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A KPI-Driven Decision Intelligence Model: Using Integrated Dashboards to Enhance Strategic Operational Control in Advanced Manufacturing

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Abstract

In the context of advanced manufacturing, maintaining operational control and making informed strategic decisions is critical to achieving competitiveness and efficiency. Traditional decision-making processes often rely on fragmented data sources and delayed insights, hindering timely actions. This proposes a KPI-driven decision intelligence model that integrates real-time data visualization through dashboards to enhance strategic operational control in manufacturing environments. Key Performance Indicators (KPIs), such as production efficiency, downtime, and quality control, serve as the foundation of this model, guiding decision-makers by providing immediate visibility into critical operational metrics. The proposed model utilizes integrated dashboards that aggregate data from various manufacturing systems (e.g., Enterprise Resource Planning (ERP), Manufacturing Execution Systems (MES), and Supervisory Control and Data Acquisition (SCADA)), presenting a cohesive view of performance across the factory floor. These dashboards support decision intelligence by offering real-time updates, drill-down capabilities, and customizable reporting, enabling manufacturers to monitor KPIs continuously and make proactive decisions based on real-time data. This approach fosters operational improvements, such as increased production efficiency, reduced downtime, and optimized resource allocation. Strategic benefits include enhanced decision-making, agility in responding to disruptions, and better alignment of operations with long-term business goals. The integration of dashboards facilitates data-driven decisions that align with operational objectives, thus promoting continuous improvement and contributing to overall competitiveness. By providing actionable insights at the strategic level, the KPI-driven decision intelligence model helps organizations enhance their operational control and adaptability in a rapidly changing manufacturing landscape. The model's ability to integrate with existing systems and offer real-time decision-making capabilities positions it as a valuable tool for modern manufacturers aiming to optimize performance and sustain competitive advantage.

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Keywords: KPI-driven, Decision intelligence model, Integrated dashboards, Strategic operational control, Advanced manufacturing

1. Introduction

Advanced manufacturing refers to the use of innovative technologies, processes, and systems to improve the production of goods (Onukwulu *et al.*, 2021). This includes techniques such as additive manufacturing, automation, robotics, and advanced materials, all of which have revolutionized the manufacturing landscape. As industries continue to evolve, advanced manufacturing has become a cornerstone for competitiveness and productivity, enabling manufacturers to deliver high-quality products at faster speeds and lower costs (Akinsooto *et al.*, 2014; Balogun *et al.*, 2023).

In this rapidly changing environment, maintaining operational control is essential for ensuring that processes remain efficient, cost-effective, and responsive to market demands. Operational control, which encompasses the monitoring, analysis, and optimization of manufacturing processes, is key to managing costs, improving product quality, and maintaining flexibility in operations.

The importance of operational control in advanced manufacturing cannot be overstated. Manufacturers who fail to optimize their operations risk losing their competitive edge (Ogunmokun *et al*., 2022). Poor decision-making, inefficient resource allocation, and unresponsive production lines can lead to increased downtime, wasted resources, and missed market opportunities. In contrast, organizations with strong operational control can swiftly identify issues, implement corrective actions, and continuously improve their processes. However, achieving this level of control requires more than just traditional oversight; it requires strategic, data-driven decision-making that leverages real-time information and aligns operations with business objectives (Afolabi and Akinsooto, 2021; Bristol-Alagbariya *et al*., 2022).

Strategic decision-making is critical to success in manufacturing environments, yet it often presents a major challenge for organizations. Manufacturers are faced with a constant flow of complex data from diverse sources such as production schedules, supply chains, and quality control systems (Fredson *et al*., 2021). Without a structured approach to analyzing this data, decision-makers may struggle to identify key issues or opportunities, leading to suboptimal decisions. This is where key performance indicators (KPIs) come into play. KPIs serve as measurable benchmarks that provide insights into the health of manufacturing operations. By monitoring KPIs like production efficiency, equipment utilization, and defect rates, manufacturers can gain a clearer understanding of their operations and make informed decisions that drive improvements. However, the challenge lies in effectively integrating and visualizing these KPIs in a way that enables timely and strategic decision-making.

The purpose of this, is to explore how integrated dashboards can enhance operational control in advanced manufacturing by applying a KPI-driven decision intelligence model (Okolie *et al*., 2021). Integrated dashboards provide a centralized platform where KPIs from various sources such as manufacturing execution systems (MES), enterprise resource planning (ERP) systems, and supervisory control and data acquisition (SCADA) systems are visualized in real-time. This integration allows decision-makers to access up-to-date, actionable information and make data-driven decisions without delay. Furthermore, these dashboards can be customized to highlight critical KPIs that align with specific organizational goals, whether it is improving production throughput, minimizing downtime, or enhancing product quality. By focusing on the integration of KPIs into a visual dashboard format, this aims to demonstrate how manufacturers can enhance their strategic decision-making capabilities, ultimately leading to improved operational performance and a more competitive position in the market.

2. Methodology

A comprehensive search of several relevant databases such as Scopus, Web of Science, and Google Scholar is conducted using specific keywords like "KPI-driven decision intelligence," "integrated dashboards," "strategic operational control," and "advanced manufacturing." Studies included in this search are those that examine the role of KPIs in manufacturing, performance optimization using dashboards, and data-driven decision-making systems. Any studies that focus on areas outside of manufacturing or that do not discuss the specific application of KPIs or dashboards are excluded.

Following the initial search, the articles are screened based on their titles and abstracts to ensure they meet the inclusion criteria. Studies that do not align with the objectives of this research, such as those outside manufacturing or not discussing relevant systems like KPIs or dashboards, are excluded. After the title and abstract review, the remaining studies undergo full-text evaluation to ensure that they are methodologically rigorous and focused on the use of KPI-driven models and dashboards for decision intelligence in manufacturing environments. Studies are considered eligible if they offer insights into the role of dashboards and KPIs in improving operational control and decision-making in advanced manufacturing.

Data is then extracted from each eligible study, focusing on key elements such as the types of KPIs used, the nature of the integrated dashboard systems, the manufacturing processes under consideration, and the outcomes associated with the application of KPI-driven models. This data is organized into thematic categories, including production efficiency, real-time data utilization, and improvements in operational decision-making. The synthesis of these findings provides insights into the effectiveness of using KPI dashboards to enhance operational performance in manufacturing.

To ensure the quality of the studies included, the methodological quality is assessed using standardized tools such as the Critical Appraisal Skills Programme (CASP) checklist. This step helps ensure that only the most reliable and methodologically sound studies are included in the analysis. Finally, a narrative synthesis of the data is performed, summarizing the key findings and providing conclusions on how KPI-driven decision intelligence, supported by integrated dashboards, can enhance strategic operational control in advanced manufacturing. The synthesis also identifies areas for future research, such as the potential integration of emerging technologies like artificial intelligence and machine learning for further optimization of manufacturing operations.

By adhering to the PRISMA methodology, this is systematically reviews and synthesizes existing literature on the integration of KPIs and dashboards in manufacturing decision intelligence, offering a comprehensive understanding of their impact on operational control.

2.1 Key concepts and frameworks

In the context of advanced manufacturing, operational efficiency and decision-making are critical components for maintaining a competitive edge (Ayodeji *et al*., 2023). To achieve this, organizations increasingly rely on key performance indicators (KPIs), decision intelligence systems, and integrated dashboards as shown in figure 1. These elements together provide the foundation for optimizing manufacturing processes and ensuring continuous improvement (Akinsooto, 2013). This section outlines the key concepts and frameworks that underpin a KPI-driven decision intelligence model for strategic operational control in advanced manufacturing.

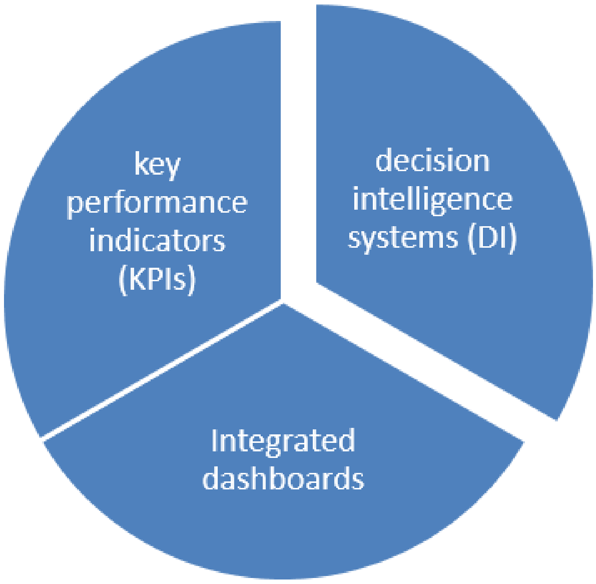

Fig 1: Key concepts and frameworks

Key performance indicators (KPIs) are essential metrics used to evaluate and track the performance of various processes within an organization. KPIs serve as quantifiable benchmarks that allow businesses to assess how well they are achieving operational objectives (Balogun *et al*., 2022). In the context of advanced manufacturing, KPIs are vital for measuring operational efficiency, identifying areas for improvement, and ensuring that production goals are met within time and budget constraints. KPIs in advanced manufacturing cover a broad spectrum, reflecting various aspects of production and resource utilization (Onukwulu *et al*., 2022). Key examples include production efficiency, which measures the output relative to input; downtime, which tracks the time lost due to machine breakdowns or maintenance; quality control, which measures the defect rate or adherence to product specifications; and cost per unit, which monitors the financial efficiency of production by calculating the cost of producing a single unit of product. These KPIs provide real-time insights into operational processes, enabling managers to pinpoint inefficiencies, reduce waste, and optimize resource allocation. Other important KPIs might include yield rates, inventory turnover, and on-time delivery, all of which contribute to a holistic view of the manufacturing process. By integrating these KPIs into decision-making frameworks, organizations can make data-driven decisions that improve both the short-term and long-term success of manufacturing operations (Adekunle *et al*., 2023).

Decision intelligence (DI) is a rapidly evolving field that integrates data analytics, artificial intelligence (AI), and decision-making processes to optimize business operations. In manufacturing, DI tools are used to process vast amounts of operational data, enabling managers to make informed decisions quickly. These tools enhance decision-making by combining historical data with predictive analytics, offering insights that traditional methods of decision-making cannot provide. Decision intelligence leverages AI algorithms and machine learning models to analyze trends and patterns in data, generating actionable insights for managers (Okeke *et al*., 2023). In advanced manufacturing, this might involve forecasting demand, predicting equipment failures, or identifying bottlenecks in the production line. DI enables manufacturers to go beyond historical performance analysis by simulating "what-if" scenarios, optimizing production schedules, and improving supply chain coordination. The integration of decision intelligence with real-time data ensures that decisions are timely, relevant, and grounded in the latest available information, which is crucial in fast-paced industrial environments. By using DI, manufacturers can achieve higher operational performance, reduced downtime, and better resource allocation, ultimately leading to improved profitability and sustainability. In particular, DI enhances agility, allowing manufacturing processes to adapt to changing conditions such as fluctuating demand, supply chain disruptions, or unexpected failures (Olorunyomi *et al*., 2023).

An integrated dashboard is a powerful tool for visualizing data and monitoring performance in real-time. It aggregates data from various sources, providing decision-makers with a centralized, interactive view of key metrics and KPIs. Dashboards are particularly effective in manufacturing environments because they facilitate quick and easy access to critical data, allowing managers to track performance, identify issues, and take corrective actions without delay. Integrated dashboards in manufacturing display KPIs in an intuitive format, often using visual elements like graphs, charts, and gauges to present performance metrics (Onukwulu *et al*., 2022). This helps users quickly grasp the current status of operations and focus on areas that need attention. Real-time data is continually updated, ensuring that decisions are based on the most current information. The primary benefit of using integrated dashboards is their ability to offer actionable insights in a single view, making it easier for managers to make informed decisions. Dashboards can be customized to display KPIs relevant to different departments or production stages, such as machine performance, material usage, or supply chain metrics. This allows for enhanced collaboration among teams, as everyone is working with the same set of data, and it ensures data-driven decision-making across the organization (Ogunsola *et al*., 2022). Another benefit of integrated dashboards is their ability to provide predictive analytics by integrating historical data with real-time inputs. In this way, dashboards do not only report what has happened but also enable proactive decision-making by forecasting potential issues.

KPIs, decision intelligence, and integrated dashboards play a critical role in the strategic operational control of advanced manufacturing environments. KPIs provide the metrics that measure the efficiency and effectiveness of manufacturing processes, while decision intelligence systems enhance decision-making by incorporating AI-driven analytics (Odunaiya *et al*., 2021). Integrated dashboards serve as the central hub for visualizing these KPIs in real-time, offering a comprehensive view of operational performance and enabling managers to make faster, more informed decisions. Together, these elements form the backbone of a KPI-driven decision intelligence model that can significantly improve operational performance, foster continuous improvement, and sustain a competitive advantage in the manufacturing sector.

2.2 The KPI-driven decision intelligence model

The KPI-Driven Decision Intelligence Model plays a pivotal role in enhancing strategic operational control within advanced manufacturing environments. By integrating Key Performance Indicators (KPIs), decision intelligence, and real-time dashboards, the model facilitates the seamless translation of data into actionable insights (EZEANOCHIE *et al*., 2022). This framework empowers manufacturing organizations to optimize performance, minimize waste, and stay competitive by making informed, data-driven decisions. This explore the design of the KPI-driven decision intelligence model, the integration of dashboards, and how the model enhances strategic control within manufacturing operations.

The KPI-driven decision intelligence model for advanced manufacturing is structured to connect operational goals with performance measurement, enabling effective management of production systems. At its core, the model is designed to align key performance indicators (KPIs) with specific operational objectives, ensuring that each metric contributes to the overarching goals of efficiency, productivity, quality, and cost reduction. KPIs are selected based on their relevance to the manufacturing environment and their ability to provide insight into critical operations. By monitoring these KPIs in real time, managers can ensure that production goals are met while identifying issues before they escalate into significant problems. Additionally, KPIs such as cost per unit and defect rates provide clear visibility into cost control and quality management, two crucial factors in maintaining profitability and competitiveness. Each KPI is linked to specific goals and objectives at various levels of the organization, from individual production units to overall company targets. This alignment enables a transparent and cohesive decision-making process, where all employees understand the performance metrics that drive success. By continuously tracking these indicators, the model supports not only operational decision-making but also long-term strategic planning (Odunaiya *et al*., 2023).

A critical component of the KPI-driven decision intelligence model is the integration of dashboards, which aggregate data from multiple sources such as enterprise resource planning (ERP), manufacturing execution systems (MES), and supervisory control and data acquisition (SCADA) systems. These platforms collect real-time operational data, providing a holistic view of the manufacturing process from raw materials to finished products (Basiru *et al*., 2022). Dashboards process this vast array of data, ensuring that it is presented in an accessible and actionable format. The integration of various data sources allows for a centralized visualization of operational metrics, eliminating the need for manual data collection and improving the accuracy of performance monitoring. Dashboards allow users to drill down into specific aspects of production, such as a machine's performance history or detailed cost breakdowns (Anaba *et al*., 2022). This drill-down capability enables manufacturing managers to investigate problems at a granular level, such as identifying the root cause of production delays or inefficiencies.

One of the key features of integrated dashboards is real-time updates, which allow managers to view live performance data and respond immediately to issues as they arise. This feature is particularly beneficial in fast-paced manufacturing environments, where even small delays or disruptions can have significant impacts on overall production (Onukwulu *et al*., 2023). Additionally, dashboards offer custom reporting, enabling users to tailor the visual display of KPIs according to their needs. Whether it's creating a report on overall production efficiency or a detailed analysis of specific equipment downtime, custom reporting helps decision makers to focus on what matters most. By enabling real-time monitoring, dashboards ensure that decision-makers have access to up-to-date and accurate data, reducing the risk of delayed responses to emerging issues. This dynamic, interactive platform enhances decision-making by providing insights into both current operations and historical trends, making it easier for managers to make proactive adjustments to the workflow.

The KPI-driven decision intelligence model enhances strategic operational control by facilitating real-time monitoring and enabling proactive decision-making. Real-time KPI monitoring ensures that manufacturing operations are continuously assessed and adjusted as necessary, helping managers identify inefficiencies, bottlenecks, and quality issues before they impact overall performance. By having direct access to critical KPIs such as production throughput, downtime, and defect rates, managers can immediately take corrective action, whether by reallocating resources, adjusting production schedules, or conducting preventive maintenance on machines. The integration of dashboards further strengthens this proactive approach by allowing managers to visualize trends and performance patterns over time (Basiru *et al*., 2023). With a few clicks, managers can identify potential issues before they escalate, enabling the swift implementation of solutions. For example, a dip in production efficiency highlighted on the dashboard can prompt a review of the assembly line process, while an increase in downtime can trigger maintenance interventions or equipment replacements.

The relationship between dashboard insights and strategic operational control is built on the ability to make data-driven decisions. Dashboards provide decision-makers with a clear, visual representation of key metrics, empowering them to respond quickly and effectively to changes in the production environment. This real-time access to information helps maintain high levels of operational efficiency, reduce waste, and optimize the allocation of resources, all of which are essential for maintaining competitiveness in an increasingly complex and fast-moving industrial landscape. By enabling better alignment of operational activities with strategic objectives, the KPI-driven decision intelligence model also supports long-term planning and continuous improvement (Onukwulu *et al*., 2022). Managers can use historical data presented by the dashboards to assess the effectiveness of past decisions and refine future strategies. This iterative, data-driven approach fosters a culture of continuous improvement within the organization, helping manufacturers stay agile and competitive in an ever-evolving market.

The KPI-driven decision intelligence model provides a robust framework for enhancing operational control in advanced manufacturing. By aligning KPIs with operational goals, integrating data from various sources through dashboards, and enabling real-time monitoring, the model empowers managers to make informed, proactive decisions that optimize manufacturing performance (Bristol-Alagbariya *et al*., 2022). The result is a more efficient, flexible, and responsive manufacturing environment capable of adapting to both immediate challenges and long-term strategic goals. Through the continuous monitoring and visualization of key metrics, this model supports ongoing operational improvements and drives sustainable competitive advantage in the manufacturing sector.

2.3 Application and benefits of the model

The KPI-driven decision intelligence model, particularly when implemented through integrated dashboards, brings a wealth of benefits to advanced manufacturing environments (Basiru *et al*., 2023). By combining real-time monitoring, data aggregation, and visual insights, the model enhances operational efficiency, strategic decision-making, and economic competitiveness as shown in figure 2. This explores the various operational, strategic, and economic benefits that come with adopting such a model, highlighting its transformative potential for modern manufacturing.

One of the primary operational advantages of the KPI-driven decision intelligence model is the significant increase in visibility into production processes. Traditionally, manufacturing systems were often siloed, with limited access to real-time performance data (Onukwulu *et al*., 2023). This lack of visibility made it challenging for managers to monitor various aspects of production, such as efficiency, quality control, or equipment health. The introduction of integrated dashboards in the model centralizes data from multiple sources, such as enterprise resource planning (ERP), manufacturing execution systems (MES), and supervisory control and data acquisition (SCADA), into a single platform. This aggregation enables managers to have a clear and real-time view of key performance metrics, ensuring that operational issues are identified swiftly. Real-time monitoring is another vital aspect of the model that leads to faster identification of inefficiencies or bottlenecks. By continuously tracking KPIs like machine uptime, production throughput, and defect rates, managers can pinpoint potential issues before they escalate. For example, if a production line is underperforming or experiencing increased downtime, the dashboard will immediately highlight the anomaly, allowing the team to take corrective action quickly (Okeke *et al*., 2022). This proactive approach not only reduces the risk of significant disruptions but also helps to maintain optimal operational flow, minimizing waste and downtime. As a result, the operational environment becomes more efficient, responsive, and adaptive to changes in demand or unforeseen issues.

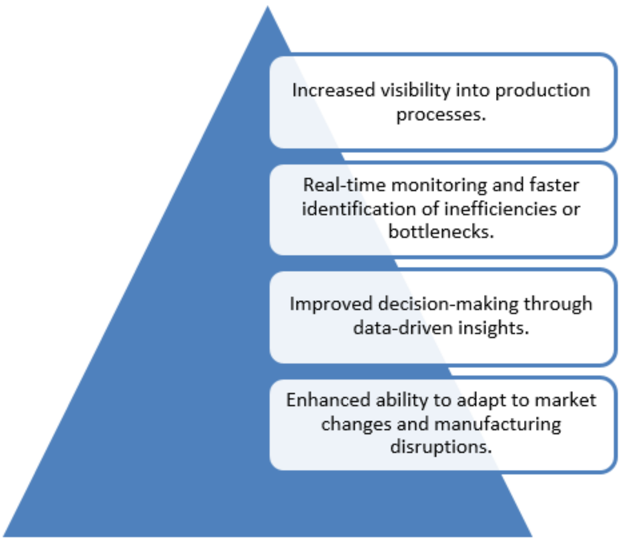

Fig 2: Benefits of the Model

Beyond the operational improvements, the KPI-driven decision intelligence model offers significant strategic benefits, particularly in improving decision-making through data-driven insights (Onukwulu *et al*., 2023). With KPIs continuously monitored and displayed through integrated dashboards, managers gain a wealth of information that helps guide both short-term decisions and long-term strategies. For example, decision-makers can track metrics related to production efficiency, cost per unit, and on-time delivery rates, providing them with a comprehensive understanding of the operational health of the manufacturing process. Such data empowers managers to make well-informed decisions that align with the company's broader strategic goals, whether related to increasing productivity, improving quality, or reducing costs. The model also enhances the ability to adapt to market changes and manufacturing disruptions. In today's dynamic business environment, manufacturers face constant pressure to meet fluctuating market demands and adapt to supply chain disruptions. The KPI-driven decision intelligence model enables organizations to remain agile by providing real-time insights into changing conditions. If production capacity needs to be adjusted due to a shift in market demand, the model allows managers to make informed decisions on resource allocation and scheduling. Furthermore, when disruptions such as machine breakdowns, labor shortages, or material supply issues occur, the model allows manufacturers to respond quickly, mitigating negative impacts on the overall production process (Basiru *et al*., 2023). This adaptability is crucial for maintaining competitive advantage in industries where responsiveness to change is key to survival.

The KPI-driven decision intelligence model offers profound economic advantages, with one of the most significant being cost reduction through improved efficiency. By providing real-time data on production processes, waste, downtime, and resource utilization, the model helps manufacturers identify areas of inefficiency that directly contribute to unnecessary costs These insights allow for targeted actions that improve resource allocation and minimize waste, leading to substantial cost savings. Moreover, the reduction in downtime and bottlenecks directly contributes to more efficient production, translating into higher output and better cost management (Onukwulu *et al*., 2023). In addition to operational cost savings, the model provides competitive advantages by enabling agile decision-making and fostering continuous improvement. In industries where time-to-market and product quality are crucial, the ability to make fast, data-driven decisions is a significant competitive differentiator. With access to real-time insights, manufacturers can quickly pivot production strategies, adjust workflows, or implement corrective actions, enabling them to meet customer demands more efficiently than competitors relying on traditional, slower decision-making processes. Furthermore, the model promotes a culture of continuous improvement, where performance is regularly monitored and adjusted based on real-time data. This continual refinement of operations contributes to sustained competitiveness, ensuring that the organization remains efficient and responsive to changes in the market (Basiru *et al*., 2023).

Additionally, continuous improvement facilitated by real-time performance data results in incremental operational enhancements, leading to long-term economic sustainability (Onukwulu *et al*., 2023). Organizations using KPI-driven decision intelligence models are more likely to identify emerging trends, optimize processes, and reduce operational costs, all of which are essential for maintaining a competitive edge in a rapidly evolving manufacturing landscape. The

KPI-driven decision intelligence model, when implemented with integrated dashboards, provides substantial operational, strategic, and economic benefits to advanced manufacturing environments. It increases operational efficiency by offering greater visibility and real-time monitoring, which allows for the quicker identification and resolution of inefficiencies. Strategically, it empowers decision-makers by providing data-driven insights that enhance decision-making and improve the organization's ability to adapt to changing market conditions. Economically, the model leads to cost reductions and a competitive edge by enabling agile decision-making and fostering continuous improvement (Fredson *et al*., 2023). With these transformative benefits, the KPI-driven decision intelligence model is an invaluable tool for manufacturers looking to maintain operational excellence and remain competitive in the modern manufacturing landscape.

2.4 Challenges and considerations

The implementation of a KPI-driven decision intelligence model in advanced manufacturing environments provides significant operational, strategic, and economic benefits (Chukwuma-Eke *et al*., 2022). However, alongside these benefits, several challenges and considerations must be addressed for successful implementation and sustainable operation. These challenges range from data quality and integration issues to resistance to change within the organization, as well as the scalability and maintenance of the system as shown in figure 3. This explores these key challenges in detail and discusses strategies to mitigate their impact.

One of the most significant challenges in implementing a KPI-driven decision intelligence model is ensuring the collection and integration of high-quality data from diverse sources (Okeke *et al*., 2023). Manufacturing environments often rely on a variety of data systems, including enterprise resource planning (ERP), manufacturing execution systems (MES), and supervisory control and data acquisition (SCADA) systems, each of which may handle different types of data in distinct formats. Integrating these systems into a single, cohesive decision intelligence model can be a daunting task, as discrepancies in data quality, inconsistencies in data definitions, and differences in data reporting structures can undermine the reliability of the insights derived from the system. Moreover, data quality is crucial for accurate decision-making. Inaccurate, incomplete, or outdated data can lead to misleading conclusions and poor operational decisions, which could negatively impact production efficiency, resource allocation, and cost management. Ensuring that data from all integrated sources is of high quality requires robust data governance practices, data cleansing procedures, and validation checks. Additionally, the integration process itself must account for any gaps in data or incompatible systems to avoid system failures or data silos (Bristol-Alagbariya *et al*., 2023). Addressing these challenges requires continuous efforts to standardize data and maintain data integrity across the entire organization.

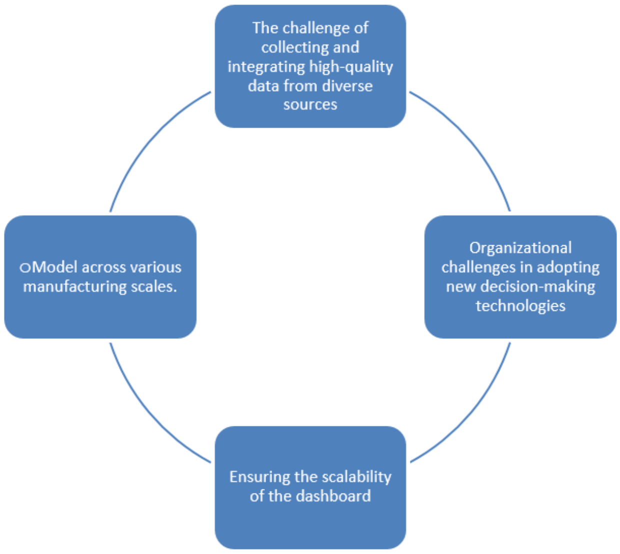

Fig 3: Challenges and considerations for successful implementation and sustainable operation

Resistance to change is a common challenge when introducing new technologies or systems into an organization, especially in established manufacturing environments (Oluwafunmike *et al*., 2023). Employees, particularly those who have been accustomed to traditional processes such as email-based workflows, may be reluctant to adopt new decision-making technologies. This resistance can stem from several factors, including a lack of familiarity with the new system, concerns about additional workload during the transition period, and a general reluctance to move away from well-established practices.

Organizational culture plays a significant role in this resistance. In many manufacturing environments, workers may feel that the new system threatens their autonomy or job security, as they may perceive technology as replacing human roles or altering their traditional ways of working (Chukwuma-Eke *et al*., 2023). Furthermore, decision-makers may fear that the new model will require significant investment in training and time before yielding tangible results. To overcome this challenge, organizations must ensure that there is strong leadership and clear communication throughout the migration process. Providing adequate training and ongoing support, involving employees early in the transition process, and showcasing the benefits of the new system can help reduce resistance and foster buy-in from key stakeholders. Additionally, demonstrating the model's capacity to empower employees and streamline their work processes can help alleviate concerns about the system's impact on job roles and responsibilities.

Another critical consideration when implementing a KPI-driven decision intelligence model is ensuring the scalability of the dashboard and model across various manufacturing scales (Oluwafunmike *et al*., 2022). Advanced manufacturing environments come in different sizes and complexities, ranging from small-scale operations to large multinational plants. The system designed to handle KPI visualization and decision intelligence needs to be flexible enough to accommodate a wide range of operational requirements. Scalability concerns primarily focus on the model's ability to scale up or down based on the size of the operation. For example, small manufacturers may not have the same level of resources or data complexity as large multinational companies, and a one-size-fits-all solution may not work effectively in all cases. Ensuring that the dashboard and decision intelligence model are adaptable to different operational scales requires careful planning and customization. Manufacturers must ensure that the system can handle a growing volume of data, more complex workflows, and expanding production lines without compromising performance or efficiency. In addition to scalability, the system must be designed for long-term maintenance. As manufacturing technologies evolve and new data sources or systems are introduced, the decision intelligence model needs to be adaptable and continuously updated (Oluwafunmike *et al*., 2022; Okeke *et al*., 2022). This includes regular system maintenance to address software updates, data integration challenges, and troubleshooting. Over time, the model's algorithms may need recalibration to account for changes in manufacturing conditions, such as new machinery, production techniques, or shifting market demands. Ensuring that the system remains functional and aligned with business objectives requires dedicated resources for ongoing system management and support.

While the KPI-driven decision intelligence model offers substantial benefits in terms of operational efficiency, strategic decision-making, and economic competitiveness, it is not without its challenges (Fredson *et al*., 2021; Okeke *et al*., 2022). Overcoming issues related to data quality and integration, addressing resistance to change from employees and management, and ensuring the scalability and maintenance of the system are critical for its successful implementation. Addressing these challenges requires careful planning, robust data governance practices, employee engagement, and the flexibility to scale the system based on organizational needs. By proactively addressing these considerations, manufacturers can maximize the potential of KPI-driven decision intelligence models, ultimately leading to enhanced operational performance and a more agile manufacturing environment.

2.5 Future Directions

The future of KPI-driven decision intelligence models in advanced manufacturing is poised to experience significant advancements as technology continues to evolve (Okeke *et al*., 2023). As industries increasingly embrace data-driven strategies, there are multiple avenues to refine, expand, and optimize these models. The convergence of artificial intelligence (AI), machine learning (ML), predictive analytics, and automation is expected to create new opportunities for operational control and decision-making across a range of manufacturing environments. This section discusses the future directions of KPI-driven decision intelligence, with a focus on technological advancements, industry-specific applications, and the integration of automation.

One of the most exciting future directions for KPI-driven decision intelligence models is the integration of artificial intelligence (AI) and machine learning (ML). These technologies can significantly enhance the decision-making capabilities of manufacturing systems by refining the accuracy and predictive power of KPIs. AI and ML algorithms can analyze vast amounts of data from various sources, identifying patterns and trends that may not be immediately apparent to human analysts. The introduction of predictive analytics further strengthens this capacity. In the context of advanced manufacturing, predictive analytics can be leveraged to anticipate potential operational issues before they manifest, allowing for proactive intervention (Ogunsola *et al*., 2021; Adewale *et al*., 2021). By analyzing data in real-time, predictive models can forecast machine failures, supply chain disruptions, or bottlenecks in production processes, enabling manufacturers to mitigate risks and optimize resources before problems escalate. This predictive capability is critical for maintaining continuous operations, minimizing downtime, and improving the overall efficiency of manufacturing processes. As the sophistication of AI and ML technologies increases, these systems will continue to refine their accuracy and become integral to daily decision-making in manufacturing operations.

While the current KPI-driven decision intelligence model has shown significant promise in general manufacturing environments, there is considerable potential to expand the model to cater to different industries, each with its own unique challenges and requirements (Adekunle *et al*., 2021). The automotive, aerospace, and electronics sectors, for instance, each operate under distinct constraints, including complex supply chains, stringent quality control standards, and rapid product life cycles. adapting the KPI-driven model to address these industry-specific needs will enable manufacturers in these sectors to enhance performance and gain a competitive edge (Elujide *et al*., 2021; Ogbuagu *et al*., 2022). In the automotive industry, for example, KPIs related to production efficiency, quality control, and inventory management can be used to optimize the assembly line process, reduce waste, and improve throughput. Similarly, in the aerospace industry, KPIs focused on precision manufacturing and regulatory compliance are crucial for ensuring product quality and safety. By integrating these industry-specific KPIs into the decision intelligence model, manufacturers can leverage real-time data to drive decisions that align with the unique demands of their industry. In electronics manufacturing, the model can be used to optimize supply chain management and monitor production cycles, ensuring the timely delivery of components and minimizing stockouts or overstocking. As industries continue to innovate and evolve, the flexibility of KPI-driven decision intelligence models will become increasingly important in addressing sector-specific challenges. Tailoring the system to meet the unique needs of different industries will require continuous collaboration between data scientists, engineers, and industry experts to ensure that the right KPIs are selected and integrated into the decision-making framework (Akinsooto *et al*., 2012; Adekunle *et al*., 2023).

The integration of automation is another key future direction for KPI-driven decision intelligence models (Ogbuagu *et al*., 2023). Automation in manufacturing has been steadily increasing, with many plants adopting automated systems for assembly, material handling, and quality control. As automated systems become more prevalent, the flow of real-time data between systems will increase, providing an opportunity for continuous monitoring and decision-making (Odunaiya *et al*., 2021; Adekunle *et al*., 2023). By integrating KPI-driven decision intelligence models with automated manufacturing systems, manufacturers can enable a seamless flow of data from production lines directly to the decision-making framework, creating a fully automated and responsive manufacturing environment. Automation can help ensure that decisions are made in real-time, based on up-to-the-minute data from machines, sensors, and production lines. By connecting automated systems with decision intelligence models, manufacturers can enhance the efficiency and accuracy of their operations, while also reducing the need for manual oversight. The use of automated decision-making systems is especially valuable in industries with high volumes of repetitive tasks or critical production deadlines, where even minor delays can lead to significant losses. The integration of AI, machine learning, predictive analytics, and automation holds the potential to transform manufacturing environments into highly efficient, adaptable, and responsive systems. As these technologies continue to evolve, manufacturers will be able to leverage real-time data and actionable insights to make more informed decisions, enhance operational control, and maintain a competitive edge in an increasingly fast-paced and dynamic market (Chukwuma-Eke *et al*., 2021).

The future of KPI-driven decision intelligence models in advanced manufacturing is bright, with numerous opportunities to enhance operational control, improve decision-making, and drive competitiveness (Adewale *et al*., 2021; Balogun *et al*., 2021). Advancements in AI, machine learning, and predictive analytics will continue to refine the model's capabilities, allowing for more proactive and data-driven decision-making. The application of these models in industry-specific contexts, such as automotive, aerospace, and electronics, will further strengthen their relevance and impact across different manufacturing sectors. Moreover, the integration of automation with KPI-driven decision intelligence systems will lead to more agile and responsive manufacturing environments, enabling continuous optimization and improvement. As these technologies mature and become more deeply integrated into manufacturing processes, the potential for greater efficiency, cost reduction, and competitive advantage will only continue to grow (Onukwulu *et al*., 2023; Basiru *et al*., 2023).

3. Conclusion

In conclusion, the KPI-driven decision intelligence model, supported by integrated dashboards, offers significant advantages across operational, strategic, and economic dimensions. By enabling real-time monitoring of key performance indicators (KPIs), this model enhances operational efficiency by providing immediate insights into production processes, helping to identify inefficiencies and bottlenecks before they escalate. The visibility provided by the integrated dashboards empowers decision-makers to make data-driven decisions that are timely and well-informed, which is critical in fast-paced manufacturing environments. Strategically, the use of these dashboards improves decision-making by ensuring alignment between operational actions and long-term business objectives, thus fostering a more agile and responsive manufacturing operation. Economically, the ability to identify cost-saving opportunities, streamline production, and reduce downtime enhances a company's bottom line and competitiveness.

Looking toward the long-term impact, the integration of a KPI-driven decision intelligence model promises sustained benefits in operational control and sustainability within advanced manufacturing. As manufacturers increasingly adopt this data-centric approach, the continuous flow of real-time data will enable more proactive management of production processes, reducing waste, optimizing resource allocation, and improving overall sustainability. Over time, the model will facilitate continuous improvement cycles, where each data point helps refine decision-making processes. Additionally, by enhancing adaptability, the model supports long-term resilience, enabling manufacturing operations to better respond to market fluctuations, technological changes, and regulatory shifts. The overall result is a more sustainable and future-ready manufacturing ecosystem that remains competitive and responsive to evolving industry demands.

4. References

1. Adekunle BI, Chukwuma-Eke EC, Balogun ED, Ogunsola KO. A predictive modeling approach to optimizing business operations: A case study on reducing operational inefficiencies through machine learning. International Journal of Multidisciplinary Research and Growth Evaluation 2021;2(1):791–9. https://doi.org/10.54660/.IJMRGE.2021.2.1.791-799.
2. Adekunle BI, Chukwuma-Eke EC, Balogun ED, Ogunsola KO. Improving customer retention through machine learning: A predictive approach to churn prevention and engagement strategies. International Journal of Scientific Research in Computer Science, Engineering and Information Technology 2023;9(4):507–23. https://doi.org/10.32628/IJSRCSEIT.
3. Adekunle BI, Chukwuma-Eke EC, Balogun ED, Ogunsola KO. Improving customer retention through machine learning: A predictive approach to churn prevention and engagement strategies. International Journal of Scientific Research in Computer Science, Engineering and Information Technology 2023;9(4):507–23. https://doi.org/10.32628/IJSRCSEIT.
4. Adekunle BI, Chukwuma-Eke EC, Balogun ED, Ogunsola KO. Developing a digital operations dashboard for real-time financial compliance monitoring in multinational corporations. International Journal of Scientific Research in Computer Science, Engineering and Information Technology 2023;9(3):728–46. https://doi.org/10.32628/IJSRCSEIT.
5. Adewale TT, Olorunyomi TD, Odonkor TN. Advancing sustainability accounting: A unified model for ESG integration and auditing. International Journal of Scientific Research Archive 2021;2(1):169–85.
6. Adewale TT, Olorunyomi TD, Odonkor TN. AI-powered financial forensic systems: A conceptual framework for fraud detection and prevention. Magna Scientific Advanced Research and Reviews 2021;2(2):119–36.
7. Afolabi SO, Akinsooto O. Theoretical framework for dynamic mechanical analysis in material selection for high-performance engineering applications. Noûs 2021;3.
8. Akinsooto O. Electrical energy savings calculation in single phase harmonic distorted systems [dissertation]. Johannesburg (ZA): University of Johannesburg; 2013.
9. Akinsooto O, De Canha D, Pretorius JHC. Energy savings reporting and uncertainty in Measurement & Verification. In: 2014 Australasian Universities Power

Engineering Conference (AUPEC). IEEE; 2014. p. 1–5.
10. Akinsooto O, Pretorius JH, van Rhyn P. Energy savings calculation in a system with harmonics. In: Fourth IASTED African Conference on Power and Energy Systems (AfricaPES); 2012.
11. Anaba DC, Agho MO, Onukwulu EC, Egbumokei PI. Conceptual model for integrating carbon footprint reduction and sustainable procurement in offshore energy operations. Fuel 2022;16:4.
12. Ayodeji DC, Oyeyipo I, Attipoe V, Isibor NJ, Mayienga BA. Analyzing the challenges and opportunities of integrating cryptocurrencies into regulated financial markets. International Journal of Multidisciplinary Research and Growth Evaluation 2023;4(6):1190–6. https://doi.org/10.54660/.IJMRGE.2023.4.6.1190-1196.
13. Balogun ED, Ogunsola KO, Ogunmokun AS. A risk intelligence framework for detecting and preventing financial fraud in digital marketplaces. IRE Journals 2021;4(8):134–40. https://irejournals.com/paper-details/1702600.
14. Balogun ED, Ogunsola KO, Ogunmokun AS. Blockchain-enabled auditing: A conceptual model for financial transparency, regulatory compliance, and security. IRE Journals 2023;6(10):1064–70. https://irejournals.com/paper-details/1704358.
15. Balogun ED, Ogunsola KO, Ogunmokun AS. Developing an advanced predictive model for financial planning and analysis using machine learning. IRE Journals 2022;5(11):320–8. https://doi.org/10.32628/IJSRCSEIT.
16. Basiru JO, Ejiofor CL, Onukwulu EC, Attah RU. Streamlining procurement processes in engineering and construction companies: a comparative analysis of best practices. Magna Scientific Advanced Research and Reviews 2022;6(1):118–35.
17. Basiru JO, Ejiofor CL, Onukwulu EC, Attah RU. Optimizing administrative operations: A conceptual framework for strategic resource management in corporate settings. International Journal of Multidisciplinary Research and Growth Evaluation 2023;4(1):760–73.
18. Basiru JO, Ejiofor CL, Onukwulu EC, Attah RU. The impact of contract negotiations on supplier relationships: A review of key theories and frameworks for organizational efficiency. International Journal of Multidisciplinary Research and Growth Evaluation 2023;4(1):788–802.
19. Basiru JO, Ejiofor CL, Onukwulu EC, Attah RU. Enhancing financial reporting systems: a conceptual framework for integrating data analytics in business decision-making. IRE Journal 2023;7(4):587–606.
20. Basiru JO, Ejiofor LC, Onukwulu CE, Attah RU. Corporate health and safety protocols: A conceptual model for ensuring sustainability in global operations. Iconic Research and Engineering Journals 2023;6(8):324–43.
21. Basiru JO, Ejiofor LC, Onukwulu CE, Attah RU. Adopting lean management principles in procurement: a conceptual model for improving cost-efficiency and process flow. Iconic Research and Engineering Journals 2023;6(12):1503–22.
22. Bristol-Alagbariya B, Ayanponle OL, Ogedengbe DE. Strategic frameworks for contract management excellence in global energy HR operations. GSC Advanced Research and Reviews 2022;11(3):150–7.
23. Bristol-Alagbariya B, Ayanponle OL, Ogedengbe DE. Developing and implementing advanced performance management systems for enhanced organizational productivity. World Journal of Advanced Science and Technology 2022;2(1):39–46.
24. Bristol-Alagbariya B, Ayanponle OL, Ogedengbe DE. Utilization of HR analytics for strategic cost optimization and decision making. International Journal of Scientific Research Updates 2023;6(2):62–9.
25. Chukwuma-Eke EC, Ogunsola OY, Isibor NJ. Designing a robust cost allocation framework for energy corporations using SAP for improved financial performance. International Journal of Multidisciplinary Research and Growth Evaluation 2021;2(1):809–22. https://doi.org/10.54660/.IJMRGE.2021.2.1.809-822
26. Chukwuma-Eke EC, Ogunsola OY, Isibor NJ. A conceptual framework for financial optimization and budget management in large-scale energy projects. International Journal of Multidisciplinary Research and Growth Evaluation 2022;2(1):823–34. https://doi.org/10.54660/.IJMRGE.2021.2.1.823-834
27. Chukwuma-Eke EC, Ogunsola OY, Isibor NJ. Conceptualizing digital financial tools and strategies for effective budget management in the oil and gas sector. International Journal of Management and Organizational Research 2023;2(1):230–46. https://doi.org/10.54660/IJMOR.2023.2.1.230-246
28. Elujide I, Fashoto SG, Fashoto B, Mbunge E, Folorunso SO, Olamijuwon JO. Application of deep and machine learning techniques for multi-label classification performance on psychotic disorder diseases. Informatics in Medicine Unlocked 2021;23:100545.
29. Ezeanochie CC, Afolabi SO, Akinsooto O. Advancing automation frameworks for safety and compliance in offshore operations and manufacturing environments. [Journal details missing].
30. Fredson G, Adebisi B, Ayorinde OB, Onukwulu EC, Adediwin O, Ihechere AO. Driving organizational transformation: leadership in ERP implementation and lessons from the oil and gas sector. International Journal of Multidisciplinary Research and Growth Evaluation [Internet] 2021.
31. Fredson G, Adebisi B, Ayorinde OB, Onukwulu EC, Adediwin O, Ihechere AO. Strategic risk management in high-value contracting for the energy sector: industry best practices and approaches for long-term success. [Journal details missing].
32. Fredson G, Adebisi B, Ayorinde OB, Onukwulu EC, Adediwin O, Ihechere AO. Revolutionizing procurement management in the oil and gas industry: innovative strategies and insights from high-value projects. International Journal of Multidisciplinary Research and Growth Evaluation [Internet] 2021.
33. Odunaiya OG, Soyombo OT, Ogunsola OY. Economic incentives for EV adoption: a comparative study between the United States and Nigeria. Journal of Advanced Education and Sciences 2021;1(2):64–74. https://doi.org/10.54660/.JAES.2021.1.2.64-74
34. Odunaiya OG, Soyombo OT, Ogunsola OY. Energy storage solutions for solar power: technologies and challenges. International Journal of Multidisciplinary Research and Growth Evaluation 2021;2(1):882–90. https://doi.org/10.54660/.IJMRGE.2021.2.4.882-890

35. Odunaiya OG, Soyombo OT, Ogunsola OY. Innovations in energy financing: leveraging AI for sustainable infrastructure investment and development. International Journal of Management and Organizational Research 2023;2(1):102–14. https://doi.org/10.54660/IJMOR.2023.2.1.102-114
36. Ogbuagu OO, Mbata AO, Balogun OD, Oladapo O, Ojo OO, Muonde M. Novel phytochemicals in traditional medicine: isolation and pharmacological profiling of bioactive compounds. International Journal of Medical and All Body Health Research 2022;3(1):63–71.
37. Ogbuagu OO, Mbata AO, Balogun OD, Oladapo O, Ojo OO, Muonde M. Artificial intelligence in clinical pharmacy: enhancing drug safety, adherence, and patient-centered care. International Journal of Multidisciplinary Research and Growth Evaluation 2023;4(1):814–22. https://doi.org/10.54660/IJMRGE.2023.4.1-814-822
38. Ogunmokun AS, Balogun ED, Ogunsola KO. A strategic fraud risk mitigation framework for corporate finance cost optimization and loss prevention. International Journal of Multidisciplinary Research and Growth Evaluation 2022;3(1):783–90. https://doi.org/10.54660/.IJMRGE.2022.3.1.783-790
39. Ogunsola KO, Balogun ED, Ogunmokun AS. Enhancing financial integrity through an advanced internal audit risk assessment and governance model. International Journal of Multidisciplinary Research and Growth Evaluation 2021;2(1):781–90. https://doi.org/10.54660/.IJMRGE.2021.2.1.781-790
40. Ogunsola KO, Balogun ED, Ogunmokun AS. Developing an automated ETL pipeline model for enhanced data quality and governance in analytics. International Journal of Multidisciplinary Research and Growth Evaluation 2022;3(1):791–6. https://doi.org/10.54660/.IJMRGE.2022.3.1.791-796
41. Okeke IC, Agu EE, Ejike OG, Ewim CP, Komolafe MO. Developing a regulatory model for product quality assurance in Nigeria's local industries. International Journal of Frontline Research in Multidisciplinary Studies 2022;1(02):54–69.
42. Okeke IC, Agu EE, Ejike OG, Ewim CP, Komolafe MO. A model for wealth management through standardized financial advisory practices in Nigeria. International Journal of Frontline Research in Multidisciplinary Studies 2022;1(2):27–39.
43. Okeke IC, Agu EE, Ejike OG, Ewim CP, Komolafe MO. A theoretical model for harmonizing local and international product standards for Nigerian exports. International Journal of Frontline Research and Reviews 2023;1(4):74–93.
44. Okeke IC, Agu EE, Ejike OG, Ewim CP, Komolafe MO. A model for foreign direct investment (FDI) promotion through standardized tax policies in Nigeria. International Journal of Frontline Research in Science and Technology 2022;1(2):53–66.
45. Okeke IC, Agu EE, Ejike OG, Ewim CPM, Komolafe MO. A conceptual model for financial advisory standardization: Bridging the financial literacy gap in Nigeria. International Journal of Frontline Research in Science and Technology 2022;1(02):038–052.
46. Okeke IC, Agu EE, Ejike OG, Ewim CPM, Komolafe MO. A framework for standardizing tax administration in Nigeria: Lessons from global practices. International Journal of Frontline Research and Reviews 2023;1(03):033–050.
47. Okolie CI, Hamza O, Eweje A, Collins A, Babatunde GO, Ubamadu BC. Leveraging digital transformation and business analysis to improve healthcare provider portal. ICONIC Research and Engineering Journals 2021;4(10):253–257.
48. Olorunyomi TD, Adewale TT, Odonkor TN. Dynamic risk modeling in financial reporting: Conceptualizing predictive audit frameworks. International Journal of Frontline Research in Multidisciplinary Studies [Internet] 2022;1(2):094–112.
49. Elumilade OO, Ogundeji IA, Ozoemenam G, Omokhoa HE, Omowole BM. The role of data analytics in strengthening financial risk assessment and strategic decision-making. Iconic Research and Engineering Journals 2023;6(10). ISSN: 2456-8880.
50. Elumilade OO, Ogundeji IA, Ozoemenam Achumie G, Omokhoa HE, Omowole BM. Optimizing corporate tax strategies and transfer pricing policies to improve financial efficiency and compliance. Journal of Advance Multidisciplinary Research 2022;1(2):28–38.
51. Elumilade OO, Ogundeji IA, Ozoemenam Achumie G, Omokhoa HE, Omowole BM. Enhancing fraud detection and forensic auditing through data-driven techniques for financial integrity and security. Journal of Advance Education and Sciences 2022;1(2):55–63.
52. Onukwulu EC, Agho MO, Eyo-Udo NL. Advances in green logistics integration for sustainability in energy supply chains. World Journal of Advanced Science and Technology 2022;2(1):047–068.
53. Onukwulu EC, Agho MO, Eyo-Udo NL. Circular economy models for sustainable resource management in energy supply chains. World Journal of Advanced Science and Technology 2022;2(2):034–057.
54. Onukwulu EC, Agho MO, Eyo-Udo NL. Decentralized energy supply chain networks using blockchain and IoT. International Journal of Scholarly Research in Multidisciplinary Studies 2023;2(2):066–085.
55. Onukwulu EC, Agho MO, Eyo-Udo NL. Developing a framework for supply chain resilience in renewable energy operations. Global Journal of Research in Science and Technology 2023;1(2):1–18.
56. Onukwulu EC, Agho MO, Eyo-Udo NL. Developing a framework for AI-driven optimization of supply chains in energy sector. Global Journal of Advanced Research and Reviews 2023;1(2):82–101.
57. Onukwulu EC, Agho MO, Eyo-Udo NL. Sustainable supply chain practices to reduce carbon footprint in oil and gas. Global Journal of Research in Multidisciplinary Studies 2023;1(2):24–43.
58. Onukwulu EC, Dienagha IN, Digitemie WN, Egbumokei PI. Framework for decentralized energy supply chains using blockchain and IoT technologies. IRE Journals 2021.
59. Onukwulu EC, Dienagha IN, Digitemie WN, Egbumokei PI. Advances in digital twin technology for monitoring energy supply chain operations. IRE Journals 2022.
60. Onukwulu EC, Fiemotongha JE, Igwe AN, Ewim CPM. Transforming supply chain logistics in oil and gas: best practices for optimizing efficiency and reducing operational costs. Journal of Advance Multidisciplinary Research 2023;2(2):59–76.

61. Onukwulu EC, Fiemotongha JE, Igwe AN, Paul-Mikki C. The role of blockchain and AI in the future of energy trading: A technological perspective on transforming the oil & gas industry by 2025. Methodology 2023:173.