Journal of Electronic Research and Application, 2025, Volume 9, Issue 7
http://ojs.bbwpublisher.com/index.php/JERA
ISSN Online: 2208-3510
ISSN Print: 2208-3502

Factory Procurement Management from the Perspective of Big Data in the Manufacturing Industry

Feifei Wu*

Shenzhen Huafeipu Technology Co., Ltd., Shenzhen 518000, Guangdong, China

**Author to whom correspondence should be addressed.*

Abstract: Big data is revolutionizing factory procurement management in the manufacturing industry. It offers comprehensive market views, predictive analytics, and new digital procurement system frameworks. Critical success factors include supplier data analytics, real-time monitoring, and predictive inventory management. Traditional procurement has inefficiencies like manual operations and data silos. Machine learning, IoT, blockchain, etc., play important roles, and various aspects like IT maturity, workforce training, and cloud deployment require attention.

Keywords: Big data; Factory procurement management; Manufacturing industry

Online publication: December 31, 2025

1. Introduction

In the contemporary manufacturing industry, factory procurement management is experiencing a significant shift, largely propelled by big data. Traditional procurement practices face numerous challenges, such as information asymmetry and inefficient decision-making. However, big data offers new opportunities to revolutionize this field. As highlighted by Chen and Zhang, big data-driven approaches can significantly enhance procurement management in smart manufacturing systems [1]. In 2020, the "Digital Economy Development Plan" was promulgated, which emphasizes the promotion of the deep integration of digital technologies like big data with the manufacturing industry. Aligning with this policy, exploring the application of big data in factory procurement management becomes crucial. This paper aims to study the applications, benefits, and challenges of integrating big data into factory procurement, providing insights for industry practitioners to enhance competitiveness in the global market.

2. Core theories of procurement management in big data era

2.1. Framework of digital procurement systems

The framework of digital procurement systems in the big data era within the manufacturing industry encompasses several key components. At the heart of it is the data collection layer. This layer is responsible for gathering vast amounts of data from various sources related to procurement, such as supplier information, market price fluctuations, inventory levels, and historical procurement records. The data can come from internal enterprise resource planning (ERP) systems, external market research platforms, and even real-time data feeds from suppliers [2].

Followed by the data storage and management module. Here, the collected data is organized and stored in a structured or unstructured format, depending on its nature. Big data technologies like Hadoop and NoSQL databases are often employed to handle the large-scale and diverse data. This module also ensures data integrity, security, and easy access for further analysis.

The data analysis layer is crucial for extracting valuable insights. Advanced analytics techniques, including predictive analytics, data mining, and machine learning algorithms, are used. Predictive analytics can forecast demand, price trends, and supplier performance, enabling manufacturers to make proactive procurement decisions. Machine learning algorithms can optimize supplier selection by analyzing multiple factors simultaneously.

Furthermore, the decision-making support layer presents the analyzed results in an actionable format. Dashboards and reporting tools are used to convey key information to procurement managers. These visual aids help managers quickly understand the situation, compare different options, and make data-driven decisions, thereby streamlining the procurement process and improving overall efficiency in the manufacturing industry.

2.2. Critical success factors in data-driven procurement

In the realm of data-driven procurement within factory procurement management in the manufacturing industry in the big data era, several critical success factors stand out. Supplier data analytics is of utmost importance. By comprehensively analyzing suppliers' historical performance data, such as delivery times, product quality, and cost-effectiveness, manufacturers can gain deep insights into their capabilities and reliability. This enables them to make more informed decisions when selecting suppliers, fostering long-term, mutually-beneficial partnerships [3].

Real-time market monitoring is another key factor. In a rapidly changing market, having access to up-to-the-minute information on raw material prices, industry trends, and competitor activities is essential. Big data technologies can collect and analyze vast amounts of market data from various sources, allowing procurement managers to adjust their strategies promptly. For instance, if real-time data shows a sudden increase in the price of a key raw material, the manufacturer can explore alternative sources or negotiate better contracts in a timely manner.

Predictive inventory management is also crucial. Leveraging big data analytics, manufacturers can forecast future demand more accurately. By considering factors like historical sales data, market trends, and even external events (such as seasonal variations or economic forecasts), they can optimize inventory levels. This not only helps to reduce inventory-holding costs but also ensures that production is not disrupted due to shortages. All these factors combined contribute to the success of data-driven procurement in the manufacturing industry's factory procurement management.

3. Challenges in traditional manufacturing procurement practices

3.1. Limitations of manual procurement operations

Manual procurement operations in traditional manufacturing procurement practices are fraught with inefficiencies.

Paper-based processes are a significant hurdle. For instance, in many factories, purchase orders are printed, filled out by hand, and then physically transferred between departments. This not only consumes a great deal of time but also increases the risk of errors such as incorrect data entry or misplacement of documents [4]. These errors can lead to delays in the procurement cycle, causing production slowdowns or even stoppages.

Fragmented supplier communications further exacerbate the problem. In manual systems, communication with suppliers often occurs through various channels like phone calls, faxes, and emails. This lack of a unified communication platform makes it difficult to keep track of conversations, agreements, and order status. For example, a change in delivery date communicated over the phone might not be properly recorded, leading to misunderstandings between the manufacturer and the supplier.

Delayed demand forecasting is another shortcoming. Manual methods rely on historical data that is often time-consuming to collect and analyze. As a result, manufacturers may find themselves unable to accurately predict future demand. For instance, if market trends change rapidly, the traditional, manual-based forecasting methods may not be able to adapt quickly enough. This can lead to over-procurement, tying up capital in excess inventory, or under-procurement, which can disrupt production schedules. All these limitations of manual procurement operations highlight the need for a more advanced and efficient approach in manufacturing procurement.

3.2. Data silos and integration barriers

In traditional manufacturing procurement practices, data silos and integration barriers pose significant challenges. Legacy ERP systems, often deeply entrenched in multi-tier supply chain networks, struggle to interoperate seamlessly with emerging big data tools. These data silos are like isolated compartments, where data from different procurement processes, such as supplier management, inventory control, and order processing, are stored separately. For example, the data on supplier performance may be locked within one system, while inventory data resides in another. This fragmentation makes it difficult to obtain a holistic view of the procurement process.

The integration barriers between legacy ERP systems and big data tools further exacerbate the problem. Legacy systems are designed with their own data structures, formats, and communication protocols, which may not be easily compatible with the more flexible and scalable big data technologies. As a result, extracting, transforming, and loading (ETL) data from legacy systems into big data platforms becomes a complex and resource-intensive task. It often requires significant manual intervention, custom-built connectors, and a deep understanding of both systems. Without effective integration, the potential of big data in optimizing procurement, such as predictive demand forecasting and real-time supplier risk assessment, remains largely untapped [5]. This lack of seamless data flow and integration hampers the ability of manufacturers to make informed, data-driven procurement decisions in a timely manner, putting them at a competitive disadvantage in the market.

4. Big data applications in procurement optimization

4.1. Predictive analytics for strategic sourcing

4.1.1. Machine learning in supplier selection

Machine learning plays a crucial role in supplier selection within the realm of procurement optimization. By leveraging historical transaction data, machine learning algorithms can effectively evaluate supplier performance metrics and supply chain risks. For instance, algorithms can analyze factors such as on-time delivery rates, product quality levels, and cost-effectiveness of past transactions with various suppliers. This analysis enables manufacturers to predict how a potential supplier might perform in the future.

Specifically, supervised learning algorithms can be trained on historical data where the performance of suppliers has been labeled as either satisfactory or unsatisfactory. These algorithms can then identify patterns in the data related to different performance indicators. Unsupervised learning algorithms, on the other hand, can be used to detect hidden patterns in the supply chain risk data, such as emerging trends in supplier-specific risks like financial instability or geopolitical risks associated with their location.

Additionally, machine learning models can continuously adapt and improve their predictions as new data becomes available. This dynamic nature of machine-learning-based supplier selection ensures that manufacturers stay ahead in making informed decisions. By accurately evaluating supplier performance metrics and supply chain risks through machine learning, factories can make strategic sourcing decisions that lead to more efficient procurement processes, reduced costs, and enhanced supply chain resilience [6].

4.1.2. Demand forecasting through data mining

Demand forecasting is a crucial aspect of strategic sourcing in factory procurement management. By leveraging data mining techniques, manufacturers can gain valuable insights into future demand for raw materials based on production schedule data patterns.

Time-series analysis is one effective data mining method for this purpose. It examines historical production schedule data, which often contains patterns such as trends, seasonality, and cycles. For example, in a manufacturing plant that experiences higher production during certain months of the year due to seasonal market demand, time-series analysis can identify these seasonal patterns. By analyzing the past production volumes month-by-month or quarter-by-quarter over several years, the model can capture the regular fluctuations.

Once these patterns are recognized, time-series models can be used to project future production requirements. These models use statistical algorithms to fit the historical data and make predictions. For instance, the autoregressive integrated moving average (ARIMA) model is a popular choice. It can take into account the autocorrelation in the production schedule data, meaning how the current production level is related to previous levels. By accurately predicting future production based on historical patterns, manufacturers can better forecast the demand for raw materials [7]. This enables them to plan their procurement activities more strategically, ensuring that they have the right amount of materials at the right time, reducing inventory costs, and avoiding production disruptions caused by shortages.

4.2. Real-time procurement process monitoring

4.2.1. IoT-enabled inventory tracking

IoT-enabled inventory tracking presents sensor network architectures for automated stock level reporting and reorder point optimization. In factory procurement management, IoT sensors play a crucial role. These sensors are deployed throughout the inventory storage areas to collect real-time data on stock levels. For example, radio-frequency identification (RFID) tags can be attached to products, enabling the system to accurately track the quantity of each item in stock.

The data collected by these IoT devices is then transmitted to a central database. Big data analytics algorithms are applied to this data to analyze trends in inventory consumption. By studying historical consumption patterns and current demand signals, the system can optimize the reorder point. If a particular raw material has been consumed at an increasing rate over a certain period, the algorithm can adjust the reorder point upwards to avoid stock-outs [8].

This real-time inventory tracking not only helps in maintaining optimal stock levels but also reduces carrying costs. Excess inventory ties up capital and incurs storage costs, while insufficient inventory can lead to production delays. With IoT-enabled inventory tracking, manufacturers can strike the right balance. The automated stock level reporting ensures that procurement managers are always aware of the inventory status, allowing for timely procurement decisions, which ultimately contributes to the overall efficiency of factory procurement management in the manufacturing industry.

4.2.2. Blockchain for contract compliance

In factory procurement management within the manufacturing industry, blockchain technology plays a crucial role in contract compliance. By leveraging blockchain, companies can ensure that service-level agreements (SLAs) and quality assurance parameters are effectively enforced across global suppliers. The distributed ledger feature of blockchain provides an immutable record of all contract-related transactions and interactions. Every detail, from the initial contract negotiation to the final delivery and payment, is securely stored on the blockchain. This transparency enables all parties involved, including the manufacturer, suppliers, and even regulatory bodies, if necessary, to have real-time access to the contract status. For instance, if a quality assurance parameter is not met, the blockchain record can be immediately referred to, providing clear evidence of non-compliance.

It also helps in automating compliance checks. Smart contracts, a key application of blockchain, can be programmed to execute predefined actions when certain conditions are met or violated. In the context of procurement, smart contracts can release payments automatically when goods meet the specified quality standards as recorded on the blockchain. Through these mechanisms, blockchain significantly enhances contract compliance in factory procurement, reducing the risk of disputes and ensuring that the procurement process runs smoothly among global suppliers [9].

5. Implementation strategies for smart procurement transformation

5.1. Organizational readiness assessment

5.1.1. Maturity evaluation of IT infrastructure

When conducting a maturity evaluation of the IT infrastructure for smart procurement transformation in the context of factory procurement management from the perspective of big data in the manufacturing industry, it is essential to propose criteria for assessing current system capabilities in handling big data volumes and processing speeds [10]. These criteria serve as a foundation for understanding the readiness of the IT infrastructure. To begin with, regarding big data volume handling, one should measure the maximum amount of procurement-related data, such as supplier information, purchase orders, and inventory data, that the current system can store and manage efficiently. This includes evaluating the storage capacity of databases, data warehouses, and any associated data storage systems.

If the system frequently encounters storage limitations or data loss during large-scale data imports, it indicates a low-maturity level in handling big data volumes. In terms of processing speed, the time taken for data analytics tasks like generating procurement reports, predicting demand based on historical data, or evaluating supplier performance is a key metric. Slow processing speeds can delay decision-making processes in procurement, leading to inefficiencies. By establishing clear and measurable criteria for both data volume handling and processing speed, manufacturers can accurately evaluate the maturity of their IT infrastructure, identify areas for improvement, and thus formulate more targeted strategies for smart procurement transformation.

5.1.2. Workforce digital literacy programs

Workforce digital literacy programs play a crucial role in the smart procurement transformation within the manufacturing industry's factory procurement management from a big-data perspective. Designing training frameworks for procurement specialists in advanced analytics tools and data visualization techniques is essential.

These training frameworks should start with a comprehensive needs assessment. Understand the current digital literacy levels of procurement staff, identifying gaps in their knowledge of advanced analytics and data visualization. For example, some may be proficient in basic data collection but lack skills in using tools like Python for in-depth data analysis or in creating interactive visualizations with Tableau.

The training content should cover a wide range of advanced analytics tools. It could include teaching how to use statistical software such as R for predictive analytics, which can help in forecasting demand for factory procurements more accurately. Regarding data visualization techniques, specialists should learn how to transform complex procurement data into clear, actionable visual representations. This not only enables better internal communication within the procurement department but also helps in presenting data-driven insights to other departments and senior management [11].

Moreover, the training should be hands-on. Provide real-world procurement datasets for specialists to practice on. They can work on case studies related to cost-savings analysis, supplier performance evaluation, etc. By applying the learned analytics and visualization skills to practical scenarios, they can enhance their digital literacy and be better prepared to contribute to the smart procurement transformation. In addition, continuous learning and up-skilling opportunities should be built into the framework, as the field of digital technologies is constantly evolving.

5.2. Technology roadmap development

5.2.1. Cloud-based procurement platform deployment

When deploying a cloud-based procurement platform, outline phased implementation plans for migrating procurement operations to secure cloud ecosystems integrated with AI. In the initial phase, conduct a comprehensive assessment of the current procurement processes, systems, and data in the factory. This involves identifying pain points, bottlenecks, and areas that can benefit most from cloud-based solutions. Analyze the existing data architecture to ensure seamless integration with the cloud-based platform [12].

After that, select a suitable cloud service provider that aligns with the factory's requirements in terms of security, scalability, and cost-effectiveness. Consider providers with a proven track record in the manufacturing industry and those that offer advanced AI capabilities for procurement, such as demand forecasting and supplier risk assessment.

During the deployment stage, focus on migrating key procurement functions, including supplier management, purchase order processing, and inventory management, to the cloud. Ensure data integrity during the migration process, and conduct thorough testing to avoid disruptions to daily operations. Integrate AI algorithms into the platform to automate repetitive tasks, such as invoice processing and contract management. This not only improves efficiency but also reduces the risk of human error.

On top of that, after the deployment, provide training to procurement staff to familiarize them with the new cloud-based platform and its AI-enabled features. Continuously monitor the platform's performance, collect user feedback, and make necessary adjustments to optimize the procurement process in the long run.

5.2.2. Cybersecurity protocols for data ecosystems

In the context of smart procurement transformation in factory procurement management from the perspective of big data in the manufacturing industry, establishing robust cybersecurity protocols for data ecosystems is of utmost importance. Given the presence of sensitive supplier information and transaction records, the following multi-layered security measures are necessary:

(1) Encryption techniques should be employed to safeguard data both at rest and in transit. This ensures that even if unauthorized access occurs, the data remains unreadable. For data at rest, such as stored supplier contracts or transaction histories in databases, strong encryption algorithms like AES (Advanced Encryption Standard) can be utilized [13]. When data is being transmitted between different systems within the procurement data ecosystem. For example, from the factory's internal system to the supplier's portal, secure communication protocols like SSL/TLS should be used to encrypt the data stream;

(2) Access control mechanisms need to be strictly defined. Only authorized personnel within the factory, such as procurement managers, relevant financial staff, and IT security administrators, should have access to specific types of data. Role-based access control (RBAC) can be implemented, where different roles are assigned different levels of access rights. For instance, a junior procurement officer may only be able to view certain aspects of supplier contact information, while a senior manager can access comprehensive transaction details;

(3) Continuous monitoring and threat detection systems should be in place. Intrusion detection systems (IDS) and intrusion prevention systems (IPS) can be deployed to identify and prevent any potential cyber-attacks targeting the procurement data ecosystem. Regular security audits and vulnerability assessments should also be carried out to ensure the effectiveness of the cybersecurity protocols and to address any emerging threats promptly.

5.3. Performance measurement framework

5.3.1. KPI system for procurement efficiency

To effectively evaluate the efficiency of procurement in the context of smart procurement transformation in factory procurement management from the perspective of big data in the manufacturing industry, a set of well-defined metrics is essential. The cost-savings ratio is a crucial KPI. It reflects the extent to which the procurement department has managed to reduce costs through various strategies such as strategic sourcing, volume discounts, and supplier negotiations. A higher cost-savings ratio indicates more efficient cost management in procurement activities [14].

The procurement cycle time reduction is another key metric. In a fast-paced manufacturing environment, shortening the time from identifying a procurement need to receiving the goods is vital. By leveraging big data analytics to streamline processes, predict demand more accurately, and improve communication with suppliers, the procurement cycle can be significantly reduced. This metric helps to assess how well the procurement process is optimized for speed and responsiveness.

Supplier on-boarding speed is also an important KPI. In the era of smart procurement, quickly and effectively bringing new suppliers into the fold is necessary to meet changing business demands. Measuring the time it takes from the initial contact with a potential supplier to the successful on-boarding can show the efficiency of the supplier evaluation and selection process. A faster on-boarding speed implies a more agile procurement function that can adapt to market changes promptly. These KPIs together form a comprehensive system to measure procurement efficiency in the smart procurement transformation journey.

5.3.2. Continuous improvement mechanisms

Developing feedback loops with real-time analytics dashboards is crucial for continuous improvement in smart procurement transformation within the manufacturing industry's factory procurement management. These dashboards offer a comprehensive view of procurement processes in real-time. By monitoring key performance indicators (KPIs) such as cost savings, delivery times, and supplier quality, managers can quickly identify areas that require attention.

For instance, if the dashboard shows a consistent increase in procurement costs from a particular supplier, it signals a need for renegotiation or a search for alternative suppliers. In a dynamic market, real-time data enables timely adjustments. This feedback mechanism not only helps in rectifying current inefficiencies but also in preventing future issues.

Moreover, the data from these dashboards can be used to benchmark performance against industry standards or internal targets. If a factory's delivery times are longer than the industry average, it can prompt the implementation of process improvements, like optimizing inventory management or enhancing communication with suppliers.

The continuous improvement process is iterative. As changes are made based on the insights from the dashboards, new data is generated. This new data is then analyzed to further refine the procurement strategies. Over time, this cycle of monitoring, analyzing, and improving leads to a more efficient, cost-effective, and competitive procurement system, enabling the manufacturing factory to thrive in the era of big data.

6. Conclusion

In conclusion, big data has emerged as a revolutionary force in manufacturing factory procurement management. Its potential to transform traditional procurement paradigms is vast, offering new ways to optimize supplier selection, enhance cost-effectiveness, and improve supply chain resilience. The critical success factors, such as data quality, skilled personnel, and organizational buy-in, are essential for unlocking the full benefits of big data in this domain. However, implementation barriers like data security concerns, integration challenges, and legacy system limitations cannot be overlooked. These need to be carefully addressed to ensure a seamless transition to data-driven procurement. Looking ahead, the proposed future research directions in AI-powered contract negotiation systems and cross-industry data sharing protocols hold great promise. AI-powered contract negotiation systems can leverage big data to analyze historical contract data, market trends, and supplier behavior, enabling more favorable contract terms. Cross-industry data sharing protocols, on the other hand, can expand the data pool, providing deeper insights for procurement decision-making. Further research in these areas will not only refine the current understanding of big-data-enabled procurement but also drive the manufacturing industry towards more efficient, intelligent, and competitive procurement practices. Overall, embracing big data in factory procurement management is not just an option but a necessity for the long-term success of manufacturing enterprises in the digital age.

Disclosure statement

The author declares no conflict of interest.

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