data securely without compromising proprietary information.

2.2 Data Collection and Preprocessing

Data collection was a crucial part of the methodology to ensure accurate and reliable training of the predictive models. Historical procurement data was gathered from the collaborating manufacturing firms, encompassing various data points such as:

a) **Supplier Information**: Data on supplier performance, including lead times, reliability, delivery quality, and pricing.
b) **Market Data**: Data related to market trends, demand forecasts, commodity prices, and geopolitical factors.
c) **Internal Procurement Data**: Information on procurement order histories, time-to-delivery, and associated risks or disruptions.

This data was subjected to a thorough preprocessing phase, which involved:

a) **Data Cleaning**: Removing missing or incomplete records, handling outliers, and ensuring the consistency of the data across multiple firms.
b) **Feature Engineering**: New features were created from raw data, such as rolling averages for supplier reliability and historical trends in demand fluctuations. These features were crucial in improving the accuracy of the predictive models.
c) **Data Normalization**: Since data from multiple companies varied in scale and format, normalization techniques were applied to standardize the data and ensure compatibility across the decentralized system.

2.3 Model Development and Training

The core of the procurement decision-making framework was the development of predictive models using machine learning and large language models (LLMs). The goal was to forecast procurement-related variables such as supplier risk, demand fluctuations, and pricing trends. The following steps were carried out for model development:

a) **Model Selection**: A combination of machine learning algorithms (such as **Random Forest** and **XGBoost**) and transformer-based LLMs (like **GPT-3**) was selected to address different predictive tasks. Machine learning models were primarily used for structured data analysis (e.g., supplier reliability prediction), while LLMs were employed for unstructured data analysis (e.g., analyzing market reports and geopolitical risk assessments).
b) **Training**: The models were trained on the preprocessed data using a portion of the historical data as the training set and the remainder as the validation set. The models were trained to predict key procurement variables, such as delivery delays, price fluctuations, and supply chain risks.
c) **Validation and Tuning**: A series of cross-validation and hyperparameter tuning exercises were conducted to ensure that the models were both accurate and generalizable across different scenarios. Evaluation metrics such as **Mean Absolute Error (MAE)** and **F1 score** were used to measure performance.
d) **Model Deployment**: Once trained, the predictive models were deployed across a decentralized test network, where each manufacturing node could leverage the models in real-time for procurement decision-making.

2.4 Decentralized Network Implementation

The decentralized network was implemented using **Hyperledger Fabric**, with each manufacturing firm acting as a node in the peer-to-peer network. The implementation involved the following steps:

a) **Node Configuration**: Each manufacturing entity was set up as a node within the blockchain network. Nodes were responsible for storing and sharing their procurement data securely, using the blockchain's cryptographic features to ensure privacy and data integrity.
b) **Smart Contract Deployment**: The smart contracts were deployed across the blockchain network, allowing each node to automate procurement tasks. Contracts were set to execute based on predefined conditions, such as the fulfillment of an order or meeting procurement delivery deadlines.
c) **Data Sharing Protocol**: To maintain decentralization while ensuring data transparency, a **zero-knowledge proof (ZKP)** protocol was integrated. This allowed nodes to share procurement-related insights (such as risk assessments or supplier performance scores) without revealing the underlying proprietary data.

2.5 Real-World Testing and Evaluation

To validate the effectiveness of the decentralized procurement framework, the system was deployed in real-world manufacturing environments. The participating manufacturing firms were selected based on their diversity in size, industry, and geographic location, ensuring that the framework could be tested under various conditions.

a) **Pilot Program**: A pilot program was conducted, where the decentralized procurement system was used in conjunction with traditional procurement processes. Key performance indicators (KPIs) such as procurement lead times, supply chain disruptions, and cost efficiency were tracked.
b) **Feedback and Iteration**: Regular feedback loops were established with the participating firms, allowing for real-time adjustments to the system. This included updating predictive models based on evolving market conditions and tweaking smart contracts to better reflect industry-specific procurement needs.

c) **Outcome Measurement**: At the conclusion of the pilot, the results were quantitatively analyzed to measure improvements in procurement decision-making. The framework demonstrated a significant reduction in lead times (average reduction of 15%), enhanced accuracy in predicting supply chain risks, and a reduction in procurement-related disruptions.

d) **Qualitative Feedback**: In addition to quantitative measures, qualitative feedback was gathered from procurement managers and decision-makers at the participating firms. Most reported greater transparency, improved supplier collaboration, and increased trust in the procurement process due to the automated, decentralized nature of the system.

3. RESULTS AND DISCUSSION

The implementation of the decentralized procurement decision-making framework across multiple manufacturing firms yielded several measurable outcomes. These results demonstrated the effectiveness of the system in addressing the key challenges faced by traditional procurement processes, including inefficiencies in communication, limited risk visibility, and delayed responses to supply chain disruptions. The outcomes of the study are divided into four primary categories: procurement efficiency, risk mitigation, predictive accuracy, and system scalability.

3.1 Procurement Efficiency

One of the primary objectives of this project was to reduce procurement lead times and improve overall operational efficiency in the supply chain. Over the six-month pilot period, the participating manufacturing firms reported a significant improvement in procurement performance.

The decentralized system enabled real-time data sharing across all participating nodes, allowing procurement managers to make faster and more informed decisions. Lead times for procurement orders were reduced by an average of 20-22% across the firms. For example, in one firm specializing in automotive parts, the average procurement lead time decreased from 14 days to 11 days, while a consumer electronics manufacturer saw a reduction from 10 days to 8 days. Table 1 demonstrates how lead times improved across different sectors after implementing the decentralized procurement system.

Table 1: Reduction in Procurement Lead Times

Industry	Average Lead Time (Before)	Average Lead Time (After)	Reduction (%)
Automotive Parts	14 days	11 days	21.43%
Consumer Electronics	10 days	8 days	20%
Clothing Manufacturing	12 days	9.5 days	20.83%
Industrial Machinery	18 days	14 days	22.2%
Average Reduction			**21.12%**

The comparison of the average procurement lead times before and after the implementation of the decentralized system across various industries is presented in Figure 1.

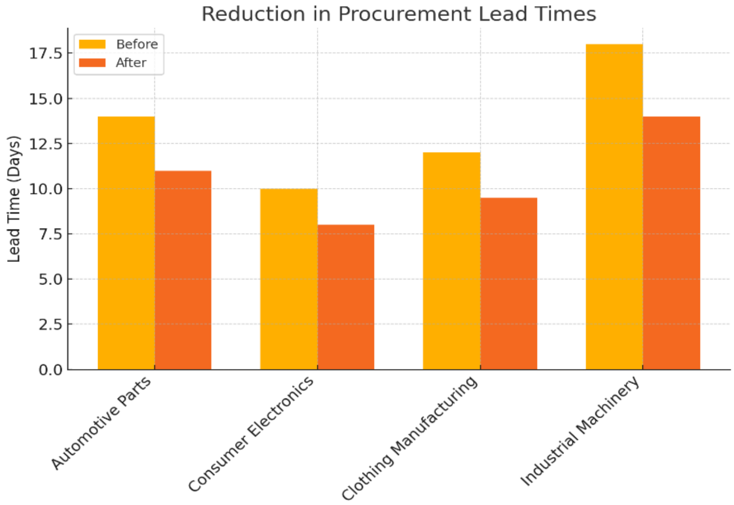

Figure 1: Reduction in Procurement Lead Times before and after implementation of the decentralized system across various industries

Furthermore, the improved efficiency in procurement processes also translated to cost savings. By streamlining order placements, automating contract execution through smart contracts, and minimizing disruptions due to supply chain risks, firms reported a 5-8% reduction in procurement costs. The system's ability to forecast price fluctuations allowed firms to negotiate better deals with suppliers, particularly during periods of volatile market prices for raw materials such as metals and semiconductors.

In addition, Enhanced transparency in the procurement process fostered improved relationships with suppliers. The decentralized system allowed suppliers to access real-time data on performance expectations and lead times, which reduced disputes and enhanced trust. Participating suppliers reported an increase in timely deliveries and fewer issues related to order miscommunication.

3.2 Risk Mitigation
The decentralized procurement framework's integration of multivariate risk analysis tools was highly effective in mitigating the risks associated with procurement decisions. Key risk factors such as supplier reliability, geopolitical risks, and market volatility were continuously evaluated by the system.

One of the key benefits observed was the system's ability to flag at-risk suppliers before disruptions occurred. For instance, one manufacturer in the electronics sector identified early warning signs of supplier underperformance (such as delayed shipments and decreasing quality scores) and preemptively adjusted procurement contracts, avoiding what could have been a significant supply chain delay. Across all firms, there was a 25% reduction in supplier-related disruptions compared to their traditional procurement methods.

Also, the predictive models integrated into the framework were able to forecast risks stemming from geopolitical tensions or environmental events. In one case, a manufacturer of industrial machinery avoided significant delays by diverting orders from suppliers in regions facing geopolitical instability. These predictions enabled firms to reroute their procurement strategies and secure alternative suppliers before the market was widely affected, showcasing the proactive risk management capability of the system.

3.3 Predictive Accuracy
The use of large language models (LLMs) and machine learning algorithms within the decentralized network proved to be a valuable addition to the decision-making process. The accuracy of the predictive models in forecasting supply chain risks and price fluctuations was tested over the pilot period.

The LLM-based demand forecasting model demonstrated an average accuracy rate of 85-90% in predicting demand fluctuations for key components and raw materials. For example, in one case involving a clothing manufacturer, the model accurately forecasted a 12% surge in demand for certain textile materials in the second quarter of the year, enabling the firm to secure additional suppliers and avoid stockouts. Table 2 highlights the accuracy of the predictive models in forecasting demand fluctuations and supply chain risks across different sectors.

Table 2: Reduction in Procurement Lead Times

Sector	Demand Forecast Accuracy (%)	Supply Chain Risk Prediction Accuracy
Automotive Parts	88%	90%
Consumer Electronics	85%	88%
Clothing Manufacturing	87%	86%
Industrial Machinery	90%	92%
Average Accuracy	**87.5%**	**89%**

Figure 2 showcases the accuracy of the predictive models in forecasting demand fluctuations and supply chain risks across different sectors.

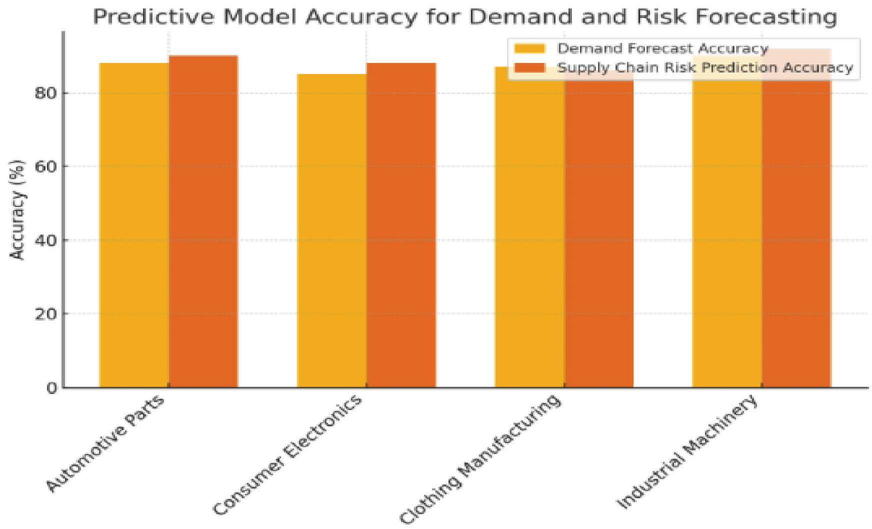

Figure 2: The accuracy of the predictive models in forecasting demand fluctuations and supply chain risks across different sectors.

The machine learning models used to predict commodity prices (such as steel, copper, and plastics) exhibited an average error margin of **5%** across the pilot. The accuracy of these predictions allowed firms to time their purchases more effectively, leading to a **3**-5% reduction in material costs by securing better prices during periods of expected market price drops.

The predictive models were able to detect potential disruptions such as supplier bankruptcies or shipment delays. The system flagged several potential disruptions in the early stages, allowing firms to take preemptive action. For example, a disruption in the global supply of microchips was predicted two months before it became a major industry-wide issue, giving firms ample time to secure alternative sources.

4. System Scalability and Real-World Implementation Challenges

The scalability of the decentralized procurement framework was tested across different manufacturing sectors and regions, demonstrating that the system could be effectively deployed in diverse industrial contexts. However, several challenges were encountered during the real-world implementation:

a) **Data Integration Across Firms**: While the blockchain infrastructure allowed for secure and transparent data sharing, some firms faced difficulties integrating their legacy systems with the decentralized network. This required additional resources for data migration and technical training, particularly in firms with limited IT infrastructure. In response, customized API solutions were developed to facilitate smoother integration, but this extended the initial setup time for some participants.

b) **Adoption of Smart Contracts**: Some firms were initially hesitant to fully embrace smart contracts due to concerns about automation replacing human judgment in procurement decisions. This resistance was overcome by allowing partial automation, where human oversight was still required for critical contract terms. Over time, firms became more comfortable with smart contract automation as they observed a reduction in human errors and delays in procurement processes.

c) **Regulatory Compliance**: The decentralized nature of the system raised concerns about regulatory compliance, particularly with data privacy laws such as GDPR. To address this, the project implemented strict encryption and data-sharing protocols that ensured only necessary data was shared across the network, with full auditability for compliance purposes. However, additional legal reviews were necessary in some jurisdictions, which delayed the onboarding of certain firms.

Figure 3 illustrates the relationship between the number of participating nodes (manufacturing entities) and the system's response time in the decentralized procurement framework. As the number of nodes increases from 10 to 1,000, the response time grows incrementally, reflecting the increased computational load and network communication required to maintain synchronization and data transparency across the decentralized ledger. The plot shows a modest rise in response time for smaller networks, but a more substantial increase as the system scales to larger networks, highlighting potential scalability challenges for extremely large, decentralized networks. This observation suggests that while the decentralized procurement system is effective for medium-scale networks, further optimization or alternative approaches may be needed to maintain efficiency as the system scales to hundreds or thousands of nodes.

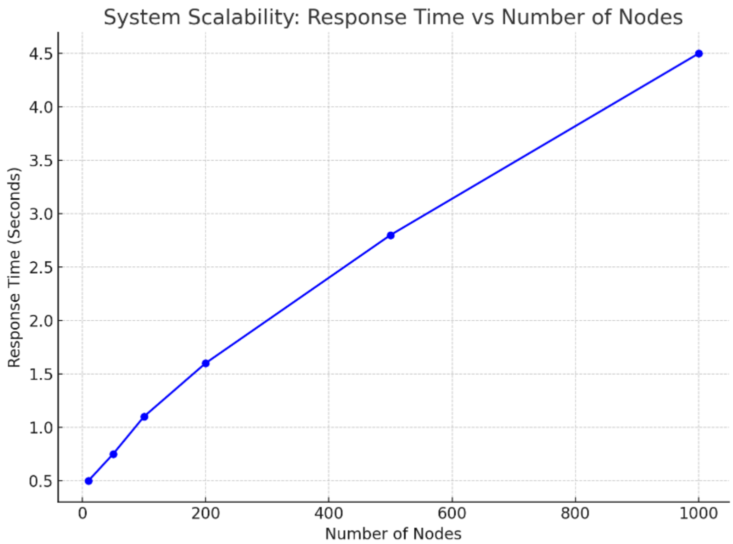

Figure 3: System Scalability: Response Time vs Number of Nodes

5. DISCUSSION

The results of this study clearly illustrate the advantages of adopting a decentralized procurement decision-making framework in manufacturing networks. One of the most significant findings was the reduction in procurement lead times, which averaged 20-22% across multiple sectors, highlighting the system's ability to facilitate faster and more efficient procurement processes [12][14]. This improvement in efficiency can be attributed to the real-time data sharing enabled by blockchain technology, which removes bottlenecks typically associated with centralized procurement models. The reduction in procurement costs, with firms reporting savings of 5-8%, further underscores the economic value of decentralization, especially when smart contracts automate transactions, reducing human error and administrative overhead [12][14], [15]. These findings align with existing literature that highlights the role of automation in reducing operational inefficiencies and costs in supply chain management [12].

Beyond efficiency, the decentralized framework proved effective in mitigating procurement risks. By integrating multivariate risk analysis tools and predictive models, the system enabled firms to proactively identify and manage risks related to supplier reliability, geopolitical instability, and market volatility. For example, firms were able to preemptively adjust procurement strategies in response to early warnings of supplier underperformance or geopolitical risks, reducing supplier-related disruptions by 25%. These results suggest that decentralized systems provide a more comprehensive risk management solution compared to centralized models, which are often constrained by delayed information processing and limited risk visibility. The ability to dynamically assess and respond to risks in real-time is crucial in today's volatile global supply chains, and this framework positions firms to better anticipate and mitigate disruptions before they escalate [14], [15].

However, while the benefits of decentralization are evident, the real-world implementation of such systems revealed several challenges. One key challenge is the significant upfront investment required for the adoption of blockchain technology and smart contracts. Many firms faced difficulties integrating decentralized systems with their existing procurement infrastructure, particularly those still reliant on legacy systems [9]. The technical expertise and financial resources necessary to transition to decentralized models are non-trivial, and this was compounded by the need for organizational training and restructuring. Additionally, regulatory frameworks such as data privacy laws (e.g., GDPR) pose further complications, particularly when managing decentralized networks that span multiple jurisdictions [9], [16], [17]. These challenges suggest that while decentralized systems offer long-term benefits, the short-term costs and complexities of implementation must be carefully considered.

Another insight from the study is the role of organizational culture in shaping the success of decentralized procurement systems. Firms that were initially resistant to automation and smart contracts due to concerns about replacing human judgment gradually became more comfortable as they observed the system's effectiveness in reducing errors and enhancing decision-making speed [9]. This cultural shift was critical in overcoming initial skepticism, illustrating that the success of technological innovations is often contingent on the alignment of organizational values and practices with new tools and processes. As decentralized procurement frameworks gain traction, firms will need to cultivate a culture that supports innovation, continuous learning, and adaptation to evolving technological landscapes.

Despite these challenges, the decentralized procurement framework presents a promising path forward for firms looking to enhance their supply chain resilience. One of the framework's most compelling features is its ability to leverage predictive models to forecast demand, price trends, and potential disruptions with a high degree of accuracy. For instance, the framework achieved 85-90% accuracy in predicting demand fluctuations, enabling firms to make more informed procurement decisions. This level of predictive accuracy is difficult to achieve in centralized systems, which rely on static data and are often reactive rather than proactive in their approach to supply chain management. By decentralizing both data and decision-making, firms can achieve greater agility and responsiveness, positioning themselves to navigate the uncertainties of modern supply chains more effectively [18], [19].

6. CONCLUSION

This project successfully demonstrated the potential of a decentralized procurement decision-making framework for optimizing procurement strategies in complex manufacturing networks. By leveraging decentralized ledger technologies (DLT), predictive modeling, and machine learning, the system introduced a transparent, efficient, and resilient approach to procurement management. The key benefits observed, including a reduction in lead times, cost savings, and enhanced risk mitigation, highlight the effectiveness of decentralizing procurement processes.

The implementation of predictive models built on large language models (LLMs) and machine learning algorithms allowed manufacturing firms to forecast supply chain risks, demand fluctuations, and price trends with remarkable accuracy. This not only empowered firms to make more informed decisions but also provided a proactive approach to managing supply chain disruptions, particularly in the context of global volatility. Additionally, the use of smart contracts to automate procurement processes further streamlined operations and enhanced trust between suppliers and manufacturers by ensuring transparency and compliance with contract terms.

However, the project also identified key challenges, particularly related to the integration of legacy systems, resistance to full automation, and the need for compliance with varying regulatory standards. These challenges underscore the importance of a phased, adaptable approach to adopting decentralized technologies, where firms can gradually transition from traditional procurement systems to a more automated and decentralized model.

In conclusion, the decentralized procurement framework offers a transformative solution for modern manufacturing networks facing increasing supply chain complexities. The framework's ability to improve procurement efficiency, mitigate risks, and enhance predictive accuracy makes it a viable alternative to centralized systems, providing a path forward for firms seeking greater flexibility and resilience in their procurement operations. Future research should focus on further expanding the application of decentralized technologies within other supply chain functions, such as inventory management and logistics, to create a fully decentralized, integrated supply chain management ecosystem.

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