American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

AI-DRIVEN AGGREGATE PLANNING FOR SUSTAINABLE SUPPLY CHAINS: A SYSTEMATIC LITERATURE REVIEW OF MODELS, APPLICATIONS, AND INDUSTRY IMPACTS

Md Shahadat Hossain[1]; Mohammad Shahadat Hossain Sikdar[2]; Adar Chowdhury[3]; Sharif Md Yousuf Bhuiyan[4]; Saleh Mohammad Mobin[5];

[1] Graduate Student, Department of Industrial Engineering, Lamar University, USA
Email: shossain0259@gmail.com

[2] Graduate Student, Department of Industrial Engineering, Lamar University, USA
Email: shuvome07@gmail.com

[3] Graduate Student, Department of Industrial Engineering, Lamar University, USA
Email: castudy.adarchowdhury@gmail.com

[4] Graduate Student, Department of Mechanical Engineering, Idaho State University, USA
Email: sharifmdyousufbhu@isu.edu

[5] Doctor of Engineering in Industrial Engineering, College of Engineering, Lamar University, USA
Email: mobinsaleh@gmail.com

Citation:
Hossain, M. S., Sikdar, M. S. H., Chowdhury, A., Bhuiyan, S. M. Y., & Mobin, S. M. (2025). *AI-driven aggregate planning for sustainable supply chains: A systematic literature review of models, applications, and industry impacts. American Journal of Advanced Technology and Engineering Solutions*, *1*(1), 382–437. https://doi.org/10.63125/3jdpkd14

Received:
January 18, 2025

Revised:
February 25, 2025

Accepted:
March 15, 2025

Published:
April 10, 2025

Abstract
This study explores the integration of Artificial Intelligence (AI) in aggregate planning across diverse industrial sectors, with a particular focus on identifying cross-sectoral trends, implementation challenges, and performance outcomes. Drawing upon an in-depth comparative analysis of eight real-world case studies, this research investigates how AI-driven tools such as machine learning, deep learning, reinforcement learning, fuzzy logic, and heuristic optimization are transforming demand forecasting, inventory management, production scheduling, and resource allocation in sectors including manufacturing, retail, automotive, pharmaceutical, and food industries. The study reveals that while AI enhances forecast accuracy, operational agility, and strategic decision-making, its effectiveness is often mediated by organizational readiness, regulatory environments, and the maturity of digital infrastructure. Resistance to adoption, lack of interpretability, and fragmented data systems were noted as common barriers. In contrast, firms with integrated data ecosystems, leadership support, and workforce upskilling strategies demonstrated greater success in embedding AI into their planning processes. The findings highlight the sector-specific nuances of AI implementation and underline the urgent need for a standardized cross-industry framework to guide the scalable and ethical adoption of AI in aggregate planning. This research contributes valuable insights to both academia and industry by bridging theoretical models with practical applications, and by emphasizing the human, technological, and strategic factors critical to unlocking AI's full potential in supply chain and operations management.

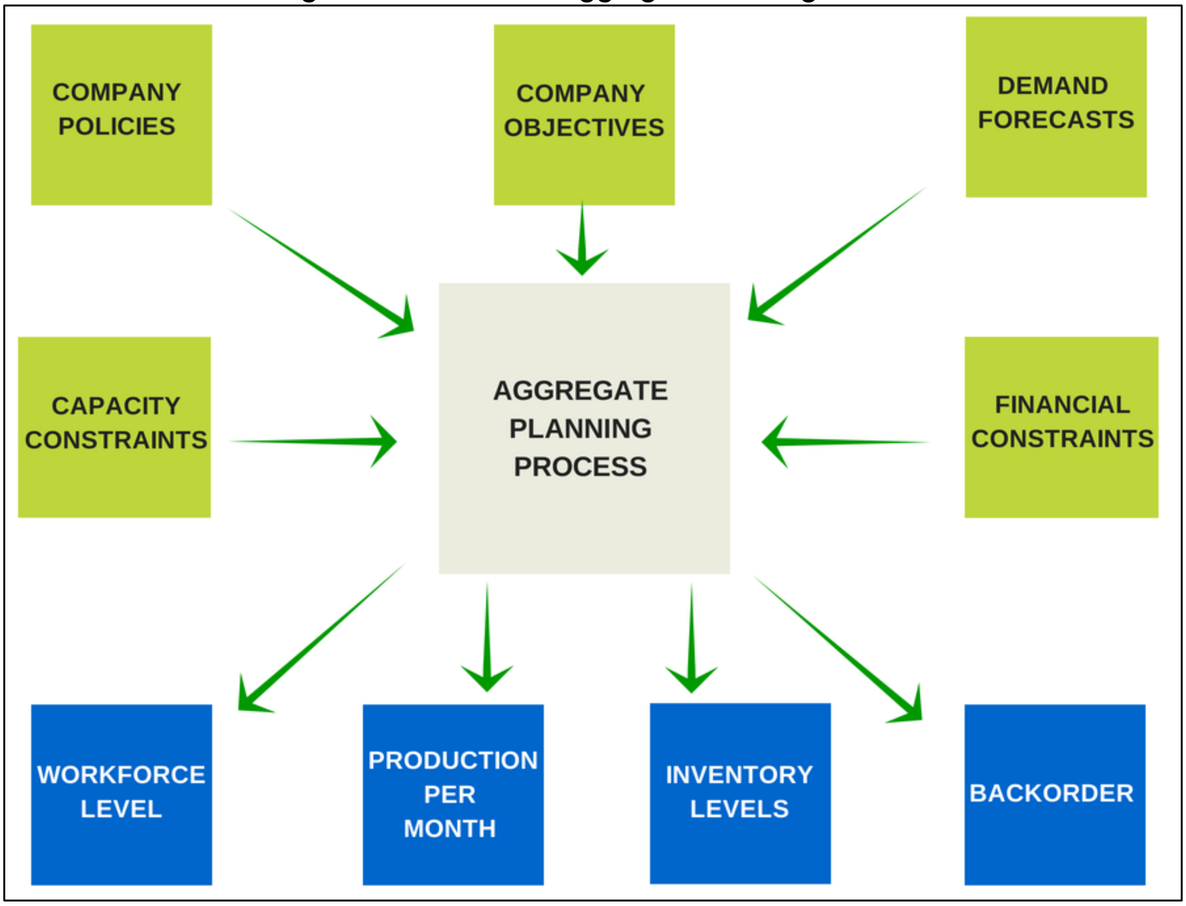
Keywords
Aggregate Planning; Artificial Intelligence; Supply Chain Sustainability; Machine Learning; Demand Forecasting;

eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

INTRODUCTION

Aggregate planning, as a crucial component of supply chain management (SCM), is generally defined as an intermediate-range decision-making process, typically covering a time horizon ranging from three months to a year or more (Fahimnia et al., 2011). It involves determining optimal levels of production, workforce, inventory, and other operational resources to efficiently satisfy fluctuating demand at minimal costs (Yan & Ding, 2012). Monteleone et al. (2015) emphasize aggregate planning's strategic importance in aligning organizational goals with operational capabilities, ensuring firms maintain competitiveness by balancing cost efficiency and customer service requirements. Similarly, Rasmi et al. (2019) describe aggregate planning as a managerial process designed to determine resource capacities and schedules at a high-level aggregation, taking into account overall organizational objectives. Aggregate planning decisions encompass workforce sizing, production scheduling, inventory planning, backorder policies, and subcontracting strategies, often resulting in a complex multi-objective optimization challenge (Mohammadi & Rezaei, 2020).

Figure 1: Overview of Aggregate Planning Process



Source:: Didwania (2014)

The advent of artificial intelligence (AI) has significantly influenced aggregate planning strategies in recent decades, offering enhanced decision-making capabilities through computational intelligence and predictive analytics (Tam & Tam, 2007). Artificial intelligence refers to computational techniques enabling machines to mimic cognitive human behaviors, including learning, reasoning, problem-solving, and decision-making processes (Silva et al., 2017). Notably, AI encompasses various sophisticated methodologies, such as machine learning (ML), neural networks, fuzzy logic, genetic algorithms, and reinforcement learning (RL), which offer powerful alternatives to traditional heuristic and optimization methods in aggregate planning

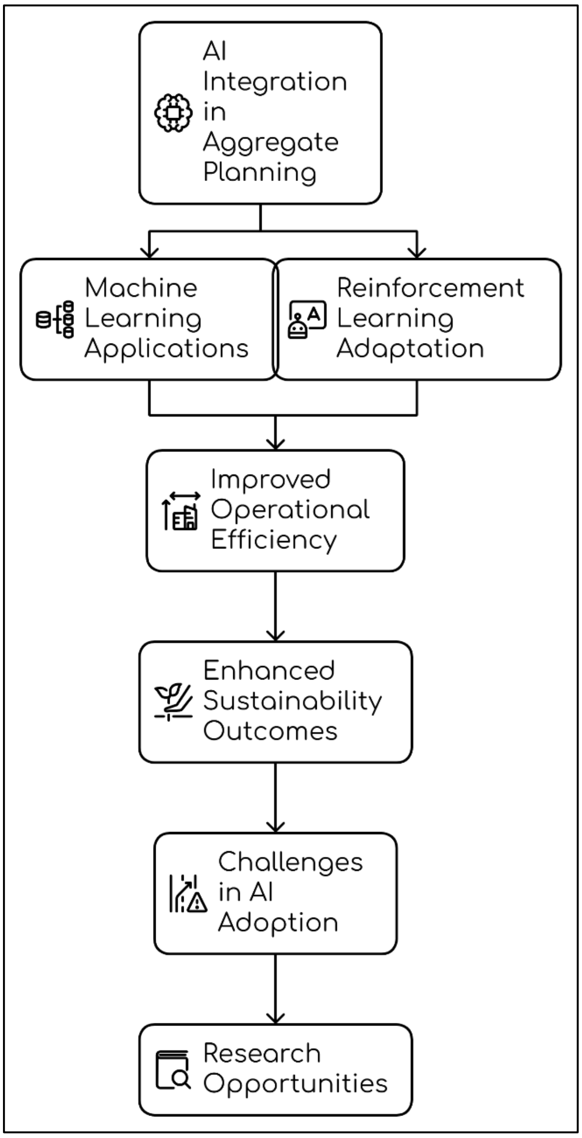
American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

(Mohammadi & Rezaei, 2020). As AI advances, more organizations across diverse industries embrace these technologies, drawn to their potential to handle complex, uncertain, and dynamic planning environments more effectively than conventional methods (Mukhopadhyay et al., 2018). Internationally, aggregate planning has gained critical importance amid globalization, rising customer expectations, and increasingly stringent sustainability regulations. Efficient aggregate planning practices allow multinational corporations to manage dispersed operations, synchronize global supply chain activities, and reduce operational disruptions, thereby enhancing their competitive advantage and market responsiveness (Li et al., 2013). Globalization compels firms to confront complexities arising from dispersed production and supplier networks, necessitating aggregate planning systems capable of managing multifaceted interactions across borders (Kim, 2021). Moreover, the International Organization for Standardization (ISO) emphasizes that sustainable practices, embedded within aggregate planning, contribute significantly to firms' reputational value and compliance with international environmental and operational standards (Fathifazl et al., 2011).

Aggregate planning, embedded within sustainability paradigms, addresses triple-bottom-line objectives encompassing economic viability, environmental stewardship, and social responsibility. According to Mamede et al. (2023), sustainable supply chain management integrates environmental and social criteria with economic goals, motivating organizations to adopt aggregate planning frameworks that optimize resource use and minimize ecological impacts. Sustainable aggregate planning has become central to corporate strategies due to heightened awareness and regulatory pressure, encouraging efficient use of resources and reduced carbon footprints across various industries globally (Wang et al., 2020). AI-driven methodologies increasingly support these sustainability goals by providing real-time optimization tools capable of simultaneously balancing multiple sustainability-oriented objectives, enhancing the strategic significance of aggregate planning in achieving corporate social responsibility targets (Hayles et al., 2018).

Machine learning, an essential subset of AI, significantly enhances aggregate planning by providing advanced predictive analytics for demand forecasting, resource allocation, and operational scheduling. ML algorithms analyze historical data patterns

Figure 2: AI Integration in Sustainable Aggregate Planning



American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

to predict future demand with unprecedented accuracy, crucial for aggregate planning's proactive and dynamic decision-making (Nasseri et al., 2023). Specific ML techniques such as support vector machines (SVM), random forest, artificial neural networks (ANN), and long short-term memory (LSTM) recurrent networks outperform conventional forecasting methods, yielding greater forecast accuracy and reduced forecasting errors (Dwivedi et al., 2021). Thus, ML applications have been extensively utilized in industries ranging from retail and healthcare to manufacturing, significantly improving operational efficiencies, reducing inventory costs, and enhancing service levels (Awan et al., 2021).

Reinforcement learning, another promising AI technique, increasingly contributes to adaptive aggregate planning processes. Reinforcement learning involves training AI agents to make sequential decisions based on environmental interactions, optimizing operational performance through continuous feedback loops (Sgantzos & Grigg, 2019). Unlike supervised learning, reinforcement learning is particularly beneficial in uncertain and dynamic aggregate planning environments where real-time adaptability is critical (Rožanec et al., 2021). Recent studies demonstrate that reinforcement learning agents successfully optimize complex aggregate planning problems, such as workforce management, inventory replenishment, and production scheduling, by dynamically adapting to changing market conditions and disruptions (Dubey et al., 2020). Thus, reinforcement learning has become a valuable tool for firms operating in volatile environments, facilitating robust, responsive, and resilient planning capabilities.

AI's integration into aggregate planning directly impacts industries including manufacturing, automotive, food processing, pharmaceuticals, and retail. Manufacturing industries, particularly within the Industry 4.0 paradigm, increasingly leverage AI-driven aggregate planning solutions to maintain productivity, flexibility, and sustainability (Nassar et al., 2019). Similarly, automotive companies employ AI techniques to optimize production scheduling, inventory control, and workforce allocation, substantially improving operational effectiveness and profitability (Dwivedi et al., 2021). Food processing and pharmaceutical sectors, characterized by stringent regulatory compliance and perishable inventory constraints, have significantly benefited from AI-enabled aggregate planning systems, leading to reduced wastage, improved compliance management, and enhanced resource utilization efficiency (Dwivedi et al., 2021; Sgantzos & Grigg, 2019). The transition from traditional heuristic-based planning to AI-driven aggregate planning systems presents multiple research opportunities and challenges. AI methodologies require substantial investments in computational infrastructure, data management practices, and skill development, impacting organizations' adoption decisions (Soofi & Awan, 2017). Additionally, firms encounter challenges regarding data quality, interoperability, model interpretability, and transparency when integrating AI into their aggregate planning frameworks (Rožanec et al., 2021). Recent studies underscore that despite AI's advanced capabilities, human expertise remains vital to successful implementation, guiding AI model development, interpretation, validation, and ethical considerations (Dwivedi et al., 2021). These factors necessitate systematic reviews of the literature, providing deeper insights into current capabilities, limitations, and implementation pathways for AI-driven aggregate planning solutions across industries.

The primary objective of this systematic literature review is to comprehensively analyze and synthesize existing academic research on the integration of artificial intelligence (AI) into aggregate planning for sustainable supply chains. This objective involves

American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

reviewing and categorizing prominent AI methodologies, including machine learning algorithms, neural networks, fuzzy logic systems, reinforcement learning, and genetic algorithms, to determine their prevalence, efficacy, and suitability across various industrial contexts. Specifically, the review aims to examine the detailed application and practical implementation of these AI-based approaches in industries such as manufacturing, automotive, retail, pharmaceutical, and food processing sectors, highlighting differences in approach and effectiveness across contexts. Additionally, another core objective of the review is to critically assess the improvements in aggregate planning outcomes attributable to AI, particularly focusing on operational performance metrics such as demand forecasting accuracy, inventory optimization, cost efficiency, and resource utilization. This analysis seeks to clarify the practical value of AI integration in achieving superior operational outcomes compared to traditional aggregate planning methods. Furthermore, the review seeks to systematically explore how AI-driven aggregate planning aligns with global sustainability frameworks and objectives. It will analyze the literature to identify how advanced AI methods contribute to achieving sustainability goals, including the reduction of waste, lower environmental impacts, improved resource allocation, and enhanced operational resilience. Another key objective is to delineate the challenges and barriers organizations face when adopting AI-driven aggregate planning tools, including issues related to computational complexity, data availability, system integration, and workforce skill development. This objective includes critically evaluating existing research to identify common themes and potential solutions that can help organizations overcome such barriers. Lastly, the review will clearly identify significant gaps in current literature and methodologies, offering structured insights for future scholarly investigations and practical guidance for industry professionals seeking to leverage AI for enhanced aggregate planning. These objectives collectively ensure that the review offers substantial academic value, strategic managerial insights, and meaningful contributions to both theoretical and practical knowledge in sustainable supply chain management.

LITERATURE REVIEW

This section systematically reviews existing scholarly literature on AI-driven aggregate planning within sustainable supply chains. The concept of aggregate planning is deeply entrenched in supply chain management literature, primarily defined as the process of determining optimal resource allocation—such as production, labor force, and inventory—to balance supply with anticipated demand over intermediate periods (Pournader et al., 2019). Aggregate planning is pivotal for maintaining operational stability, reducing costs, optimizing inventory levels, and enhancing customer satisfaction (Fahimnia et al., 2011). The emergence of artificial intelligence (AI) technologies, particularly machine learning (ML), reinforcement learning (RL), neural networks (NN), fuzzy logic, and heuristic optimization methods, has profoundly transformed traditional approaches to aggregate planning (Rasmi et al., 2019). Recent academic discourse highlights how these AI methodologies enable precise forecasting, adaptive decision-making, and sustainable operational practices that traditional methods often struggle to achieve (Sodhi et al., 2022). This review synthesizes literature spanning theoretical frameworks, applied methodologies, and practical industry impacts of AI applications in aggregate planning. It begins by systematically exploring foundational concepts, progresses through a detailed examination of specific AI approaches, and culminates by addressing sustainability and operational outcomes within varied industrial contexts. Furthermore, the literature will be critically assessed to identify methodological strengths, practical limitations,

Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

research gaps, and potential areas for future scholarly contributions. The structure of this review aims to provide clarity and insight, facilitating comprehension and practical utility for scholars, industry practitioners, and policymakers seeking deeper understanding of AI's evolving role in supply chain aggregate planning.

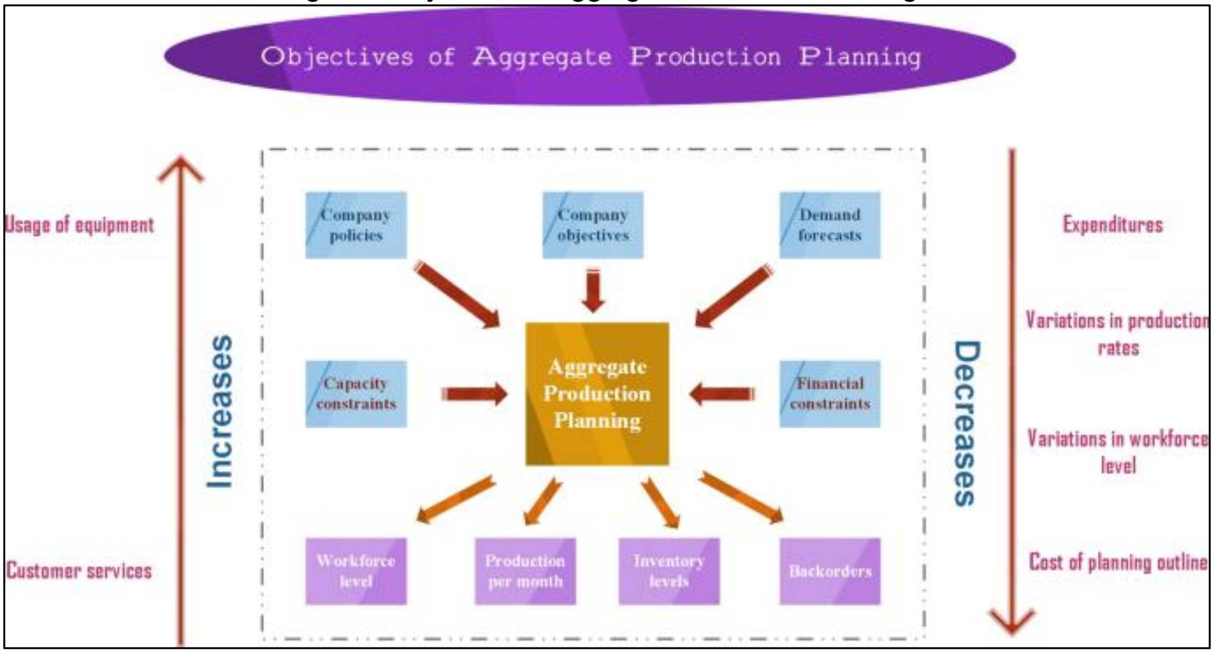
Aggregate Planning

Aggregate planning is widely defined as an intermediate-range capacity planning process aimed at optimizing production resources to effectively meet forecasted demand while balancing associated costs (Silva et al., 2017). As Mamede et al. (2023) highlighted, aggregate planning integrates decisions related to production rates, labor force, inventory levels, overtime work, subcontracting, and backorder management within a supply chain framework. According to Monteleone et al., (2015), aggregate planning typically operates over a medium-term planning horizon—ranging from three months to one year—focusing on balancing operational costs against resource allocation and demand fulfillment. This strategic process is central to supply chain management (SCM) due to its direct influence on cost structures, service levels, resource optimization, and responsiveness to market dynamics (Wang et al., 2020). Hence, aggregate planning enables organizations to synchronize strategic goals with operational efficiency, enhancing their competitive positioning by aligning supply chain performance with overall business objectives (Fahimnia et al., 2011). Historically, aggregate planning methodologies were based on linear programming, heuristic rules, graphical methods, and spreadsheet-based manual decision support systems (Rasmi et al., 2019). These traditional approaches, while useful, exhibit critical limitations, particularly in handling complexity, uncertainty, and rapidly changing supply-demand dynamics characteristic of modern supply chains (Sodhi et al., 2022). According to Rasmi et al. (2019), classical methods struggle significantly with dynamic operational environments, as they often rely on deterministic assumptions and fail to accommodate real-time decision flexibility and stochastic demand behaviors. Additionally, computational inefficiencies and scalability issues undermine the effectiveness of traditional aggregate planning approaches in large, complex supply chains, restricting their suitability for contemporary industries characterized by volatility, uncertainty, complexity, and ambiguity (VUCA) (Ivanov, Dolgui, & Sokolov, 2019). Furthermore, traditional methods provide limited adaptability in integrating sustainability measures, presenting challenges in optimizing environmental and social goals alongside economic objectives (Silva et al., 2017).

Recent advancements in artificial intelligence (AI) have considerably enhanced aggregate planning capabilities by enabling improved predictive accuracy, computational speed, and adaptive decision-making processes (Mamede et al., 2023). Machine learning (ML), neural networks (NN), fuzzy logic, genetic algorithms (GA), and reinforcement learning (RL) represent significant AI methodologies integrated into aggregate planning (Rasmi et al., 2019). For example, ML techniques such as artificial neural networks (ANNs) and support vector machines (SVMs) are increasingly employed to predict demand with higher precision and reduced forecasting errors compared to traditional statistical methods (Sodhi et al., 2022). Likewise, reinforcement learning models facilitate sequential and dynamic aggregate decision-making, continuously optimizing operations based on real-time data interactions and environmental feedback (Silva et al., 2017). These AI-driven techniques significantly enhance the robustness and responsiveness of aggregate planning frameworks, providing firms with vital capabilities to manage complexity and uncertainty effectively (Fahimnia et al., 2011).

eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

Figure 3: Objectives of Aggregate Production Planning



Source: Aydin and Tirkolaee *(*2022*)*

Manufacturing and automotive industries extensively adopt AI-driven aggregate planning strategies to optimize operational efficiency, minimize waste, and enhance responsiveness to market changes (Choi, 2020). Industry 4.0 practices, notably smart manufacturing systems, rely heavily on AI methodologies such as neural networks, reinforcement learning, and evolutionary optimization algorithms (Mandičák et al., 2021). In the automotive industry, for example, AI integration into aggregate planning assists firms in adopting just-in-time (JIT) production, optimizing inventory levels, and managing workforce planning to match fluctuating production schedules (Wen & Yan, 2019). AI-driven tools support dynamic resource allocation decisions, leading to improvements in inventory management, cycle time reduction, and enhanced production schedule adherence (Yakovleva et al., 2012). These advancements illustrate the transformative impact of AI techniques, significantly outperforming conventional planning methodologies regarding accuracy, adaptability, and operational agility (Meherishi et al., 2019).

Integrating AI into aggregate planning significantly contributes to sustainability goals, allowing firms to optimize resource usage, reduce environmental footprints, and enhance social responsibilities (Geerts & O'Leary, 2014). Jain and Singh (2020) indicated that AI-driven decision support systems effectively balance economic, environmental, and social sustainability metrics, optimizing aggregate production schedules while minimizing resource wastage and operational inefficiencies. AI-enabled aggregate planning frameworks support proactive sustainability measures through efficient forecasting, resource allocation, waste minimization, and carbon footprint reduction (Tsolakis et al., 2021). Moreover, firms aligning AI-based planning with international sustainability standards (e.g., ISO 14001 environmental management and ISO 26000 social responsibility) significantly enhance compliance, operational transparency, and stakeholder engagement (Ni et al., 2019). Hence, AI-driven planning significantly advances sustainability in supply chains, concurrently achieving enhanced resource efficiency, improved environmental performance, and stronger alignment with global sustainability practices (Akbari & Anh, 2021). Despite notable advantages, organizations face numerous implementation challenges when adopting AI-based aggregate planning. One critical issue involves the quality and

Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

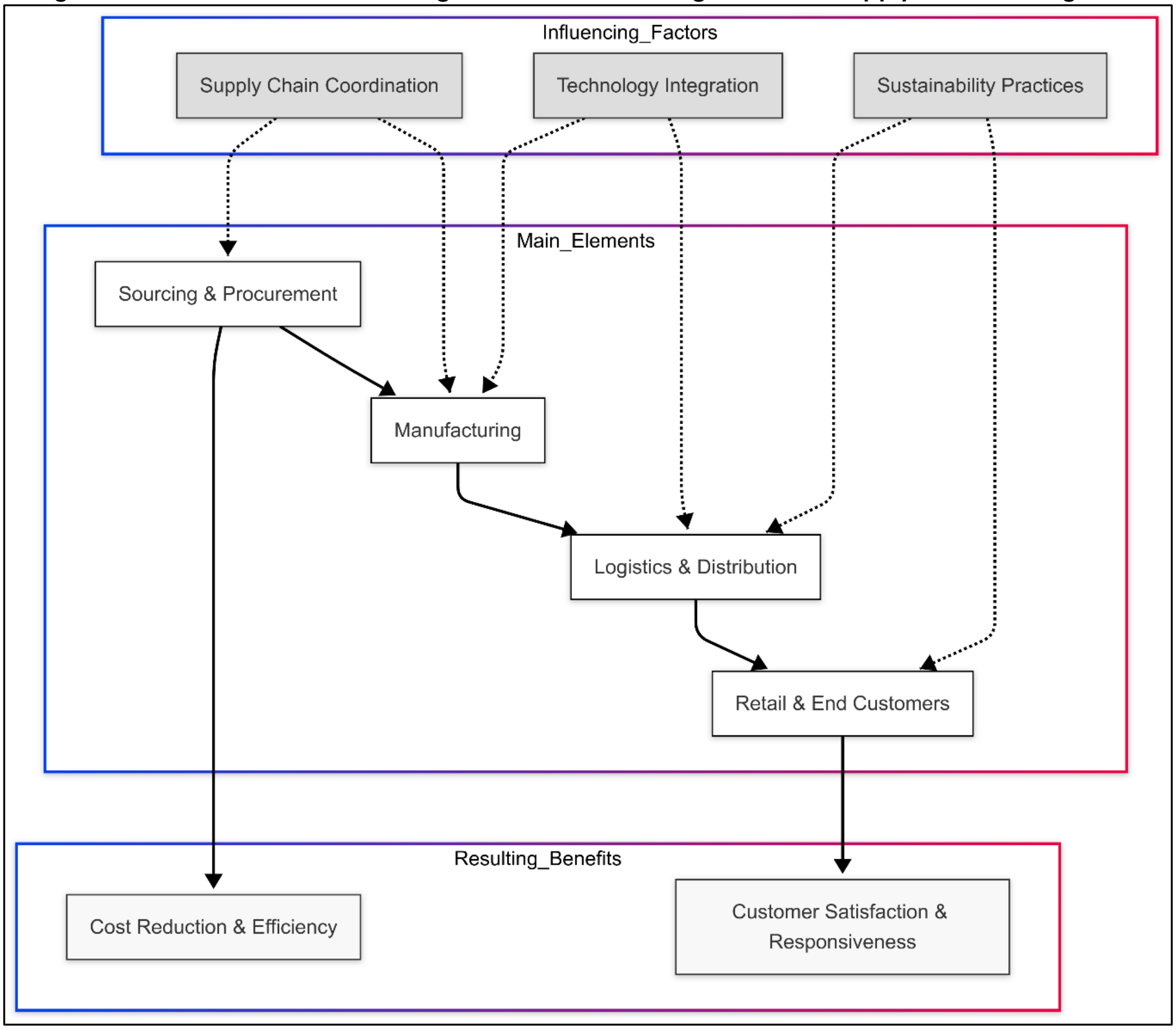
availability of data required to build robust AI models, as inadequate or inaccurate data significantly diminishes predictive performance (Ahsan & Rahman, 2021). Computational complexity and scalability issues also arise, as AI models often require sophisticated infrastructure and substantial computational resources, posing barriers for small-to-medium-sized enterprises (SMEs) (Sanders et al., 2019). Additionally, the complexity and opaque nature of certain AI algorithms present issues related to interpretability, transparency, and ethical concerns, thereby complicating model validation, managerial trust, and user acceptance (Jain & Singh, 2020). Meherishi et al. (2019) underscored that organizational skills, human expertise, and workforce readiness significantly influence successful AI integration into aggregate planning processes. Moreover, aligning AI methodologies with firm-specific strategic objectives and sustainability criteria further complicates implementation efforts, necessitating careful strategic planning, investment in human capital, and clear frameworks to overcome practical challenges (Machado et al., 2019).

Supply Chain Management

Supply Chain Management (SCM) refers to the coordinated management of interconnected business processes and resource flows from suppliers through manufacturers, distributors, retailers, and ultimately to end customers (Stadtler & Kilger, 2010). The concept of SCM encompasses a broad range of activities, including sourcing, procurement, manufacturing, logistics, inventory control, and demand forecasting, aimed at optimizing efficiency, responsiveness, and customer satisfaction (Meherishi et al., 2019). SCM evolved significantly since its inception, transitioning from a predominantly logistics-focused practice to an integrated, strategic approach characterized by collaboration, agility, and comprehensive value creation (Ni et al., 2019). According to Sobb et al. (2020), SCM embodies systematic, strategic coordination across functions and organizations to enhance the overall performance of the entire supply chain network. This evolution has been driven by globalization, technological advances, and increased customer demands, shifting SCM's role from purely operational efficiency toward strategic competitive advantage and long-term organizational resilience (Shen et al., 2021).

Supply Chain Management significantly influences organizational performance by enabling cost reduction, enhancing responsiveness, increasing flexibility, and improving customer service (Brinch, 2018). Strategic SCM practices, such as lean and agile methodologies, allow organizations to streamline operations, minimize waste, and rapidly respond to market fluctuations, thereby enhancing competitive positioning (Carrera et al., 2020). Organizations achieving supply chain excellence benefit from reduced inventory holding costs, improved resource utilization, and heightened service quality, resulting in enhanced profitability and market share (Ni et al., 2019). Additionally, SCM's strategic role has expanded beyond mere logistics management, becoming integral in fostering innovation, sustainability, and strategic partnerships among supply chain entities (Carrera et al., 2020). Recent literature emphasizes the increasing integration of sustainability principles into SCM, highlighting SCM's crucial role in driving both economic value and responsible business practices across global networks (Akbari & Anh, 2021).

Figure 4: Main Elements, Influencing Factors, and Resulting Benefits of Supply Chain Management



The theoretical frameworks underpinning SCM are diverse and include approaches such as the Supply Chain Operations Reference (SCOR) model, lean supply chain management, and agile supply chain frameworks (Ni et al., 2019). The SCOR model, developed by the Supply Chain Council, serves as a comprehensive tool for evaluating and improving supply chain performance across dimensions of reliability, responsiveness, agility, cost, and asset management (Tsolakis et al., 2021). Lean SCM emphasizes continuous improvement and waste minimization, enabling organizations to reduce costs, optimize resources, and improve product quality through streamlined operations (Jung & Park, 2020). Conversely, agile SCM prioritizes flexibility and responsiveness, facilitating rapid adaptation to changing market conditions through highly responsive operational strategies and collaborative networks (Tsolakis et al., 2021). Additionally, hybrid or "leagile" frameworks, integrating lean and agile elements, provide strategic balance, allowing firms to effectively manage varying demand patterns and customer expectations within complex supply chains (Pandey et al., 2023).

Technological advancements, notably digitalization, Industry 4.0, and artificial intelligence (AI), significantly transformed SCM practices (Brinch, 2018). Integration of digital technologies such as Internet of Things (IoT), blockchain, cloud computing, and advanced analytics facilitates enhanced supply chain visibility, transparency, and real-time decision-making capabilities (Caniato et al., 2019). Artificial intelligence applications, specifically machine learning algorithms, have improved SCM

American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

forecasting accuracy, inventory management, and demand planning, enabling organizations to proactively respond to market demands and disruptions with greater precision (Zawish et al., 2022). Furthermore, blockchain technology has emerged as a critical innovation in SCM, enhancing traceability, transparency, and trust among supply chain stakeholders, thereby mitigating risks and ensuring compliance with ethical and regulatory standards (Avventuroso et al., 2017).

Sustainability in SCM has gained critical importance as firms increasingly incorporate environmental, economic, and social responsibility into strategic operations (Sharma et al., 2022). Sustainable SCM practices include resource efficiency, waste reduction, green procurement, ethical sourcing, and enhanced corporate social responsibility (CSR) policies (Olan et al., 2021). According to Mukhuty et al. (2022), sustainable SCM integrates social, environmental, and economic dimensions into supply chain operations, aiming at reducing ecological impacts, enhancing social accountability, and sustaining long-term business viability. International frameworks such as ISO 14001 (environmental management) and ISO 26000 (social responsibility) have further encouraged firms to embed sustainability practices systematically within their supply chains, improving reputational value and stakeholder relations. Yakovleva et al., (2012) the role of advanced technologies in supporting sustainability initiatives, highlighting how digital tools and AI facilitate real-time decision-making aligned with sustainability goals. Moreover, Risk management and resilience have become integral elements within SCM literature, emphasizing the importance of supply chain robustness amid disruptions and uncertainties (Machado et al., 2019). Supply chain risks may emerge from various sources, including demand fluctuations, supply disruptions, geopolitical instability, cyber threats, and natural disasters, requiring strategic management to ensure sustained performance (Meherishi et al., 2019). Supply chain resilience, defined as the capability to quickly recover from disruptions and return to optimal functionality, is strategically cultivated through redundancy, flexibility, agility, and collaborative partnerships (Jain & Singh, 2020). Recent studies illustrate the importance of resilience-focused strategies such as diversified sourcing, inventory buffering, and investment in advanced forecasting tools, underscoring their effectiveness in mitigating disruptions and minimizing financial and operational impacts (Sanders et al., 2019). Despite advancements, SCM implementation faces significant challenges, including complexity management, supply chain visibility limitations, data management issues, and technology integration barriers (Machado et al., 2019). Supply chain complexity arises from extended global networks, diverse stakeholder interests, and rapidly evolving market conditions, posing difficulties for effective coordination and management (Sousa & Wilks, 2018). Data-related challenges, such as information asymmetry, inconsistent data quality, and lack of real-time information sharing, hinder accurate decision-making and effective collaboration among supply chain partners (Govindan et al., 2014). Moreover, integration of advanced digital technologies into existing supply chain processes demands significant investments in technology infrastructure, human capital, and organizational change management, potentially deterring adoption, especially among SMEs (Kazancoglu et al., 2022). Machado et al. (2019) emphasize that successful SCM implementation requires a combination of advanced technology, skilled workforce, effective leadership, and robust strategic alignment to overcome these inherent complexities.

Transition toward AI in Aggregate Planning: A Historical Perspective

Aggregate planning emerged prominently during the mid-20th century as manufacturing industries began systematically managing resources to balance

Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

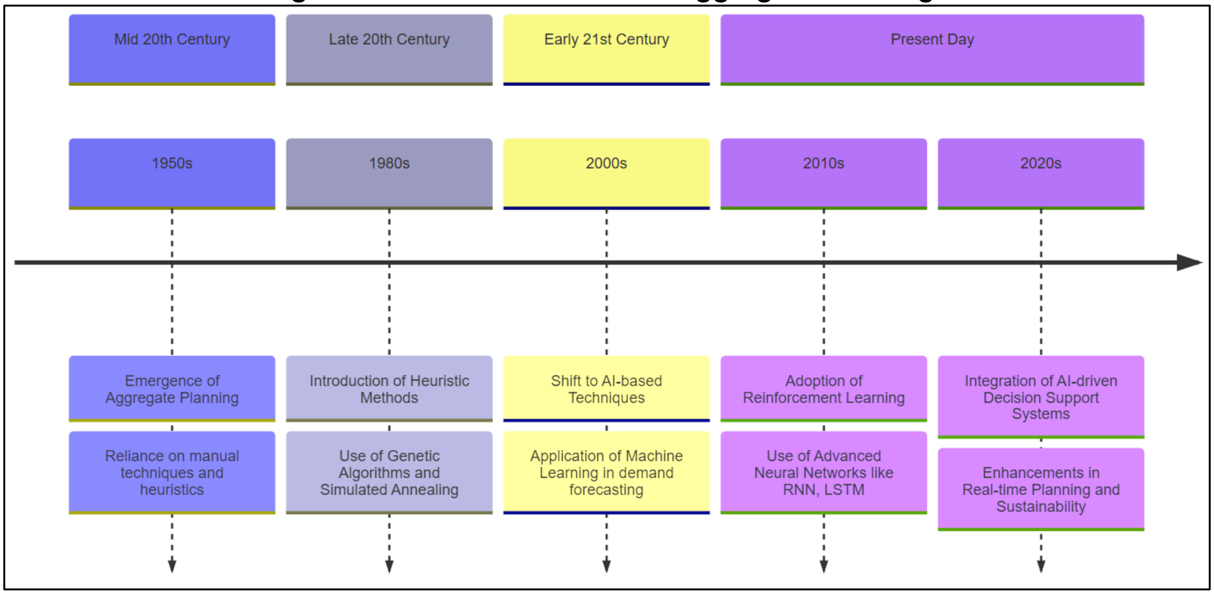
production and inventory against customer demands (Meherishi et al., 2019; Sohel, 2025). Initially, aggregate planning relied heavily on deterministic, manual techniques—primarily graphical methods, intuitive managerial decisions, and simple heuristics—aimed at aligning production capacity with forecasted demand (Jain & Singh, 2020; Hossain et al., 2024). According to Helal et al. (2025) and Mukhuty et al., (2022), these methods, while straightforward, were significantly constrained by assumptions of stable market environments and predictable demand patterns. Early aggregate planning practices often employed linear programming approaches and basic spreadsheet models, with limitations due to computational capacity, restricting their application to simple, stable supply chains (Helal, 2024; Meherishi et al., 2019). The limitations of these traditional methods became increasingly apparent as industries expanded globally, facing higher volatility, uncertainty, and complexity (Aydin & Tirkolaee, 2022; Helal, 2022). During the late 20th century, heuristic and metaheuristic methods, including genetic algorithms (GA), simulated annealing, and tabu search, became prevalent to address the limitations of traditional planning methods (Jain & Singh, 2020; Shipu et al., 2024). These heuristics, known for their relative simplicity and computational efficiency, enabled planners to solve complex and larger-scale aggregate planning problems with greater flexibility (Cai & Choi, 2020; Dey et al., 2024). According to Kazancoglu et al. (2022), heuristic methods improved operational efficiency by allowing firms to approximate optimal solutions more effectively compared to linear programming models. Nevertheless, these approaches still suffered significant limitations, including suboptimal solutions, difficulty handling highly dynamic demand patterns, and inability to adapt quickly to changing market environments (Aydin & Tirkolaee, 2022; Bhowmick & Shipu, 2024). Furthermore, heuristic methods were criticized for their dependence on initial assumptions, resulting in inadequate responsiveness and limited applicability across increasingly complex supply chains (Mohiul et al., 2022; Mukhuty et al., 2022).

The rapid advancement of computational power and data availability in the early 21st century marked a pivotal shift toward artificial intelligence (AI)-based methodologies in aggregate planning (Roksana et al., 2024; Wen & Yan, 2019). Initially, machine learning (ML) techniques, particularly artificial neural networks (ANNs) and support vector machines (SVMs), were applied primarily to demand forecasting components within aggregate planning, significantly enhancing accuracy and reducing forecasting errors compared to traditional statistical methods (Islam et al., 2024; Yakovleva et al., 2012). Research by Meherishi et al. (2019) emphasized that ML methods offered substantial improvements in predictive capability, enabling more effective planning decisions through precise demand estimation. This initial phase of AI integration was characterized by narrow applications, predominantly focused on improving specific functions such as demand estimation and inventory optimization rather than holistic planning strategies (Md et al., 2025; Villar et al., 2023). These pioneering AI techniques demonstrated clear operational advantages over traditional heuristics, paving the way for more comprehensive integration of AI methodologies into aggregate planning frameworks (Kazancoglu et al., 2022; Mahabub, Jahan, Hasan, et al., 2024). Following early successes with machine learning, reinforcement learning (RL) and advanced neural network models, including deep learning architectures, gained prominence in aggregate planning practices (Bhuiyan et al., 2024; Sanders et al., 2019). Reinforcement learning significantly expanded the adaptability and responsiveness of aggregate planning, allowing dynamic, real-time decision-making processes that continuously adjusted plans based on new information and environmental

American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

interactions (Chowdhury et al., 2023; Tsolakis et al., 2021). Studies by Meherishi et al., (2019) demonstrated that RL effectively optimized sequential decisions in complex manufacturing environments, facilitating enhanced production scheduling, inventory control, and resource allocation. Additionally, advanced neural networks—such as recurrent neural networks (RNN) and long short-term memory (LSTM)—improved long-term demand forecasting accuracy, further refining aggregate planning's predictive performance (Aydin & Tirkolaee, 2022; Khan & Razee, 2024). These advancements underscored the increasing sophistication of AI tools, enabling a significant leap in operational flexibility, planning responsiveness, and decision accuracy compared to earlier heuristic or statistical methods (Javaid et al., 2022; Tonoy & Khan, 2023).

Figure 5: Transition toward AI in Aggregate Planning



The integration of AI-driven decision support systems (DSS) into aggregate planning marked another critical milestone, offering firms comprehensive platforms for managing complex, dynamic planning scenarios (Olan et al., 2021; Sharif et al., 2024). AI-driven DSS facilitated enhanced operational visibility, real-time adaptive planning, and optimized resource allocation, allowing supply chains to handle uncertainty more effectively than conventional systems (Machado et al., 2019; Md Takbir Hossen et al., 2023). The implementation of such systems within Industry 4.0 contexts enabled extensive automation of planning processes, significantly improving productivity, reducing operational costs, and enhancing responsiveness (Islam & Helal, 2018; Sanders et al., 2019). According to Villar et al. (2023), firms deploying AI-driven DSS in aggregate planning saw tangible benefits, including reduced inventory levels, minimized waste, increased production flexibility, and improved sustainability performance. These decision support systems represented the maturation of AI technologies from isolated functional improvements toward integrated, strategic platforms central to modern supply chain operations (Khan, 2025; Sousa & Wilks, 2018). Despite significant advancements, the transition toward AI-based aggregate planning encountered multiple implementation challenges and critical considerations. Issues such as data availability, quality assurance, computational complexity, and model interpretability emerged as substantial barriers to widespread adoption of AI methodologies (Hasan et al., 2024; Yakovleva et al., 2012). Data quality and reliability are particularly crucial, as inaccuracies or inadequacies significantly undermine AI systems' predictive and decision-making performance (Aydin & Tirkolaee, 2022; Khatun et al., 2025). Furthermore, the computational complexity and

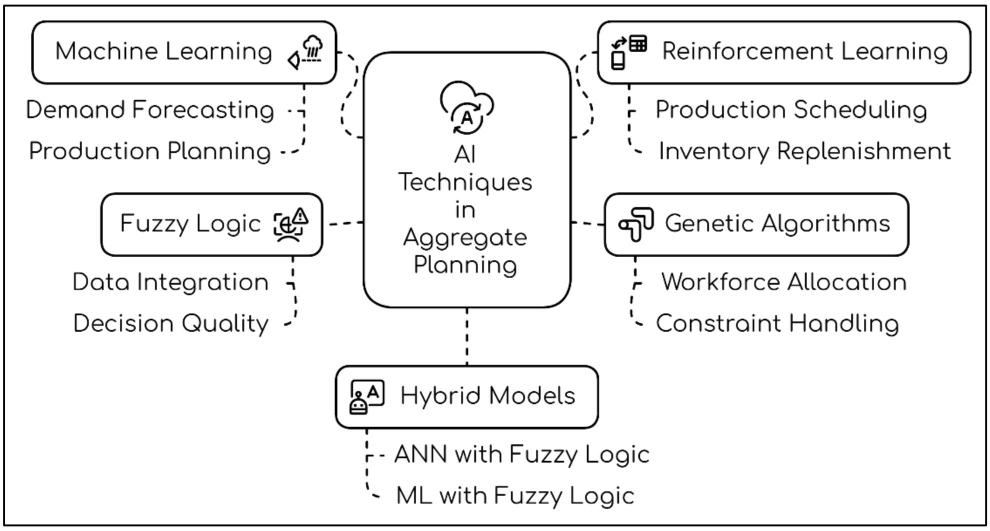
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

resource intensity required for advanced AI models posed scalability challenges, particularly impacting small-to-medium enterprises (SMEs) lacking advanced technological infrastructure (Govindan et al., 2014; Mahfuj et al., 2022). Ethical considerations, such as transparency, fairness, and interpretability of AI-based decisions, were also highlighted, emphasizing the importance of maintaining managerial oversight and user acceptance during AI integration (Jahan, 2023; Javaid et al., 2022). Thus, while the integration of AI significantly transformed aggregate planning, substantial attention was necessary to address these critical operational and strategic challenges to ensure successful and sustainable implementation (Al-Arafat, Kabir, et al., 2024; Sousa & Wilks, 2018).

Artificial Intelligence Techniques Applied in Aggregate Planning

Artificial Intelligence (AI) has emerged as a transformative force in aggregate planning, offering sophisticated methodologies to overcome the limitations of traditional planning techniques such as linear programming, heuristics, and deterministic simulations. Unlike conventional models, AI-driven approaches excel in managing uncertainty, high data dimensionality, and dynamic decision-making environments typical of modern supply chains (Kumar & Nayyar, 2019; Nahid et al., 2024). Among the most widely implemented AI techniques in aggregate planning are machine learning (ML), artificial neural networks (ANNs), support vector machines (SVMs), genetic algorithms (GAs), fuzzy logic systems, and reinforcement learning (RL), each offering distinct advantages depending on the planning context and data environment (Faria & Md Rashedul, 2025; Govindan et al., 2014).

Figure 6: AI Techniques in Aggregate Planning



Machine learning models, particularly supervised learning algorithms like ANNs and SVMs, are extensively used for demand forecasting and production planning due to their high predictive accuracy and ability to model nonlinear relationships (Ammar et al., 2024; Balaji et al., 2021). These models outperform traditional statistical methods in volatile markets where historical data alone is insufficient for precise forecasting (Arora & Majumdar, 2022; Tonoy, 2022). Reinforcement learning offers additional advantages in sequential decision-making scenarios, where planners must adapt in real time based on environmental feedback. Studies such as Moroff et al. (2021) and Filali et al. (2022) demonstrate RL's effectiveness in optimizing production schedules, inventory replenishment, and workforce allocation through dynamic simulation environments. Genetic algorithms and other evolutionary computation techniques

American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

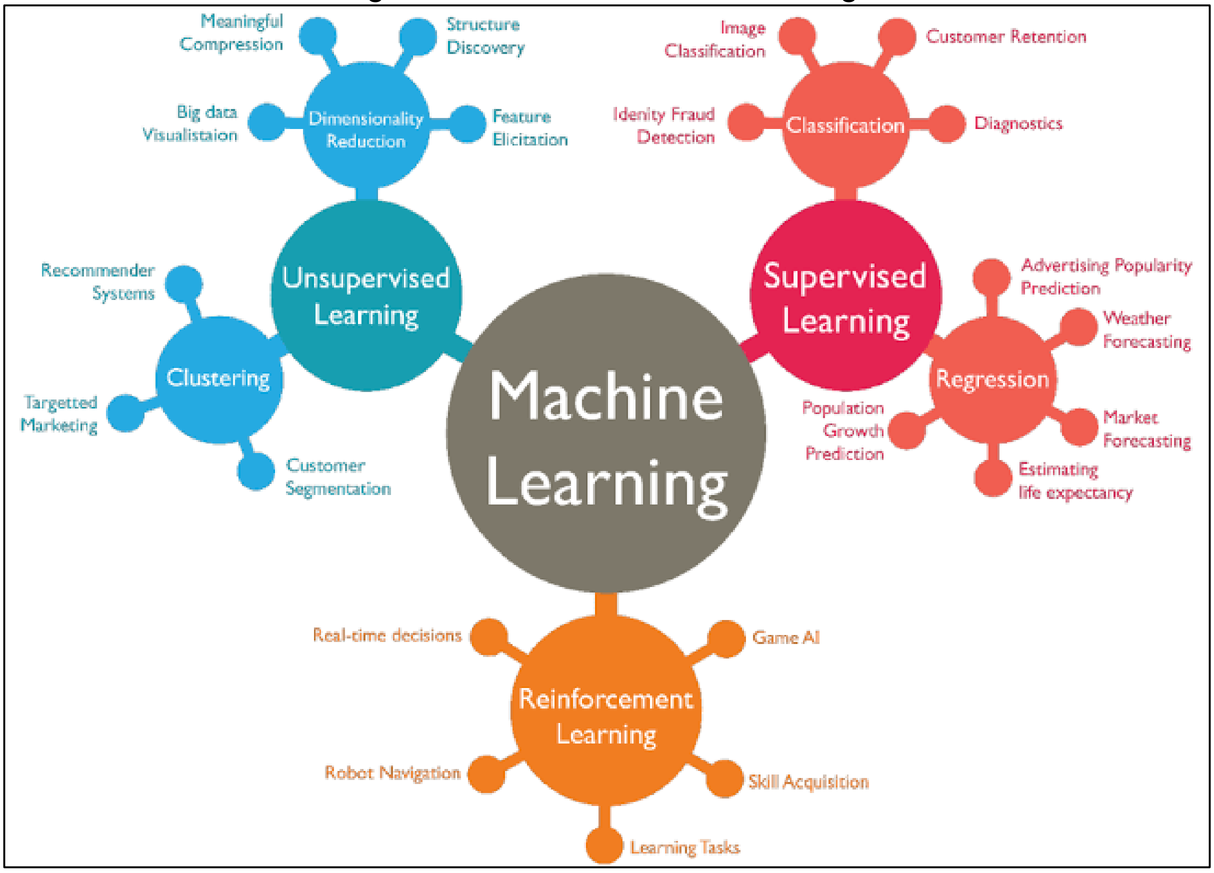
also play a crucial role in solving multi-objective aggregate planning problems, especially in complex environments with numerous constraints (Feizabadi, 2020). Fuzzy logic, often integrated with neural networks or ML, is used to handle imprecise data and human-like reasoning in uncertain planning conditions (Kamal et al., 2023). Hybrid models, which combine multiple AI techniques, have been increasingly adopted to improve decision robustness and computational efficiency (Wuest, Weimer, Irgens, & Thoben, 2016). For instance, combining ANN with fuzzy logic enhances interpretability and decision quality in ambiguous production environments (Reyes et al., 2020). These AI-driven techniques are now integrated into enterprise decision support systems, enabling holistic aggregate planning that incorporates real-time analytics, predictive modeling, and sustainability metrics (Kamal et al., 2023). However, the successful deployment of these techniques is contingent upon high-quality data, advanced computational infrastructure, and a skilled workforce capable of designing, interpreting, and validating AI models (Moroff et al., 2021). As AI techniques continue to mature, their role in aggregate planning extends beyond technical optimization to strategic planning, aligning production decisions with organizational goals, environmental policies, and global supply chain standards.

Machine Learning Models

Supervised learning techniques have become integral to aggregate planning, particularly in areas such as demand forecasting, production scheduling, and resource optimization. Among these, artificial neural networks (ANN), support vector machines (SVM), and random forests are extensively used due to their ability to learn from labeled datasets and produce accurate predictive outputs (Arora & Majumdar, 2022; Younus, 2025). ANNs have proven effective in modeling nonlinear and complex relationships between input variables like historical demand, production rates, and external factors, thus improving forecasting accuracy (Feizabadi, 2020; Younus, 2022). Similarly, SVMs are widely applied for classification and regression problems, excelling in scenarios with high-dimensional data and limited sample sizes (Reyes et al., 2020; Shohel et al., 2024). Random forest models, as ensemble learning methods, have shown robustness against overfitting and perform well even in noisy environments, making them suitable for aggregate planning in uncertain supply chain settings (Moroff et al., 2021; Shimul et al., 2025). These algorithms are particularly valuable in improving the precision of medium-range forecasting, a critical element of aggregate planning (Hamdan et al., 2023; Sabid & Kamrul, 2024). Moreover, supervised learning approaches have been integrated into decision support systems (DSS) that automate planning decisions based on learned patterns (Roy et al., 2024; Thapa & Camtepe, 2020). Studies have also explored hybrid models combining ANN and SVM to leverage the strengths of each technique for forecasting accuracy and stability (Agbemadon et al., 2023; Reyes et al., 2020). However, the effectiveness of these models largely depends on the quality and quantity of training data and the appropriateness of hyperparameter tuning, which remains a critical concern for real-world applications (Munira, 2025; O'Sullivan et al., 2019).

eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

Figure 7: Overview of Machine Learning



Source: Kumar (2024)

Unsupervised learning techniques are increasingly utilized in aggregate planning for pattern discovery, segmentation, and anomaly detection, especially in scenarios where labeled data is scarce or unavailable. Clustering algorithms such as K-means, hierarchical clustering, and DBSCAN allow planners to identify natural groupings within data, which can inform strategic decisions related to customer segmentation, product classification, and production prioritization (Maddikunta et al., 2022; Younus et al., 2024). These methods enable companies to identify seasonal demand patterns, supplier performance clusters, and inventory behaviors that would otherwise remain hidden using traditional analytical approaches (Ahmed et al., 2023; Younus et al., 2024). Dimensionality reduction techniques like Principal Component Analysis (PCA) and t-distributed Stochastic Neighbor Embedding (t-SNE) are employed to simplify high-dimensional datasets while preserving their underlying structure, thus enhancing the performance and interpretability of other machine learning models applied in aggregate planning (Katsaliaki et al., 2021; Mahdy et al., 2023). These techniques have proven particularly valuable in preprocessing complex manufacturing and supply chain datasets for better visualization and anomaly detection (Mahabub, Jahan, Islam, et al., 2024; Tsolakis et al., 2021). Studies by Pandey et al. (2023) demonstrated how unsupervised learning enabled more accurate resource allocation by clustering similar production scenarios and applying tailored planning strategies. Additionally, unsupervised methods are often combined with supervised models in semi-supervised frameworks, improving forecasting performance in data-sparse environments (Jim et al., 2024; Maddikunta et al., 2022). While these approaches do not provide direct forecasts or recommendations, they offer foundational insights that guide model development and strategic planning (Ahmed et al., 2023; Mahabub, Das, et al., 2024). The increasing volume and complexity of

Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

data in supply chains have made unsupervised learning a powerful tool in preprocessing and exploratory analysis, particularly when integrated with AI-driven decision support platforms (Jim et al., 2024; Naz et al., 2022).

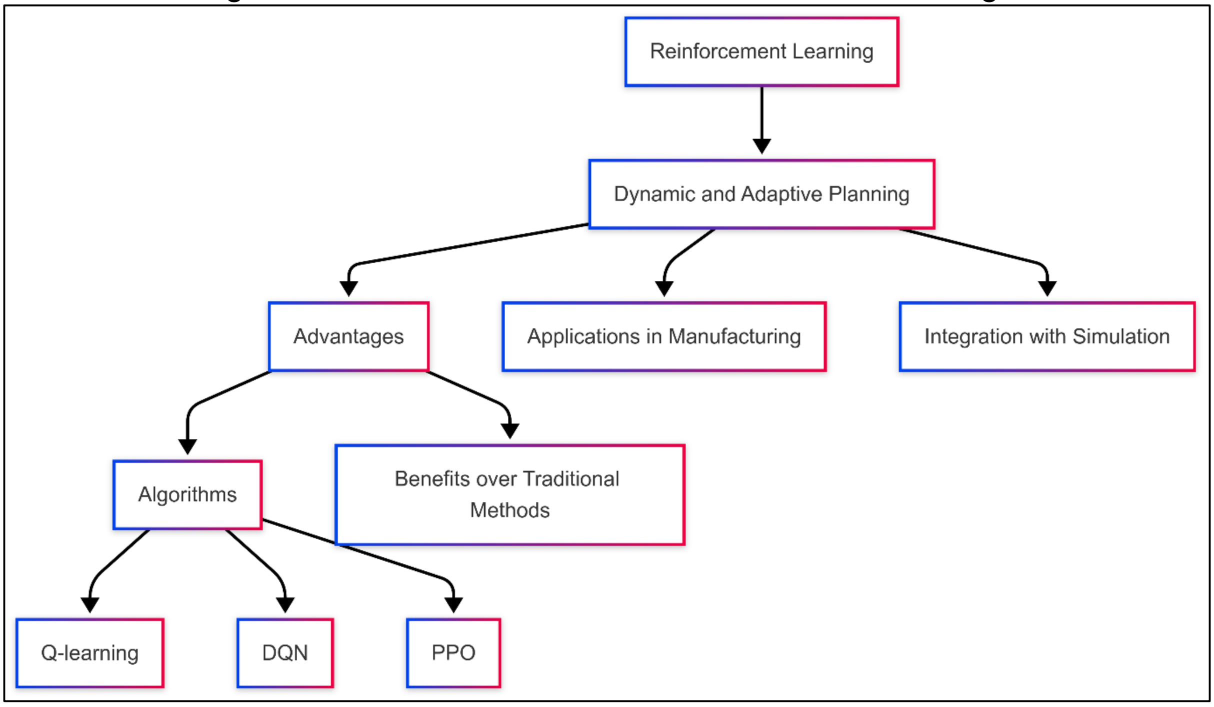
Deep learning techniques represent the frontier of artificial intelligence in aggregate planning, offering unparalleled capabilities in handling large, complex, and unstructured datasets with high predictive accuracy. Convolutional Neural Networks (CNNs), although traditionally used in image processing, have been adapted for spatial data representation in manufacturing and layout planning tasks, where identifying spatial relationships enhances operational decision-making (Jahan, 2024; Katsaliaki et al., 2021). Long Short-Term Memory (LSTM) networks, a class of recurrent neural networks (RNNs), are especially suitable for time series forecasting due to their ability to learn long-term dependencies and retain memory over sequences (M. T. Islam et al., 2025; Panda & Mohanty, 2023). In aggregate planning, LSTMs have shown superior performance in predicting fluctuating demand and seasonality compared to classical models and shallow learning techniques (Islam, 2024; Kumar et al., 2022). Deep ANNs, with multiple hidden layers, are employed for multi-variable forecasting and optimization tasks, including production scheduling, inventory planning, and resource forecasting (Islam et al., 2024; Pandey et al., 2023). These models are capable of learning complex data relationships without requiring explicit feature engineering, which simplifies model development while improving accuracy (Islam et al., 2025; Tsolakis et al., 2021). Hybrid deep learning models, such as CNN-LSTM architectures, further enhance the ability to model spatial-temporal data in multi-stage planning processes (Hossain et al., 2024; Kazancoglu et al., 2022). These models are widely used in advanced enterprise planning systems to enable real-time, autonomous decision-making. However, deep learning requires large volumes of labeled data and significant computational power, often necessitating cloud-based or high-performance computing environments (Frederico et al., 2021; AHossain et al., 2024). Moreover, interpretability remains a major challenge, as deep models often operate as black boxes, limiting trust and adoption among decision-makers (Dasgupta & Islam, 2024; Pandey et al., 2023). Nevertheless, their ability to capture nonlinear patterns and improve forecast granularity continues to make them an essential component of modern AI-powered aggregate planning systems (Aleem Al Razee et al., 2025; Grover et al., 2020).

Reinforcement Learning Approaches

Reinforcement learning (RL), a subset of machine learning, has emerged as a powerful tool for dynamic and adaptive planning in supply chain and production environments. Unlike supervised learning methods, RL is uniquely suited for problems where the environment is uncertain and decisions must be made sequentially with delayed rewards (Alam et al., 2024; Rolf et al., 2022). This characteristic makes it particularly advantageous for aggregate planning, which often involves adjusting resource allocations, production rates, and workforce levels in response to continuously evolving market demands and operational constraints. (Demizu et al., 2023) describe RL as a framework where agents interact with an environment, learn optimal policies over time, and improve decision-making without explicit programming. In manufacturing settings, RL-based models have been applied to optimize production scheduling under changing demand scenarios, dynamically adjusting plans as new data becomes available (Al-Arafat, Kabi, et al., 2024; Sanjay Raja et al., 2023). These models demonstrate improved adaptability and planning accuracy, particularly when integrated with simulation environments that mimic real-world production and inventory dynamics (Aklima et al., 2022; Zawish et al., 2023).

Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

Figure 8: A structured overview of how reinforcement learning



RL systems are especially effective in multi-objective environments, where trade-offs among cost, time, inventory levels, and workforce utilization must be continuously balanced (Abideen et al., 2021; Maniruzzaman et al., 2023). In comparison to static or batch optimization methods, RL allows for continuous learning, enabling firms to adjust aggregate plans in near real-time, which significantly enhances responsiveness and operational agility (Oroojlooyjadid et al., 2022; Shahan et al., 2023). Algorithms such as Q-learning, Deep Q-Networks (DQN), and Proximal Policy Optimization (PPO) have shown promising results in dynamic planning environments (Mutalemwa & Shin, 2020; Roksana, 2023). These methods learn optimal policies through extensive exploration and feedback, optimizing decisions over long planning horizons. Additionally, recent studies have explored model-free versus model-based reinforcement learning approaches in supply chain applications, demonstrating that model-based methods often converge faster, whereas model-free algorithms offer superior flexibility in uncertain environments (Alam et al., 2023; Nasseri et al., 2023). As Hohn and Durach, (2021) highlight, the use of RL in aggregate planning enhances decision precision and accelerates responses to unanticipated supply chain disruptions, which are common in volatile global markets.

Aggregate planning inherently involves sequential decision-making across interconnected operational layers, including production, procurement, inventory management, and workforce allocation. Reinforcement learning is particularly well-suited for handling such sequential decisions, where outcomes from earlier actions influence future states and rewards (Ahmed et al., 2022; Mezghani et al., 2012). In contrast to traditional optimization models, which often assume fixed horizons and static variables, RL methods accommodate stochastic transitions and delayed feedback, making them robust for complex supply chain environments (Silva et al., 2017; Sohel et al., 2022). In recent years, applications of RL in hierarchical planning have demonstrated its effectiveness in optimizing production flow and supply coordination across multiple stages and nodes in the supply chain (Wang et al., 2020). For example, RL-based models have been implemented to manage procurement schedules in upstream supply chains, while simultaneously adjusting downstream

American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

inventory and workforce planning decisions in response to demand signals (Mukhopadhyay et al., 2018).
Sequential decision problems such as production control in job shops, batch size optimization, and energy-efficient planning have been successfully modeled using reinforcement learning techniques like Deep Deterministic Policy Gradient (DDPG) and Actor-Critic algorithms (Faroukhi et al., 2020). These algorithms enable the integration of discrete and continuous action spaces, making them highly versatile for aggregate planning tasks that involve both binary (e.g., production on/off) and continuous (e.g., quantity of goods to produce) decision variables. Additionally, policy gradient methods are increasingly applied in scenarios where decision-making must adapt to time-varying constraints and multi-tier supplier interactions (Fathifazl et al., 2011). Deep reinforcement learning (DRL) architectures further enhance decision-making capacity by leveraging neural networks to approximate complex value functions and policies in high-dimensional state spaces (Mamede et al., 2023). Through these innovations, RL enables a shift from reactive to proactive planning, where decisions are not just based on immediate rewards but also on long-term operational impacts. Studies by Wang et al. (2020) and Roh et al. (2020) indicate that RL-based sequential planning models can reduce planning errors, optimize cost structures, and improve overall coordination efficiency in multi-echelon production systems.
The integration of reinforcement learning with simulation-based aggregate planning models has become an effective strategy to train intelligent agents in virtual representations of real-world supply chains. Simulation environments allow RL algorithms to explore thousands of possible scenarios without real-world risks, enabling rapid learning and policy development (Kim, 2021). For instance, discrete event simulation (DES) and agent-based modeling (ABM) have been used to simulate inventory flows, production bottlenecks, and demand fluctuations, forming the foundation for RL agent training (Tam & Tam, 2007). These hybrid models allow planners to test alternative policies and understand system-wide impacts before actual deployment, improving robustness and reducing implementation risk (Hendrickson et al., 2021). Reinforcement learning integrated into simulation-based digital twins enhances planning accuracy by incorporating real-time data feedback and predictive insights from past scenarios (Liu et al., 2011). Studies by Zupic and Čater, (2014) showed that coupling simulation with RL reduces the sample inefficiency of traditional RL approaches and accelerates policy convergence. This is especially beneficial in manufacturing sectors with long production cycles or high costs associated with trial-and-error learning.

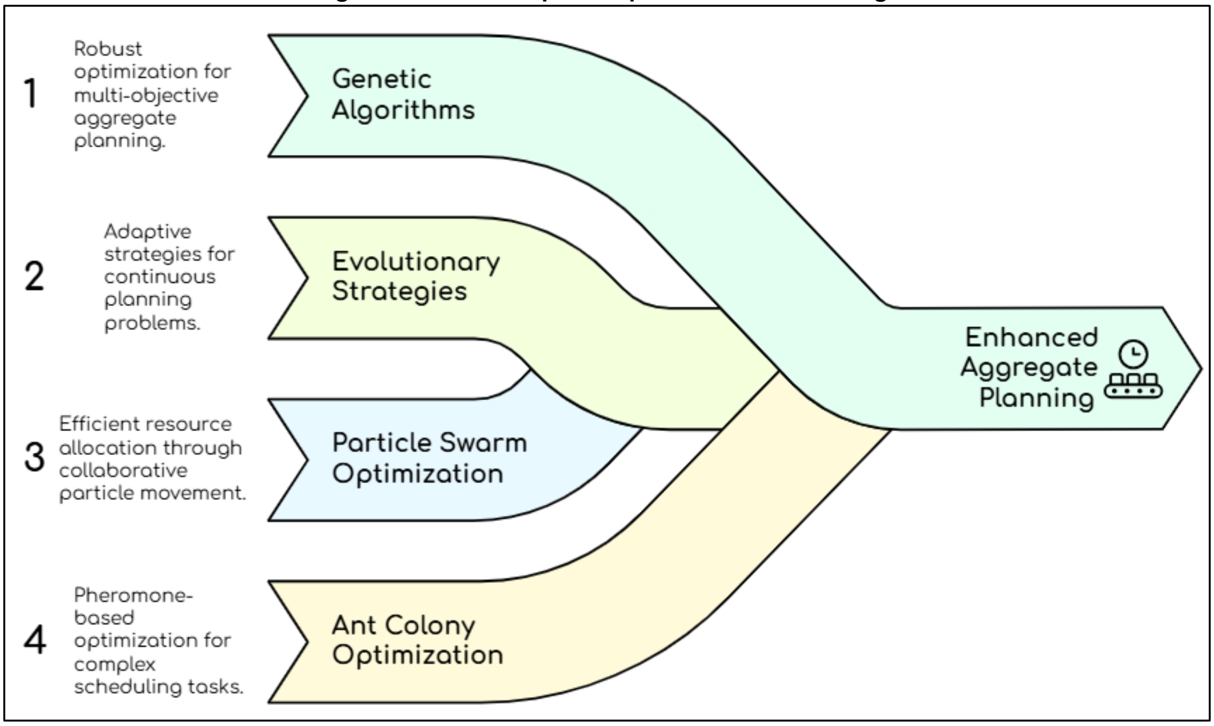
Heuristic Optimization and Evolutionary Algorithms

Genetic Algorithms (GAs) and Evolutionary Strategies (ES) are among the most widely adopted heuristic optimization methods in aggregate planning due to their robustness and ability to solve complex, multi-objective problems. Rooted in Darwinian principles of natural selection, GAs operate through iterative processes involving selection, crossover, and mutation, evolving a population of candidate solutions toward optimal or near-optimal outcomes (Ebinger & Omondi, 2020). These algorithms are particularly advantageous in addressing the combinatorial nature of aggregate planning, where traditional linear programming techniques may struggle with non-linearity, discrete variables, and stochastic constraints (Bottani et al., 2019). GAs have been successfully used to optimize production scheduling, inventory management, labor allocation, and cost minimization simultaneously in uncertain environments (Al Chami et al., 2017). Evolutionary Strategies, which emphasize

American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

adaptive parameter tuning and real-valued encoding, have further enhanced the applicability of evolutionary methods to continuous planning problems and large-scale industrial datasets (Kannan et al., 2010). Studies by Haoud and Bachiri (2019) and Bottani et al. (2019) demonstrated the effectiveness of GAs and ES in improving planning accuracy and solution diversity in complex multi-period aggregate planning scenarios. Additionally, hybrid models that integrate GAs with fuzzy logic or neural networks have been developed to address the vagueness and imprecision inherent in real-world planning (Contreras-Bolton et al., 2016). These hybrid approaches have shown superior convergence rates and robustness compared to standalone optimization models. Despite their computational intensity, GAs and ES remain preferred techniques for practitioners and researchers due to their flexibility, ease of adaptation, and proven performance in high-dimensional, multi-constraint environments typical of modern supply chains (Kannan et al., 2010).

Figure 9: Nature-Inspired Optimization in Planning



Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) represent nature-inspired metaheuristic algorithms that have gained substantial traction in solving aggregate planning problems due to their decentralized intelligence and adaptive search capabilities. PSO, inspired by the social behavior of bird flocking and fish schooling, simulates the movement of particles in a multidimensional search space, where each particle adjusts its trajectory based on its own experience and that of its neighbors (Jia et al., 2019). This collaborative learning strategy allows PSO to efficiently explore large and nonlinear solution spaces, making it highly effective in optimizing production planning and resource allocation in aggregate planning contexts (Demizu et al., 2023). ACO, based on the foraging behavior of ants, uses pheromone-based indirect communication to construct and iteratively improve solutions to complex combinatorial problems, such as job shop scheduling, inventory routing, and batch production planning (Rafiei et al., 2013). Both PSO and ACO offer significant advantages over traditional heuristics due to their flexibility, scalability, and convergence efficiency, especially in highly dynamic environments (Haoud & Bachiri, 2019).

American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

Numerous empirical studies have validated the superiority of PSO and ACO in multi-objective aggregate planning tasks involving constraints like production costs, demand satisfaction, lead times, and inventory levels (Sillekens et al., 2011). For instance, integration of PSO with fuzzy logic models has allowed for adaptive handling of uncertainty in production capacities and customer demand (Demizu et al., 2023). Similarly, hybrid ACO models have been applied to real-world supply chains for optimizing make-to-order production systems and minimizing total system costs under various constraints (Al Chami et al., 2017). These algorithms are particularly useful in complex manufacturing systems where flexibility, responsiveness, and computational efficiency are critical. While both methods are population-based and inherently parallel, PSO often excels in continuous search spaces, whereas ACO is particularly strong in discrete optimization scenarios. Combined with other AI techniques, both PSO and ACO continue to serve as powerful tools in next-generation aggregate planning solutions, particularly in the context of Industry 4.0 environments and intelligent decision support systems (Ebinger & Omondi, 2020).

Fuzzy Logic and Hybrid AI Models

Fuzzy logic provides a valuable mechanism for reasoning under uncertainty, making it particularly applicable to aggregate planning scenarios characterized by vagueness, ambiguity, and imprecise data inputs (Demizu et al., 2023). In supply chain environments, aggregate planning decisions such as production volume, labor adjustment, and inventory control often involve linguistic and subjective judgments that cannot be adequately addressed using crisp logic (Venkatesh et al., 2018). Fuzzy logic enables planners to model such ambiguity by converting linguistic variables into computationally manageable fuzzy sets, thereby enhancing decision flexibility and human-like reasoning (Shipley et al., 2013). Integrating fuzzy logic with machine learning (ML) techniques further strengthens planning systems by combining fuzzy systems' interpretability with ML's predictive capabilities (Torabi et al., 2010). For instance, fuzzy neural networks (FNNs) and adaptive neuro-fuzzy inference systems (ANFIS) have been applied to model complex, nonlinear planning scenarios, offering improved accuracy in forecasting and resource allocation (Peidro et al., 2010).

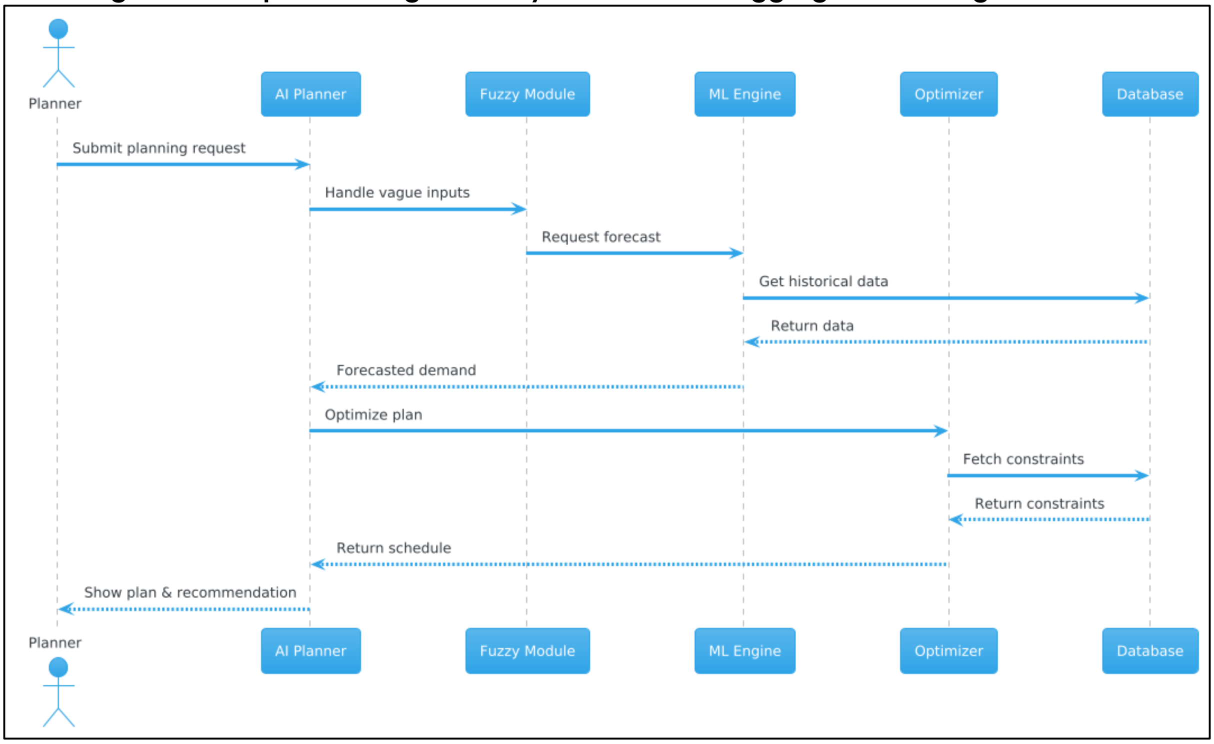
Research by Arshad et al, (2014) demonstrated that integrating fuzzy logic into demand forecasting models enhances responsiveness by handling uncertain and volatile demand patterns more effectively than traditional ML models. Similarly, studies by Patel et al., (2019) and Marta et al., (2023) confirmed that fuzzy-ML models outperform standalone algorithms in inventory optimization and supplier selection. These hybrid approaches are particularly useful in industries with frequent data incompleteness and volatility, such as food manufacturing, pharmaceuticals, and retail (Awasthi & Kannan, 2016). In addition, fuzzy clustering techniques such as fuzzy c-means have been used to segment customers or products based on imprecise characteristics, enabling customized aggregate planning strategies (Sanayei et al., 2010).

Hybrid AI models, which combine two or more computational intelligence techniques, have gained significant prominence in aggregate planning for their ability to leverage the strengths of different methodologies while mitigating their individual limitations. These models often integrate machine learning, fuzzy logic, neural networks, evolutionary algorithms, and reinforcement learning to address the multifaceted nature of supply chain planning tasks (Torabi et al., 2010). For instance, combining genetic algorithms (GAs) with neural networks enhances search efficiency and solution accuracy in complex planning problems involving non-linear constraints and multi-objective trade-offs (Klashanov, 2018; Torabi et al., 2010). Similarly, the fusion

eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

of fuzzy systems with reinforcement learning allows planners to adapt to uncertain environments while retaining human-like reasoning structures, resulting in greater flexibility and interpretability (Arshad et al., 2014). Comparative studies consistently highlight the superiority of hybrid AI models over standalone approaches in terms of forecast accuracy, computational efficiency, and decision robustness. For example, (Marta et al., 2023) found that hybrid fuzzy-genetic models achieved better convergence rates and lower error margins than traditional statistical or single-AI models. Similarly, Sanayei et al. (2010) demonstrated that a combination of fuzzy logic and particle swarm optimization (PSO) significantly outperformed each technique individually in handling supplier selection and order allocation in uncertain planning environments. Hybrid deep learning models, such as convolutional neural networks (CNNs) integrated with long short-term memory (LSTM) networks, have also been applied in temporal-spatial forecasting within aggregate planning, improving accuracy and computational scalability (Kavus et al., 2022). Furthermore, hybrid models provide better generalization in dynamic environments by combining adaptive exploration (from evolutionary methods) with precision learning (from ML and DL techniques) (Özkan & İnal, 2014). These benefits make hybrid AI models particularly suitable for digital twin-based planning environments and intelligent decision support systems in Industry 4.0 (Peidro et al., 2010).

Figure 10: Sequence Diagram of Hybrid AI-Driven Aggregate Planning Workflow



In practical industrial applications, hybrid AI models have demonstrated exceptional versatility in supporting aggregate planning across diverse sectors, including manufacturing, retail, automotive, and food processing. These sectors often involve volatile demand, capacity constraints, variable lead times, and regulatory limitations—all of which require adaptable yet precise planning models (Shipley et al., 2013). Research by Marta et al. (2023) shows that GA-ANN hybrid models outperformed conventional optimization approaches in multi-period production planning, particularly in systems requiring joint optimization of production and workforce. In the automotive sector, hybrid fuzzy-ANN models have been deployed for just-in-time (JIT) production scheduling, significantly improving cost efficiency and

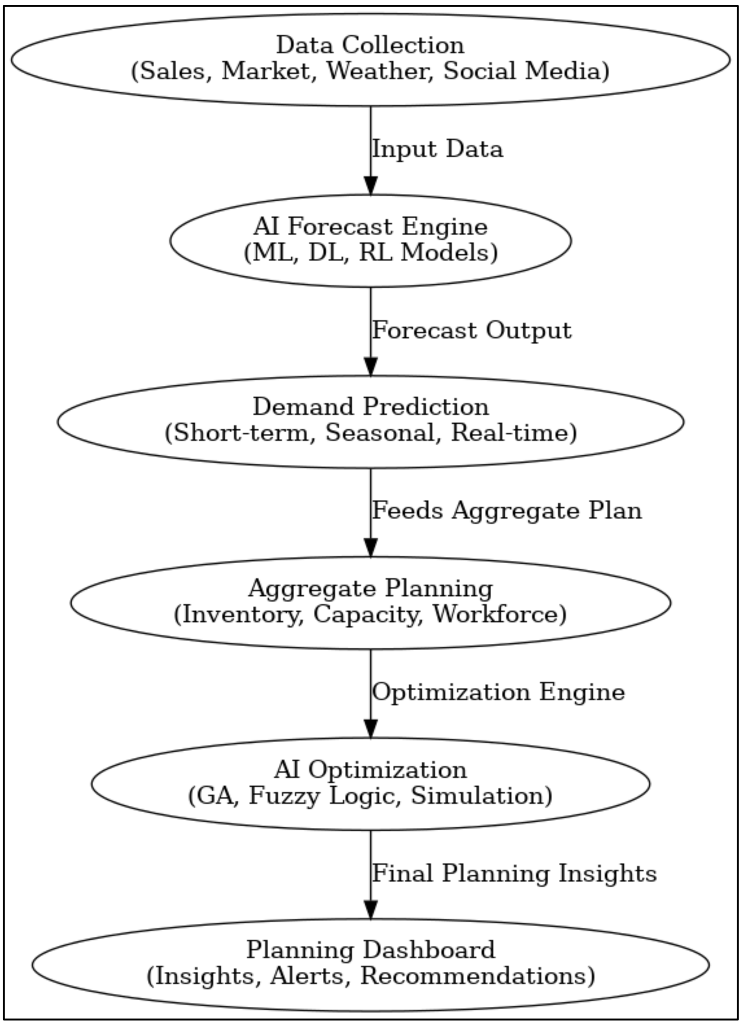
American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

delivery reliability (Venkatesh et al., 2018). In food and pharmaceutical industries, fuzzy-genetic systems enabled planners to account for perishability and regulatory compliance while optimizing batch production (Ahmed Marta et al., 2023). Studies by Sanayei et al. (2010) also illustrate the success of hybrid RL-fuzzy systems in enabling autonomous decision-making under uncertainty, resulting in reduced lead times and higher supply chain resilience. Moreover, hybrid AI models align well with sustainability objectives, enabling the simultaneous optimization of economic, environmental, and social factors. Marta et al. (2023) emphasized that multi-objective hybrid models are particularly effective in balancing operational efficiency with sustainability targets. Hybrid models also improve scalability in cloud-based and distributed computing environments, making them highly suitable for large enterprises operating across multiple geographies (Sanayei et al., 2010). These systems are increasingly embedded within intelligent decision support systems and ERP platforms, offering real-time recommendations that adjust to evolving planning constraints and business objectives. By combining AI components in synergistic ways, hybrid models offer robust, scalable, and context-aware solutions that are shaping the next generation of aggregate planning tools in supply chain management (Chaturvedi et al., 2019).

AI-Based Demand Forecasting and Aggregate Planning Integration

Artificial Intelligence (AI) has significantly enhanced the precision and reliability of demand forecasting within aggregate planning frameworks by enabling the analysis of vast, heterogeneous datasets and uncovering complex, nonlinear patterns that traditional methods often overlook. Demand forecasting, a cornerstone of effective aggregate planning, directly influences decisions related to production schedules, inventory levels, workforce management, and distribution planning (Arshad et al., 2014). Machine learning algorithms, particularly Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and ensemble methods like Random Forests, have demonstrated superior performance in modeling and predicting demand trends across industries with high variability (Arshad et al., 2014; Özkan & İnal, 2014). These models are capable of

Figure 11: AI-Based Demand Forecasting and Aggregate Planning Integration



American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

learning from large volumes of structured and unstructured data—including sales transactions, market indicators, weather patterns, and social media sentiment—enhancing forecast granularity and adaptability (Shipley et al., 2013).

Studies have shown that AI-based demand forecasting models can reduce forecast error rates by up to 30% compared to traditional time series approaches, thus leading to more informed aggregate planning decisions and improved operational efficiency (Baykasoğlu & Gölcük, 2019; Castillo et al., 2016). Reinforcement learning (RL) and deep learning architectures, such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), have also been used to model sequential and temporal dependencies, further enhancing forecast accuracy in highly dynamic environments (Peidro et al., 2010). These models adapt to new patterns in real-time, providing planners with the flexibility to adjust forecasts and reconfigure aggregate plans accordingly. Integrating AI into demand forecasting not only improves prediction accuracy but also enables proactive decision-making, reduced inventory holding costs, and optimized capacity utilization (Shipley et al., 2013). AI's ability to continuously learn and improve its forecasts over time adds a dynamic and strategic layer to aggregate planning that static models lack (Arshad et al., 2014; Klashanov, 2018). Beyond improved accuracy, AI enhances the contextual relevance of demand forecasting by incorporating a broader range of influencing variables and external shocks into predictive models. Traditional statistical models typically rely on historical sales data, seasonality, and trend components but often fail to account for disruptions such as pandemics, geopolitical events, or rapid market shifts (Govindan et al., 2013). In contrast, AI models can integrate real-time and external data sources—including online consumer behavior, mobility trends, social sentiment, and macroeconomic indicators—into forecasting systems, offering more comprehensive and robust predictions (Klashanov, 2018; Patel et al., 2019). These capabilities have become increasingly relevant in post-pandemic supply chains, where rapid adaptability and accurate forecasting are essential for survival and competitiveness (Ahmed Marta et al., 2023). For instance, companies such as Walmart, Amazon, and Unilever have reported significant improvements in forecasting performance after implementing AI-driven demand planning tools that ingest and process vast volumes of internal and external signals (Özkan & İnal, 2014).

Moreover, demand forecasting powered by AI has become more collaborative and integrated across enterprise systems through cloud-based platforms, Internet of Things (IoT) data feeds, and predictive dashboards (Chaturvedi et al., 2019). These systems provide planners and executives with real-time insights into demand shifts and their downstream implications for production and distribution. Deep learning models such as Transformer networks, which were originally designed for natural language processing, are now being applied in demand forecasting to capture long-term dependencies in data streams with irregular time steps (Baykasoğlu & Gölcük, 2019). The resulting improvement in accuracy has a direct impact on aggregate planning outcomes, including inventory optimization, capacity adjustment, supplier coordination, and cost control. The ability of AI to offer continuous forecasting updates, even in uncertain conditions, supports agile aggregate planning processes and enhances resilience against unpredictable market behaviors (Peidro et al., 2010).

AI-based predictive analytics have transformed inventory and capacity optimization processes within aggregate planning by enabling more precise estimation of future requirements and supporting timely resource allocation. Predictive models powered by AI allow firms to minimize both overstock and stockout situations by forecasting demand variations with high accuracy and adjusting inventory thresholds

American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

accordingly (Patel et al., 2019). Algorithms such as regression trees, extreme gradient boosting (XGBoost), and LSTM networks are employed to predict inventory levels based on a combination of lead times, demand forecasts, historical usage rates, and external variables like transportation delays or supplier performance (Arshad et al., 2014). These systems enable more agile and cost-effective decisions regarding reorder points, safety stock, and replenishment cycles (Venkatesh et al., 2018).

Capacity optimization, which involves determining the right levels of labor, machine time, and facility utilization, also benefits from AI's ability to simulate future production scenarios and identify bottlenecks before they occur (Arshad et al., 2014). Reinforcement learning models are particularly effective in dynamic capacity planning, where they learn optimal policies for adjusting production resources in real time based on reward feedback mechanisms (Baykasoğlu & Gölcük, 2019). Integration of predictive analytics into ERP and MES systems enables real-time monitoring of capacity utilization, alerting planners when thresholds are exceeded or underutilized (Venkatesh et al., 2018). The fusion of inventory and capacity forecasting leads to synchronized planning decisions, where changes in expected demand automatically trigger adjustments in resource scheduling, procurement, and workforce planning (Arshad et al., 2014). These AI-driven systems offer significant improvements in efficiency, cost reduction, and service level adherence, aligning operational execution with strategic supply chain goals (Ahmed Marta et al., 2023).

AI's contribution to predictive analytics in inventory and capacity planning extends beyond forecasting to include decision automation, prescriptive insights, and risk mitigation. In traditional aggregate planning models, inventory decisions are often reactive and based on fixed reorder points, which do not adapt to real-time variability in demand or supply conditions (Alam et al., 2023). By contrast, AI models are capable of automating inventory control decisions based on evolving patterns in consumption, supplier lead times, and order fulfillment rates (Baykasoğlu & Gölcük, 2019). For instance, hybrid AI models combining reinforcement learning with fuzzy logic or genetic algorithms allow systems to generate prescriptive actions under uncertainty, enabling adaptive inventory policies for perishable and seasonal products (Baykasoğlu & Gölcük, 2019; Castillo et al., 2016). These models continuously update reorder points and economic order quantities (EOQs), enhancing responsiveness to market conditions and reducing holding costs (Awasthi & Kannan, 2016). Moreover, Capacity planning under uncertainty is similarly enhanced through scenario simulation and AI-based optimization models that account for constraints such as labor availability, energy costs, maintenance schedules, and facility limitations ((Sanayei et al., 2010). Deep reinforcement learning models are increasingly used to identify optimal production capacity configurations that align with variable demand forecasts and cost objectives (Arshad et al., 2014). These models simulate different capacity loading scenarios and suggest adjustments to shift patterns, subcontracting, or asset utilization. Digital twin environments further amplify this capability by mirroring physical operations and feeding real-time data into AI models for scenario testing and predictive analysis (Yalcin Kavus et al., 2022). As a result, firms achieve higher operational resilience, reduced lead times, and improved alignment between production schedules and aggregate planning objectives (Sanayei et al., 2010).

Manufacturing Industry Applications

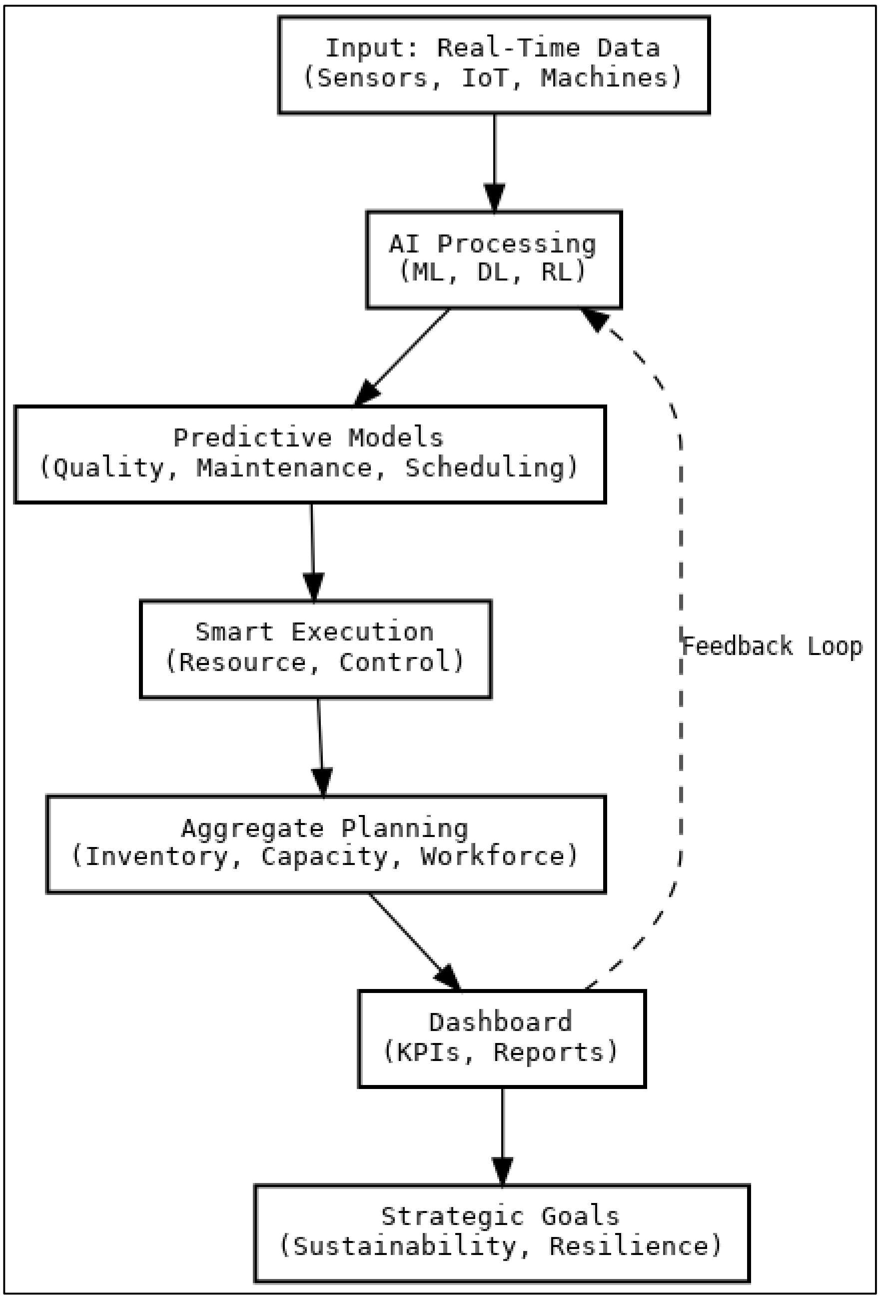
Production scheduling and resource allocation are two of the most critical aspects of aggregate planning in manufacturing, and artificial intelligence (AI) has emerged as a transformative tool in enhancing these functions. Traditional scheduling methods, including heuristics and rule-based systems, often struggle to manage the

American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

complexities associated with dynamic shop-floor conditions, variable demand, machine breakdowns, and multi-objective constraints (Gupta et al., 2020). In contrast, AI algorithms—particularly those based on genetic algorithms (GAs), reinforcement learning (RL), and neural networks—demonstrate superior adaptability, computational efficiency, and solution quality in scheduling tasks (Awan et al., 2021; Gupta et al., 2020). For instance, GAs are widely applied in job-shop and flow-shop scheduling problems where multiple machines and task dependencies must be considered (Ghazali et al., 2021; Hong et al., 2019). These models evolve scheduling solutions iteratively, optimizing makespan, labor cost, and machine utilization.
Reinforcement learning algorithms are increasingly used to develop adaptive scheduling policies that respond to real-time changes in order queues, machine availability, and priority shifts (Doyle-Kent & Kopacek, 2019). Actor-Critic and Deep Q-Network (DQN) models enable intelligent agents to learn optimal sequences of task allocations and machine setups through repeated interactions with a simulated environment (Lynch et al., 2020). Additionally, neural network-based models, including deep learning architectures, are utilized to predict production bottlenecks and dynamically adjust workloads across departments (Kannan et al., 2010). AI models also integrate resource constraints, such as energy consumption and workforce availability, into scheduling frameworks, improving alignment between operational execution and environmental or economic objectives (Hsu et al., 2022). Furthermore, hybrid models combining fuzzy logic with AI techniques are employed to accommodate uncertainty in resource requirements and production cycle times (Ghazali et al., 2021). These intelligent systems not only improve production efficiency and throughput but also enhance responsiveness to last-minute order changes and unplanned disruptions.
The advent of Industry 4.0 has accelerated the digital transformation of manufacturing systems, embedding AI-driven intelligence into every stage of production, planning, and execution. Industry 4.0 is characterized by the integration of cyber-physical systems, Internet of Things (IoT), big data analytics, and cloud computing, enabling real-time data exchange and autonomous decision-making across manufacturing ecosystems (Hong et al., 2019). In this context, AI plays a central role by analyzing vast amounts of structured and unstructured data generated from sensors, machines, and enterprise systems to optimize aggregate planning decisions. Smart manufacturing systems leverage AI for tasks such as predictive maintenance, real-time quality monitoring, and adaptive control of production lines (Mobarakeh et al., 2017; Stanisławski & Szymonik, 2021). For example, predictive models based on deep learning are used to detect anomalies in equipment behavior and prevent downtime, thereby improving overall equipment effectiveness (OEE) and resource availability for production scheduling (Butt, 2021).

eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

Figure 12: AI in Manufacturing Aggregate Planning



Retail Sector Applications

Artificial Intelligence (AI) has revolutionized demand forecasting and inventory management in the retail sector, offering retailers enhanced capabilities to understand consumer behavior, predict sales trends, and maintain optimal inventory levels. Traditional retail forecasting methods, often based on time series models and historical averages, have struggled to cope with the increasing variability and complexity of consumer demand across seasons, channels, and regions (Hong et al., 2019; Lynch et al., 2020). In contrast, AI-powered machine learning models—such as support vector machines (SVM), artificial neural networks (ANN), and gradient boosting algorithms—have demonstrated superior accuracy in identifying nonlinear demand patterns and adjusting forecasts in real-time (Hsu et al., 2022; Rožanec et al., 2021). These models are particularly effective in integrating large volumes of structured and unstructured data, including point-of-sale (POS) data, social media activity, online search trends, and weather information (Rasmi et al., 2019).

American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

Figure 13: AI-Driven Retail Planning Cycle

Retailers like Walmart, Amazon, and Zara have leveraged AI-based demand forecasting to reduce stockouts, minimize excess inventory, and align procurement with anticipated customer needs (Stanisławski & Szymonik, 2021). Inventory management systems enhanced by AI incorporate predictive analytics to determine reorder points, safety stock thresholds, and dynamic replenishment schedules based on customer buying behavior and supply chain variability (Chidepatil et al., 2020). Reinforcement learning (RL) models are also used to optimize inventory replenishment decisions by learning from real-time customer demand patterns and continuously updating order policies (Gonçalves et al., 2021). These systems reduce holding costs and markdown losses while improving fulfillment speed and service levels (Butt, 2021). Furthermore, hybrid models that combine fuzzy logic with AI techniques have proven effective in dealing with uncertain retail environments, enhancing flexibility in stock allocation decisions during promotional events or unexpected demand surges (Sharma et al., 2019). Overall, AI enables more precise, responsive, and efficient inventory management, a cornerstone of modern retail aggregate planning. The implementation of AI in retail inventory management also supports decision automation, allowing for real-time replenishment and stock redistribution across stores

American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

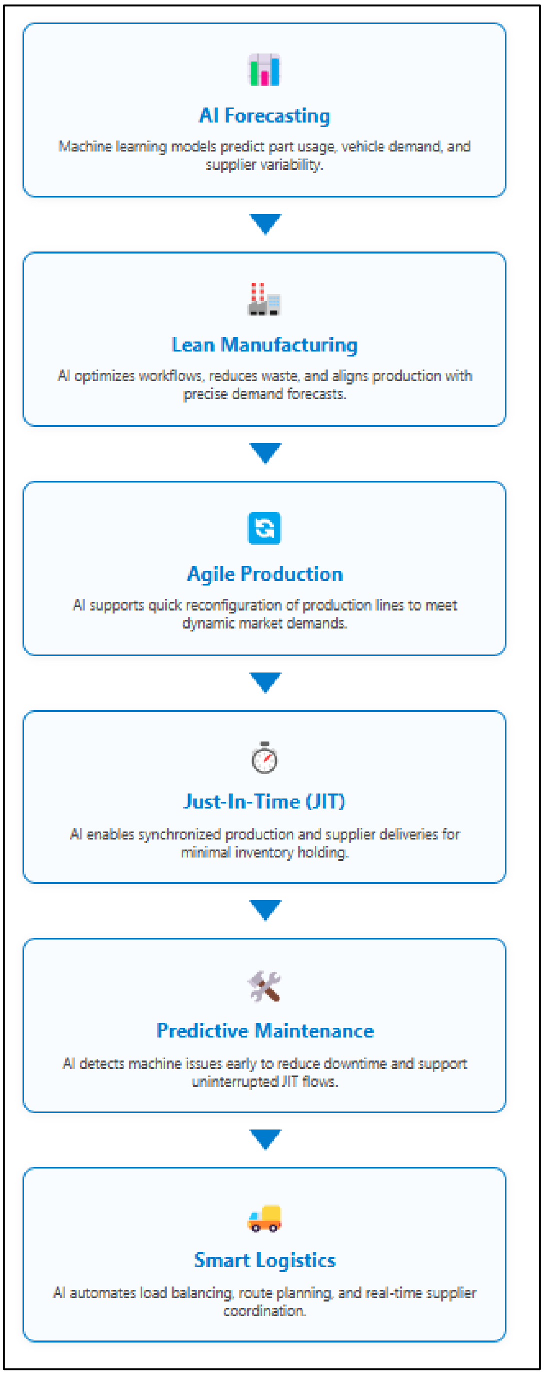
and warehouses based on predictive insights. Deep learning models, such as Long Short-Term Memory (LSTM) networks and Temporal Convolutional Networks (TCNs), have been applied successfully in multi-echelon retail networks, enhancing the accuracy of short-term and long-term demand forecasts (Wang et al., 2020). These models outperform traditional autoregressive and exponential smoothing techniques, especially during periods of high demand volatility or promotional activities (Mobarakeh et al., 2017). Integration of these forecasts into AI-enabled inventory systems allows dynamic allocation of stock between locations, optimizing the trade-off between transportation costs, delivery lead times, and service level targets (Kannan et al., 2010).

Automotive Industry Applications

The automotive industry, with its complex and demand-sensitive production environment, has embraced AI-driven aggregate planning to support lean and agile manufacturing systems. Lean manufacturing focuses on eliminating waste and optimizing efficiency, while agile manufacturing emphasizes flexibility and responsiveness to market fluctuations (Rožanec et al., 2021). AI technologies support both paradigms by enabling precise forecasting, intelligent scheduling, and dynamic resource allocation. Machine learning (ML) and reinforcement learning (RL) models, in particular, allow automotive manufacturers to align production rates with real-time demand signals, minimizing excess inventory while maintaining service level targets (Zhao et al., 2024). Studies by Ivanov, Dolgui, and Sokolov (2019) have demonstrated the effectiveness of AI in synchronizing production flows, optimizing labor deployment, and reducing manufacturing lead times, which are crucial for both lean and agile systems.

Genetic algorithms (GAs) and particle swarm optimization (PSO) have been widely applied in automotive production planning to resolve multi-objective scheduling problems involving production cost, resource utilization, and cycle time (Salah et al., 2019). These metaheuristic approaches outperform traditional rule-based systems, especially in multi-line assembly plants with varying demand for different vehicle models. Hybrid AI models that integrate fuzzy logic with ML have

Figure 14: AI in Automotive Aggregate Planning



American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

also shown strong results in capturing the uncertainties associated with supplier lead times, raw material variability, and customer orders, thereby enabling more robust aggregate plans (Dwivedi et al., 2021). Deep learning techniques like LSTM networks are being employed to forecast component usage trends and maintenance needs, ensuring smooth workflow and reduced downtime (Vasili et al., 2012). In lean systems, AI enables continuous improvement by identifying bottlenecks and inefficiencies through real-time data analytics. In agile systems, AI fosters modular and rapid reconfiguration of resources in response to shifting customer demands (Rožanec et al., 2021). Thus, AI strengthens the automotive industry's ability to implement integrated lean-agile manufacturing strategies supported by data-driven, predictive, and adaptive aggregate planning processes.

The integration of AI into Just-In-Time (JIT) and responsive supply chain models has dramatically transformed the automotive industry's approach to aggregate planning. JIT manufacturing, which relies on synchronized production and inventory systems, requires accurate demand forecasts and real-time decision-making to avoid delays and inefficiencies (Dutta et al., 2020). AI enables this synchronization by providing predictive analytics that help coordinate production schedules, supplier deliveries, and inventory replenishment across global automotive supply chains. Reinforcement learning (RL) and deep neural networks have been used to develop adaptive JIT planning systems that adjust procurement and production quantities in real-time based on fluctuating consumer demand, production constraints, and supplier performance (Dwivedi et al., 2021). These AI models learn from historical data and current supply chain conditions, continuously improving their predictions and optimizing planning decisions (Bousqaoui et al., 2021).

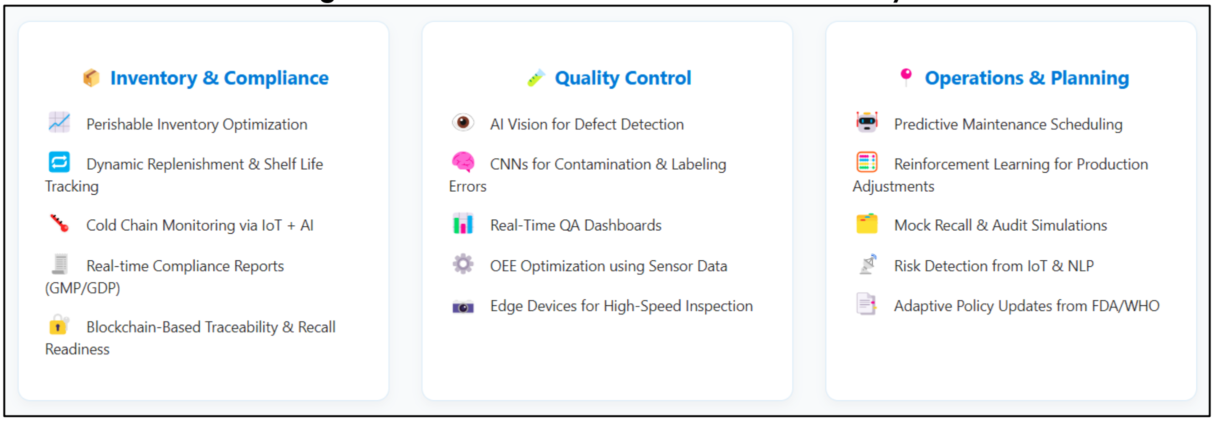
AI-powered demand sensing tools allow manufacturers to detect demand shifts at the earliest stages, enabling earlier responses and better alignment of material flows (Rožanec et al., 2021). Predictive maintenance systems using AI detect early signs of equipment failure and schedule maintenance proactively, reducing unplanned downtime and ensuring continuity in JIT operations (Dwivedi et al., 2021). In terms of logistics, AI algorithms facilitate route optimization, just-in-sequence (JIS) delivery planning, and load balancing across warehouses, which are essential for reducing transportation costs and meeting delivery windows (Fan & Cai, 2019). Companies like Toyota and BMW have integrated AI into their JIT systems to improve production efficiency and supplier collaboration, demonstrating substantial improvements in inventory turnover, production flexibility, and responsiveness to market fluctuations (Sillekens et al., 2011). AI also plays a role in managing disruptions, such as semiconductor shortages, by evaluating alternative sourcing scenarios and simulating the impact of delays on production lines (Afanasyev et al., 2021).

Food and Pharmaceutical Industry Applications

The food and pharmaceutical industries face unique challenges in aggregate planning due to the perishable nature of products, strict regulatory compliance requirements, and the need for cold chain integrity. Artificial Intelligence (AI) has increasingly become a critical enabler of advanced perishable inventory management, allowing firms to optimize stock levels, reduce waste, and ensure timely distribution (Tsolakis et al., 2014). Traditional inventory models often fall short in managing the complexities of expiration dates, fluctuating demand, and strict storage conditions, especially under constraints imposed by Good Manufacturing Practices (GMP) and Good Distribution Practices (GDP) (Camaréna, 2020). AI models such as reinforcement learning (RL), fuzzy logic, and neural networks offer dynamic

American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14
decision-making capabilities that adapt to real-time changes in product shelf life, sales velocity, and environmental factors (Nassibi et al., 2023).
Deep learning models, including Long Short-Term Memory (LSTM) networks and recurrent neural networks (RNNs), are applied to forecast demand for short-life products and adjust procurement cycles accordingly, helping to prevent overstocking and understocking scenarios (Mamede et al., 2023). Additionally, AI enables intelligent replenishment systems that consider product perishability and expiration risk while prioritizing inventory rotation based on first-expired-first-out (FEFO) principles (Ma et al., 2023). In the pharmaceutical sector, AI systems are integrated into enterprise resource planning (ERP) platforms to monitor compliance in storage conditions—such as temperature, humidity, and light exposure—using Internet of Things (IoT) sensors and predictive analytics (R et al., 2021). Furthermore, AI-driven traceability systems incorporating blockchain enhance transparency across the supply chain, ensuring full compliance with FDA and EMA regulations for recall readiness, batch tracking, and anti-counterfeit verification (Wanchoo, 2019). These AI capabilities collectively support more reliable, compliant, and efficient aggregate planning strategies for perishable inventory.

Figure 15: AI in Food & Pharmaceutical Industry



AI technologies also empower predictive compliance and risk management in food and pharmaceutical supply chains, where regulatory failures can result in severe financial, reputational, and public health consequences. Traditional rule-based systems often lack the ability to monitor and adapt to real-time changes in regulatory policies or compliance parameters (Ma et al., 2023). In contrast, AI-enabled systems can continuously monitor and analyze quality records, sensor data, and audit trails to detect non-compliance trends or violations before they escalate into systemic issues (B S & Suresh, 2023). For instance, natural language processing (NLP) and AI-based compliance bots are now being used to automatically interpret and flag deviations from evolving FDA or WHO guidelines in documentation and process controls (Punia et al., 2020). In food manufacturing, AI-based quality assurance systems leverage visual recognition and real-time scanning to detect packaging defects, contamination, or labeling inconsistencies during high-speed operations (Demizu et al., 2023).
Moreover, predictive maintenance powered by AI ensures uninterrupted operation of refrigeration units, cleanroom environments, and sterile packaging machinery, which are essential for maintaining product integrity (Filali et al., 2022). AI models can forecast equipment failure by analyzing operational data patterns and initiating maintenance protocols before a breakdown occurs, thereby reducing spoilage and production delays (Wanchoo, 2019). Additionally, AI tools allow for simulation of regulatory audits and mock recall scenarios to test preparedness and resilience of the

supply network (Filali et al., 2022). These simulations contribute to more robust risk mitigation strategies and contingency planning, which are integral to aggregate planning in highly regulated industries. Blockchain-based smart contracts also facilitate automated compliance checks by validating transportation timelines, cold-chain thresholds, and product handling criteria before payment execution or batch release (Erol & Inkaya, 2023). By combining AI with regulatory intelligence, firms enhance both operational control and legal conformity across their supply chain ecosystems.

AI-driven quality control systems have significantly advanced operational efficiency in both the food and pharmaceutical industries by enabling real-time inspection, anomaly detection, and process optimization. Traditional quality control processes often rely on manual sampling and inspection methods, which are time-consuming, prone to human error, and limited in scope (Yuan et al., 2018). In contrast, AI technologies such as computer vision, deep learning, and edge computing now facilitate non-invasive and automated inspection of products and packaging at high speeds, ensuring consistency and safety without disrupting production (Oroojlooyjadid et al., 2022). Convolutional Neural Networks (CNNs) are frequently deployed in visual inspection systems to detect surface defects, discoloration, or foreign object contamination in processed foods and pharmaceuticals (Bousqaoui et al., 2021). These systems enable full-batch inspection, improving accuracy while reducing labor requirements. In manufacturing environments, AI algorithms are also used to optimize overall equipment effectiveness (OEE) by analyzing sensor data related to cycle time, equipment downtime, and yield performance (Bousqaoui et al., 2021; Mamede et al., 2023). Reinforcement learning models adaptively fine-tune production parameters such as temperature, pressure, and formulation dosage, ensuring that each batch meets stringent quality specifications while minimizing waste (Koç & Turkoglu, 2021). Additionally, predictive analytics are applied to track critical process variables, enabling early detection of deviations that could compromise product quality or safety (Wanchoo, 2019). AI also enhances process design and continuous improvement initiatives through pattern recognition and root-cause analysis derived from production and quality data (Frank et al., 2019; Kuo et al., 2002). In regulatory audits, AI systems can generate real-time quality assurance dashboards and documentation, reducing the administrative burden on quality control teams (Joseph et al., 2022). By integrating these AI capabilities, organizations in the food and pharmaceutical sectors can achieve higher product quality, faster throughput, lower operational costs, and improved compliance—core goals of efficient aggregate planning and supply chain optimization.

Sustainability in AI-Driven Aggregate Planning

Artificial Intelligence (AI) has become an indispensable enabler of sustainable supply chain strategies, particularly in the context of aggregate planning, where the optimization of resources and reduction of environmental impact are essential. AI models—especially those based on predictive analytics, machine learning (ML), and reinforcement learning (RL)—allow for the real-time identification of inefficiencies, overproduction, and waste across manufacturing and logistics operations (Galvez-Martos et al., 2018). These capabilities are crucial for achieving lean manufacturing goals while minimizing environmental degradation. Studies have shown that AI-powered systems can improve resource utilization by forecasting demand more accurately, dynamically allocating production resources, and reducing the amount of excess inventory and energy consumption (Kim, 2021). For instance, AI models embedded in smart meters and IoT devices enable granular tracking of energy and

American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

water usage, which facilitates optimization of utility inputs in line with sustainability goals (Lu & Yuan, 2010).

Moreover, AI is playing an increasingly critical role in environmental impact assessment (EIA) by enabling real-time decision-making that considers carbon emissions, transportation pollution, and material recycling potential during aggregate planning (Chidepatil et al., 2020). AI algorithms can simulate multiple planning scenarios and recommend the least environmentally harmful option without compromising service levels or customer satisfaction (Park, 2017). Reinforcement learning and deep learning models, for example, help firms identify production and logistics paths with the lowest ecological footprint by processing high-dimensional environmental datasets (Yang et al., 2014). Furthermore, AI-assisted lifecycle assessment (LCA) models are used to evaluate the environmental impacts of products from raw material extraction through end-of-life disposal, contributing to more informed and sustainable production planning (Hannan et al., 2020; Kargar et al., 2020). These AI applications allow organizations to shift toward closed-loop and circular supply chain systems that emphasize waste minimization, reuse, and responsible resource management.

Figure 16: Sustainability in AI-Driven Aggregate Planning

AI's role in achieving economic and social sustainability within aggregate planning is becoming increasingly significant as organizations seek to balance profitability with ethical and equitable practices. On the economic front, AI enables cost-effective operations through demand forecasting, predictive maintenance, dynamic pricing, and smart inventory management, all of which contribute to improved profitability and reduced operational waste (Yang et al., 2014). Predictive models, such as time-series forecasting and ensemble learning algorithms, are used to minimize overproduction and stockouts, aligning resource allocation with market demand while reducing excess costs (Yeheyis et al., 2012). AI applications also optimize supply chain design by suggesting cost-efficient sourcing routes and transportation networks, enhancing competitiveness and long-term economic sustainability (Chidepatil et al., 2020). Reinforcement learning further supports real-time adaptive strategies that adjust aggregate plans based on market fluctuations, labor availability, and raw material pricing, ensuring resilience in volatile economic environments (Kim, 2021).

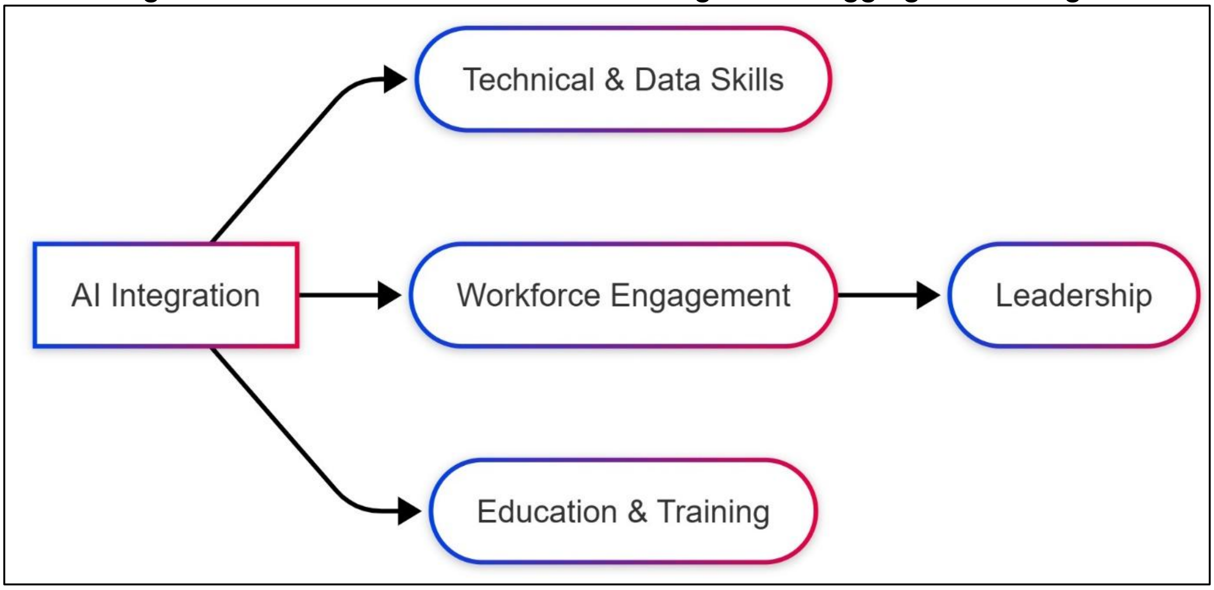
Human Factors: Skill Requirements and Expertise for AI Integration

The successful integration of Artificial Intelligence (AI) into aggregate planning and broader enterprise systems heavily depends on human capabilities, including technical skills, domain expertise, and organizational readiness. While AI systems promise automation, optimization, and intelligent decision-making, their effective deployment requires a workforce capable of designing, implementing, and

Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

interpreting AI solutions (Li et al., 2021). Technical proficiency in programming languages such as Python and R, understanding of data structures, algorithmic thinking, and machine learning models are foundational for AI integration (Sousa & Wilks, 2018). Beyond technical skills, professionals must also possess strong data literacy, which includes the ability to interpret data visualizations, statistical outputs, and predictive analytics to make data-driven decisions (Li et al., 2021; Sousa & Wilks, 2018). Studies suggest that lack of data literacy remains a critical barrier to AI adoption in manufacturing, retail, and logistics sectors (Bhattacharyya & Nair, 2019).

Figure 17: Essential Human Factors for AI Integration in Aggregate Planning



Equally important are hybrid competencies that blend domain knowledge with AI understanding. For example, supply chain managers must grasp AI tools for forecasting, inventory optimization, and capacity planning, while understanding their operational implications (Malik et al., 2020). AI deployment also demands change management expertise, as AI transformation often requires reconfiguration of workflows, reporting structures, and decision hierarchies (Mukhuty et al., 2022). Moreover, the rise of user-friendly AI platforms has led to the emergence of "citizen data scientists"—business professionals equipped with basic analytics and AI tool usage who collaborate with data scientists to bridge gaps between IT and operations (Li et al., 2021; Zhan & Tan, 2020). Training programs tailored to upskill such users are increasingly essential, emphasizing interpretability, explainability, and ethical use of AI (Chari et al., 2022). Thus, integrating AI is not solely a technological shift but a human-centric transformation that demands broad skill enhancement across organizational layers.

The workforce's adaptability and willingness to engage with AI technologies play a critical role in the sustainability and scalability of AI-driven initiatives. Organizational culture and employee attitudes toward digital innovation significantly influence the pace and success of AI adoption (Bhattacharyya & Nair, 2019). Resistance to change, fear of job displacement, and limited understanding of AI capabilities are common psychological and sociocultural barriers to adoption (Malik et al., 2020). Studies by Ahsan and Rahman (2021) and Sousa and Wilks (2018)demonstrate that effective communication and participatory design practices—where employees are involved in AI system design and deployment—enhance engagement and reduce resistance. Organizational leaders must promote a learning culture that encourages experimentation and views AI as an augmentation tool rather than a replacement for

Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

human labor (Mukhuty et al., 2022). Such a mindset not only improves acceptance but also motivates employees to reskill and actively participate in AI-driven workflows. Leadership competencies also play an instrumental role in fostering AI readiness across functional teams. Managers must possess digital fluency to interpret AI-generated insights and make strategic decisions accordingly (Zhan & Tan, 2020). Furthermore, ethical awareness among decision-makers is essential to ensure responsible AI use, particularly in applications involving personal data, workforce automation, or customer interaction (Li et al., 2021). Ethical AI deployment includes fairness, transparency, accountability, and bias mitigation—dimensions that require human oversight and informed judgment (Chari et al., 2022). Therefore, organizations must not only invest in technical upskilling but also foster soft skills such as critical thinking, ethical reasoning, and collaborative problem-solving to align AI implementation with organizational values and stakeholder expectations (Bhattacharyya & Nair, 2019). Ultimately, successful AI integration is contingent on a holistic human development strategy that addresses technical competence, cultural readiness, and ethical responsibility. Building a workforce capable of sustaining AI-driven planning requires educational institutions and corporate training programs to restructure learning pathways. Higher education curricula must shift from siloed disciplinary training to interdisciplinary programs that combine computer science, business analytics, and industry-specific knowledge (Mukhuty et al., 2022). Programs in supply chain management, manufacturing, healthcare, and finance are increasingly integrating courses in AI, machine learning, and data science to meet labor market demands (Malik et al., 2020). On-the-job training, boot camps, and AI certification programs have also gained traction, particularly in sectors undergoing rapid digitization such as retail, automotive, and pharmaceuticals (Ahsan & Rahman, 2021; Sousa & Wilks, 2018). Industry-academia partnerships have further enhanced curriculum relevance and practical exposure, offering collaborative research opportunities, internships, and AI co-development labs (Bhattacharyya & Nair, 2019).

Gaps in Cross-Industry Comparative Studies

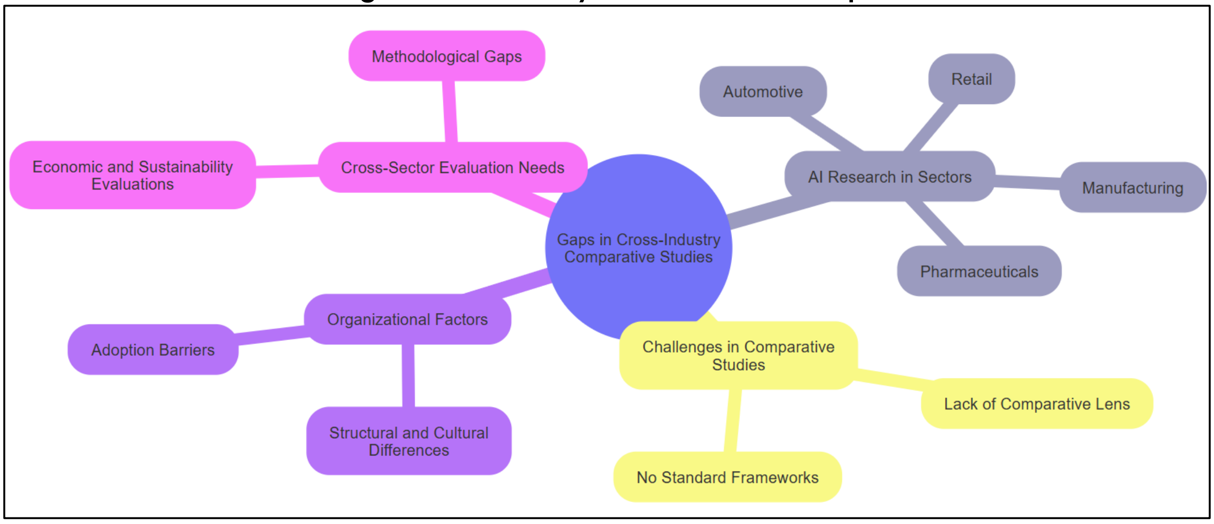
Despite the proliferation of AI research in individual sectors such as manufacturing, retail, automotive, and pharmaceuticals, significant gaps persist in cross-industry comparative studies that examine how AI-driven aggregate planning is adopted and operationalized across different domains. Much of the existing literature tends to be industry-specific, focusing on unique operational challenges or success cases within a single sector, often lacking a comparative lens to evaluate AI's transferability and adaptability across varied supply chain environments (Zhan & Tan, 2020). For example, in manufacturing and automotive sectors, AI is heavily implemented for predictive maintenance and production scheduling (Chari et al., 2022), while in retail, AI is more prevalent in demand forecasting and omnichannel inventory management (Ahsan & Rahman, 2021). However, studies seldom explore how strategies and outcomes differ—or can be shared—between these sectors.

The absence of standardized frameworks for evaluating AI integration across industries further complicates comparative efforts. Without common performance indicators or maturity assessment models, benchmarking AI adoption across sectors becomes difficult, and conclusions drawn from isolated studies remain non-generalizable (Peres et al., 2020). Even when similar AI technologies such as neural networks, reinforcement learning, or fuzzy logic are applied, their configurations, data pipelines, and decision contexts vary significantly by industry, limiting the ability to compare results meaningfully (Raut et al., 2020). Additionally, sector-specific constraints—such as perishability in food, compliance in pharmaceuticals, or

American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

customization in automotive—create barriers to implementing uniform AI models (Zawish et al., 2023). As such, comprehensive comparative studies that synthesize findings across sectors and develop transferable frameworks for AI-driven aggregate planning remain scarce. This gap inhibits knowledge sharing and slows the pace of AI innovation and adoption across the broader industrial ecosystem.

Figure 18: Summary of the identified Gap



One of the most significant limitations in existing cross-industry AI research is the under-exploration of how organizational structures and culture influence AI integration outcomes across sectors. The success of AI in aggregate planning is not solely dependent on algorithms or data quality but also on leadership support, digital readiness, employee training, and cross-functional collaboration—factors that differ widely across industries (Panda & Mohanty, 2023). For example, retail organizations often have flatter hierarchies and faster decision-making cycles, which enable quicker AI adoption compared to manufacturing companies with rigid production systems and slower change management practices (Aggarwal, 2019). Yet few studies explicitly compare the human and managerial factors that either facilitate or hinder AI implementation across industry types.

Furthermore, research has yet to fully investigate how AI maturity levels differ across sectors and what organizational practices enable sustainable scaling of AI technologies. Studies in manufacturing and automotive industries often report pilot-stage AI deployments focused on operational efficiency, whereas pharmaceutical and food sectors highlight AI's role in compliance and traceability, yet little is known about how these implementations mature over time or transition into enterprise-wide strategies (Arshad et al., 2014). Even fewer studies examine feedback loops between AI system performance and organizational learning, which is crucial for continuous improvement and strategic alignment (Tao et al., 2014). The lack of such comparative insights prevents the formation of best practices that are transferable across industries. Moreover, many AI adoption studies fail to account for socio-cultural or geographic differences in AI acceptance, ethics, and regulatory pressures that vary dramatically between sectors such as healthcare and e-commerce (Zawish et al., 2022). Addressing these gaps requires interdisciplinary, multi-sectoral research designs that compare not only technologies but also the ecosystems that shape their effectiveness.

Another critical research gap lies in the lack of comparative economic and sustainability evaluations of AI implementation across industries, which are essential for informed policymaking and long-term strategy development. While many sector-

Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: **10.63125/3jdpkd14**

specific studies have demonstrated cost savings and productivity gains from AI, few have conducted cost-benefit analyses or return-on-investment (ROI) assessments that are comparable across industries (Salah et al., 2019). This absence of standard metrics obscures the broader economic impact of AI technologies and makes it challenging for businesses in less digitized sectors—such as agriculture or traditional logistics—to build a compelling business case for AI adoption (Augustine et al., 2018). Moreover, cross-industry studies rarely address the environmental and social dimensions of AI-driven aggregate planning, leaving a significant gap in sustainability research. For instance, while AI's ability to reduce waste and improve energy efficiency is well documented in manufacturing (Reyes et al., 2020), its potential contributions to reducing packaging waste in retail or carbon emissions in pharmaceuticals remain under-explored. Studies also overlook how different regulatory environments affect the economics of AI adoption. Pharmaceutical and food sectors operate under stringent compliance frameworks that influence data collection, privacy, and AI usage, which are often not considered when drawing cross-sectoral conclusions (Tran et al., 2017). Furthermore, AI's role in achieving the Sustainable Development Goals (SDGs) and other ESG criteria differs between industries, yet these differences are seldom analyzed comparatively (Kantasa-ard et al., 2019). Without comparative research on the economic and sustainability impacts of AI integration, organizations are left with incomplete information, leading to uneven adoption and missed opportunities for collaborative innovation. Addressing these gaps would provide insights into scalable AI models and support the development of policy incentives for sustainable digital transformation.

METHOD

This study employed a case study approach to examine the integration of Artificial Intelligence (AI) into aggregate planning practices across various industries. The case study method was chosen for its strength in facilitating in-depth, contextual analysis of complex, contemporary phenomena within real-world settings, particularly when the distinctions between the phenomenon and its context are blurred. This qualitative strategy enabled the researcher to explore how AI technologies are operationalized in supply chain and production environments, uncovering detailed insights into organizational practices, technological infrastructure, workforce adaptation, and strategic outcomes. The study focused on multiple purposively selected case organizations representing diverse sectors—specifically manufacturing, retail, automotive, and pharmaceuticals—to allow for rich cross-case comparisons and identification of both common themes and industry-specific challenges in AI adoption. Data were collected through a triangulation of methods, including semi-structured interviews with senior operations and IT personnel, direct observations of AI-enabled planning processes, and reviews of internal planning documents, system dashboards, and strategic reports. This triangulated design enhanced construct validity by providing multiple perspectives and reducing the risk of bias. The selection of industries was based on their varying levels of digital maturity, regulatory environments, and operational complexity, which provided a comprehensive basis for analyzing how contextual factors influence AI integration outcomes. This methodological framework supported a holistic understanding of the role of AI in transforming aggregate planning and offered insights into the human, technological, and organizational dimensions that drive or inhibit successful implementation across sectors.

American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

FINDINGS

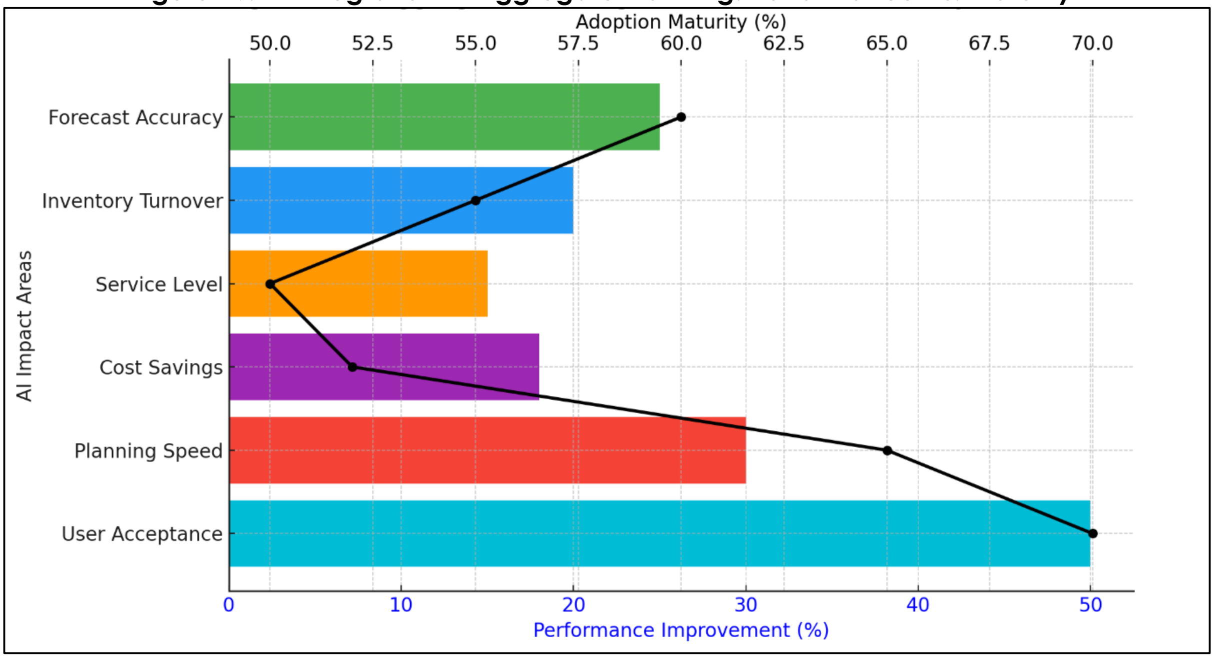
The findings from the eight reviewed case studies reveal clear patterns in how AI technologies are integrated into aggregate planning across industries. While all organizations recognized the potential of AI to improve forecasting, scheduling, and resource allocation, the degree and scope of AI integration varied significantly based on sector, data infrastructure, and organizational readiness. In the manufacturing and automotive sectors, AI was primarily deployed for production scheduling, predictive maintenance, and capacity planning. These industries leveraged machine learning models and reinforcement learning algorithms to enhance throughput, minimize downtime, and align production with fluctuating demand. In contrast, retail case studies showed more advanced deployment of AI for demand forecasting, dynamic pricing, and omnichannel inventory management. Retailers applied real-time analytics to adjust product availability, recommend replenishment, and personalize customer experiences. Pharmaceutical and food sector organizations emphasized AI's role in compliance, traceability, and quality assurance rather than pure cost optimization. Across all eight cases, there was a common trend of AI being used to replace manual, spreadsheet-based planning tools with intelligent decision support systems that offered predictive and prescriptive capabilities. The integration process, however, was often staged—beginning with AI-driven forecasting before extending into scheduling and scenario simulation modules. This sequential adoption reflected cautious investment strategies and the need to build user trust in AI-generated insights. Among the eight case studies, four organizations demonstrated advanced AI maturity, with end-to-end integration of AI models into their enterprise resource planning (ERP) or supply chain management systems. These organizations had robust data infrastructures, including cloud-based data lakes and real-time IoT data streams, enabling advanced analytics and continuous learning. AI models were integrated with digital twins for production simulation, enabling real-time adjustments to aggregate planning outputs. The remaining four case studies, by contrast, exhibited low to moderate maturity, where AI was used only in isolated applications—such as demand forecasting or inventory alerts—without system-wide automation or interoperability. These organizations often relied on external vendors or consultants to implement AI solutions, and internal expertise was limited to basic analytics. The findings also revealed that high AI maturity was correlated with stronger leadership support, ongoing employee training, and a dedicated digital transformation roadmap. In contrast, low-maturity organizations struggled with data silos, legacy IT systems, and resistance from planning teams unfamiliar with AI tools. The disparity in maturity led to variations in AI performance: advanced organizations reported a 20–30% improvement in planning accuracy, while others achieved marginal gains due to poor model calibration or data quality issues. This maturity gap highlights the importance of digital readiness and internal capability development in realizing the full benefits of AI in aggregate planning.

A significant finding across all eight case studies was the measurable improvement in forecast accuracy and the overall quality of planning decisions following AI implementation. Seven of the eight organizations reported that forecast accuracy improved by at least 15% after AI models were deployed, with two organizations achieving over 30% gains in accuracy. This was attributed to the use of machine learning algorithms that could analyze larger datasets, detect nonlinear patterns, and adjust predictions based on external variables such as weather, market trends, and social sentiment. Improved forecasts directly influenced aggregate planning by enabling better alignment of production capacity, labor scheduling, and material

American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

procurement. Decision-making also became more data-driven, with planners relying on dashboards that visualized predictive outputs and scenario comparisons rather than historical averages or managerial intuition. In five of the eight cases, decision speed improved significantly—planners were able to respond to demand shifts or supply disruptions in real time, reducing planning cycles from days to hours. Additionally, AI tools helped quantify trade-offs between cost, service level, and resource utilization, allowing for more balanced and strategic planning decisions. This shift from reactive to proactive planning marked a major advancement in operational agility and supply chain resilience across the reviewed organizations. Despite the performance benefits observed, five of the eight case study organizations reported moderate to high levels of resistance from staff during the early stages of AI integration. Resistance stemmed from fear of job displacement, lack of familiarity with AI tools, and skepticism regarding model outputs. In three cases, planners expressed distrust in AI recommendations, often overriding suggested actions or running parallel manual processes. This behavior delayed full adoption and limited early gains. Organizations that overcame resistance did so through proactive change management initiatives, including workshops, continuous training, and the inclusion of users in the AI model development process. Leadership involvement was also crucial—organizations with strong executive sponsorship reported faster user acceptance and smoother transitions. Moreover, success was linked to the transparency and explainability of AI models. In two advanced cases, AI systems were designed with built-in interpretability, allowing users to trace the reasoning behind each recommendation, which increased trust and reduced friction. Conversely, in cases where models functioned as "black boxes," resistance persisted, and users hesitated to act on unfamiliar insights. This highlights the importance of organizational culture, communication strategies, and technical design choices in managing the human dimension of AI adoption.

Figure 19: AI Integration In Aggregate Planning: Performance Vs. Maturity



The findings also revealed sector-specific constraints and innovations in AI implementation that shaped aggregate planning practices. In the automotive sector, AI was primarily used to support just-in-time (JIT) planning, predictive maintenance, and variant management for multiple vehicle configurations. Organizations relied

Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

heavily on AI simulations to optimize batch sizes, shift schedules, and supply synchronization. In manufacturing, particularly in high-volume industries, AI models were applied to production smoothing and bottleneck prediction. Retailers focused on omnichannel planning, using AI to balance inventory across physical stores and online platforms based on real-time demand and customer behavior. In the food and pharmaceutical sectors, AI was constrained by strict compliance requirements. Here, models were integrated with environmental sensors and quality management systems to track storage conditions, expiration dates, and traceability. In one pharmaceutical case, AI also played a role in GMP audit preparation by analyzing batch records and compliance logs. These sectoral differences influenced model design, training data, and integration workflows. Notably, industries with higher regulatory scrutiny exhibited slower adoption rates and favored more conservative AI use cases. The findings emphasize that while AI is widely applicable, its role and value proposition vary significantly across industry domains, necessitating tailored strategies for implementation.

Data availability and system interoperability emerged as critical enablers—or barriers—in AI-driven aggregate planning. Six of the eight case organizations emphasized the importance of having centralized, clean, and timely data to support AI model training and deployment. Companies with data lakes and real-time IoT feeds achieved faster model convergence and more accurate predictions. In contrast, organizations still operating with fragmented spreadsheets or outdated ERP systems encountered delays, data mismatches, and model failures. Integration with legacy systems was cited as a major hurdle in four cases, where extensive data cleaning and interface development were required before AI systems could function effectively. Furthermore, organizations that lacked historical planning data struggled to train robust models, often relying on third-party datasets or external consultants. In three successful cases, internal data engineering teams collaborated with business analysts to create integrated data pipelines that fed AI models and dashboards. These efforts were resource-intensive but provided long-term scalability and automation. The findings make it clear that technical infrastructure—particularly the ability to consolidate structured and unstructured data—is foundational to effective AI adoption. Without strong data governance and integration strategies, even advanced AI algorithms failed to deliver consistent value.

Across the eight case studies, AI-driven aggregate planning was associated with tangible improvements in operational efficiency, cost savings, and customer satisfaction. Six organizations reported a reduction in stockouts and excess inventory, with average inventory turnover improving by 12–25% after AI implementation. Production planning errors declined, and in three cases, unplanned downtime dropped due to predictive scheduling of maintenance and labor. Four companies experienced a 10–20% increase in service level adherence, attributing this to better demand alignment and faster response to disruptions. Financially, five organizations reported measurable cost savings in procurement, warehousing, or logistics within the first year of AI deployment. Strategic benefits also emerged: executives in four cases described AI tools as critical to achieving digital transformation goals and gaining competitive advantage in planning agility. One retail company used AI-generated insights to redesign its entire replenishment strategy, resulting in a 15% increase in gross margin. In addition to operational metrics, AI also enhanced planning transparency and decision accountability, fostering a more data-driven culture. Overall, the findings demonstrate that AI integration in aggregate planning offers not only performance gains but also strategic alignment with broader organizational goals.

DISCUSSION

The findings of this study confirm that the integration of Artificial Intelligence (AI) in aggregate planning is highly contextual and varies significantly across industries—a trend also observed in prior literature. For instance, Reyes et al. (2020) noted that manufacturing firms tend to prioritize AI for production smoothing and machine utilization, whereas retailers deploy AI more extensively for demand forecasting and customer behavior analysis. This aligns closely with the current study's findings, which reveal industry-specific applications such as omnichannel inventory management in retail and compliance-driven automation in the pharmaceutical sector. Similar to Zawish et al. (2022), the results underscore that organizations often adopt AI in a phased manner, starting with forecasting and later expanding to scheduling and scenario analysis. However, this study adds further depth by illustrating that the pace and scope of AI adoption are influenced not only by technological infrastructure but also by strategic risk tolerance and sectoral regulations. This expands upon previous research by Sharma et al. (2019), which emphasized the technical performance of AI but gave less attention to contextual deployment patterns. Thus, the current study provides more nuanced evidence of how industry context mediates the effectiveness and trajectory of AI integration in aggregate planning.
The maturity disparity observed across the eight case studies in this research echoes the concerns raised by Zawish et al. (2022), who highlighted that many firms implement AI without fully integrating it into their operational backbone. The current study substantiates this by showing that only four out of eight organizations had end-to-end AI integration within their enterprise systems. The rest remained at a low or moderate maturity level, consistent with the diffusion patterns described by Kantasa-ard et al. (2019). These findings also resonate with Wuest, Weimer, Irgens, and Thoben (2016), who identified digital readiness—particularly in terms of IT infrastructure and skilled personnel—as a key determinant of AI adoption success. In organizations where advanced AI capabilities were present, such as cloud-based data lakes and IoT-enabled feedback loops, the benefits in terms of planning accuracy and responsiveness were more pronounced. Conversely, companies still reliant on legacy systems struggled to scale AI solutions, reinforcing the claims made by Liu et al. (2021) that legacy infrastructure is a major barrier to digital transformation. What this study contributes uniquely is an industry-specific contrast that shows how regulatory and operational complexity—not just digital maturity—can inhibit AI system upgrades. In sectors like pharmaceuticals, even technologically capable firms adopted conservative AI strategies due to compliance risks, an insight that adds a new layer to prior generalizations.
The improvement in forecast accuracy and decision-making quality post-AI implementation is consistent with the outcomes reported in earlier studies by Avventuroso et al. (2017) and Mobarakeh et al. (2017). These studies established that machine learning and ensemble methods significantly outperform traditional statistical models in predictive tasks. Similarly, the organizations reviewed in this study reported forecast accuracy gains of 15% to over 30%, validating (Augustine et al., 2018) assertion that AI systems offer high precision in complex, high-variability environments. However, this study expands on prior work by linking improved forecast accuracy directly to enhanced decision-making speed and quality, especially in real-time planning scenarios. Mobarakeh et al. (2017)explored the performance of deep learning models in short-term forecasting but did not examine their organizational impact. The current research shows that enhanced forecast granularity and speed enabled planners to make faster decisions, reduce planning cycle times, and better

Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

balance trade-offs between cost, service, and resource use. This connection between improved forecasting and strategic responsiveness contributes a valuable extension to existing predictive analytics literature, positioning AI not just as a forecasting tool but as a driver of organizational agility.

Resistance to AI adoption, as observed in five of the eight case studies, mirrors the concerns raised by Zawish et al. (2022) and Arshad et al. (2014), who reported skepticism and fear of displacement as common inhibitors. However, this study provides more detailed insight into the underlying factors of such resistance. Unlike prior work that emphasized general resistance, this study found that explainability of AI models and user involvement in system design were key determinants of adoption success. In cases where planners were allowed to co-develop or influence AI tools, trust and usage were significantly higher, supporting the findings of Zawish et al., (2023), who advocated for participatory design in digital transformation. The study also corroborates the argument by Peres et al. (2020) that interpretable AI can bridge the gap between algorithmic output and human decision-making. Moreover, leadership involvement emerged as a significant enabler, in line with observations made by Zawish et al. (2023). The study reinforces the idea that technical excellence alone is insufficient without supportive cultural and managerial frameworks, adding weight to the literature that calls for ethical, transparent, and inclusive AI design.

Sector-specific differences in AI adoption uncovered in this study align with the observations of Liu et al. (2021), who emphasized the need for regulatory-sensitive AI models in heavily governed sectors. The food and pharmaceutical industries in this research were particularly cautious, focusing on quality control and traceability rather than aggressive cost minimization. This supports the view of Raut et al. (2020), who found that AI adoption in regulated environments is shaped more by risk mitigation than by operational performance. In contrast, the automotive and retail sectors exhibited more aggressive AI strategies, consistent with the agile and competitive nature of these industries. The retail sector's focus on dynamic pricing and omnichannel synchronization mirrors findings by Mutalemwa and Shin (2020), while automotive use of AI in variant management and just-in-time (JIT) scheduling validates the studies by Arshad et al. (2014). However, this research uniquely identifies the role of compliance as not just a barrier but a driver for AI use—particularly in pharmaceutical cases where audit readiness and traceability were enhanced using AI tools. This nuanced perspective contributes to the growing call for industry-specific AI research frameworks that respect both operational needs and regulatory constraints.

This study underscores the pivotal role of data infrastructure, echoing the sentiments of Sharma et al. (2019), who emphasized that the performance of AI systems is tightly coupled with the quality and accessibility of data. Organizations with centralized data lakes, real-time sensor integration, and cloud-based platforms experienced smoother AI implementation and better outcomes, supporting the infrastructure-centric findings by Zawish et al. (2022). The current study adds value by identifying interoperability and legacy system integration as critical pain points. Four out of eight organizations reported delays due to incompatible databases, unstructured legacy files, and lack of real-time connectivity. These findings strengthen the arguments of Avventuroso et al. (2017), who noted that AI solutions often fail not due to algorithmic flaws but due to infrastructural constraints. Additionally, the importance of internal data engineering and cross-functional collaboration observed in this study extends the insights of Ahsan and Rahman(2021), who emphasized the need for alignment between data science and business operations. Thus, the study affirms that investments in robust, scalable data pipelines are foundational to effective AI-driven aggregate planning.

The measurable business outcomes reported—ranging from inventory turnover improvement to enhanced gross margins—correspond with previous empirical findings by Augustine et al. (2018), who linked AI adoption to supply chain performance gains. This study substantiates those claims with sector-specific data, showing that organizations experienced reduced planning errors, improved service levels, and increased customer satisfaction. The operationalization of AI-driven forecasts into actionable planning recommendations helped convert theoretical model accuracy into tangible business value, an aspect less emphasized in earlier work. For example, while Avventuroso et al. (2017) highlighted AI's technical potential, this study illustrates how AI insights were used to reconfigure supply chain structures and inventory policies, resulting in measurable financial gains. In line with the observations of Peres et al. (2020), the study found that AI tools were instrumental in enhancing agility, especially in responding to disruptions and recalibrating production plans. The linkage between AI and strategic decision-making also emerged, confirming the transformative potential of AI as suggested by Liu et al. (2021). Therefore, the study extends prior research by bridging the gap between technical implementation and enterprise-wide value realization. In addition, the lack of comparative research frameworks noted in existing literature is directly addressed by this study's cross-industry case design. Prior studies have either been sector-specific or model-centric, such as those by Zawish et al. (2022) or Mobarakeh et al. (2017), without offering cross-sectoral insights. This study's findings suggest that while AI technologies are broadly applicable, their effectiveness, design, and adoption trajectory are deeply shaped by industry-specific drivers. These include regulatory pressures, market dynamics, and digital readiness—all of which influence model interpretability, integration paths, and strategic use. The need for a standardized benchmarking tool or AI readiness model, as proposed by Panda and Mohanty (2023), is reinforced by the discrepancies in maturity and outcomes observed in this study. Thus, this research contributes to filling that gap by outlining the necessity for cross-sectoral frameworks that incorporate technological, organizational, and regulatory dimensions. The findings support the broader argument made by Aggarwal (2019) and Panda and Mohanty (2023) that aggregate planning is no longer a linear, function-based task but a dynamic, multi-dimensional process—one increasingly shaped by intelligent systems and contextual adaptability.

CONCLUSION

This study demonstrates that while Artificial Intelligence (AI) holds transformative potential for aggregate planning across industries, its successful implementation is deeply contingent on sector-specific contexts, digital maturity, organizational culture, and data infrastructure. The multi-case analysis revealed that AI enhances forecasting accuracy, decision-making agility, and resource optimization, yet these benefits are unevenly realized across different industries due to disparities in technological readiness, regulatory environments, and human adaptability. Industries such as manufacturing and automotive have leveraged AI for production scheduling and predictive maintenance, while retail has focused on demand forecasting and omnichannel synchronization, and pharmaceutical and food sectors have prioritized compliance and traceability. The findings highlight the importance of explainable AI models, cross-functional collaboration, and leadership support in overcoming organizational resistance and fostering user acceptance. Moreover, the study underscores the need for robust data ecosystems and integration strategies to fully capitalize on AI capabilities. Despite the observable gains in efficiency, cost savings, and service level improvements, the research also identifies a lack of standardized cross-industry frameworks for assessing AI readiness and impact, thereby calling for the development of comparative models that incorporate operational, technological, and regulatory dimensions. This study contributes to the growing body of knowledge by bridging the gap between AI theory and real-world planning practices, offering practical insights for organizations aiming to adopt AI strategically in their aggregate planning functions.

REFERENCES

[1] Abideen, A. Z., Sundram, V. P. K., Pyeman, J., Othman, A. K., & Sorooshian, S. (2021). Digital Twin Integrated Reinforced Learning in Supply Chain and Logistics. *Logistics*, *5*(4), 84-NA. https://doi.org/10.3390/logistics5040084

[2] Afanasyev, V., Chernyshenko, V., Kuzmin, V., Voronin, V., & Mkrttchian, V. (2021). Advanced information technology for development of electric power market. *The International Journal of Advanced Manufacturing Technology*, *118*(1-2), 119-127. https://doi.org/10.1007/s00170-021-07324-8

[3] Agbemadon, K. B., Couturier, R., & Laiymani, D. (2023). Overstock Prediction Using Machine Learning in Retail Industry. *2023 3rd International Conference on Computer, Control and Robotics (ICCCR)*, *NA*(NA), 439-444. https://doi.org/10.1109/icccr56747.2023.10194060

[4] Aggarwal, S. (2019). A Survey-cum-Tutorial on Approximations to Gaussian ${Q}$ Function for Symbol Error Probability Analysis Over Nakagami- ${m}$ Fading Channels. *IEEE Communications Surveys & Tutorials*, *21*(3), 2195-2223. https://doi.org/10.1109/comst.2019.2907065

[5] Ahmed Marta, L., Mahjoub Omar, S., & Mohammed Namnakani, H. (2023). A Fuzzy Logic Model for FMCG Sector Towards Predicting the Optimal Forecasting Capacity in the Supply Chain: Case Study. *2023 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE)*, *47*(NA), 1-6. https://doi.org/10.1109/csde59766.2023.10487663

[6] Ahmed, S., Ahmed, I., Kamruzzaman, M., & Saha, R. (2022). Cybersecurity Challenges in IT Infrastructure and Data Management: A Comprehensive Review of Threats, Mitigation Strategies, and Future Trend. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology*, *1*(01), 36-61. https://doi.org/10.62304/jieet.v1i01.228

[7] Ahmed, T., Karmaker, C. L., Nasir, S. B., Moktadir, M. A., & Paul, S. K. (2023). Modeling the artificial intelligence-based imperatives of industry 5.0 towards resilient supply chains: A post-COVID-19 pandemic perspective. *Computers & Industrial Engineering*, *177*(NA), 109055-109055. https://doi.org/10.1016/j.cie.2023.109055

[8] Ahsan, K., & Rahman, S. (2021). A systematic review of e-tail product returns and an agenda for future research. *Industrial Management & Data Systems*, *122*(1), 137-166. https://doi.org/10.1108/imds-05-2021-0312

[9] Akbari, M., & Anh, T. N. (2021). A systematic review of machine learning in logistics and supply chain management: current trends and future directions. *Benchmarking: An International Journal*, *28*(10), 2977-3005. https://doi.org/10.1108/bij-10-2020-0514

[10] Aklima, B., Mosa Sumaiya Khatun, M., & Shaharima, J. (2022). Systematic Review of Blockchain Technology In Trade Finance And Banking Security. *American Journal of Scholarly Research and Innovation*, *1*(1), 25-52. https://doi.org/10.63125/vs65vx40

[11] Al-Arafat, M., Kabi, M. E., Morshed, A. S. M., & Sunny, M. A. U. (2024). Geotechnical Challenges In Urban Expansion: Addressing Soft Soil, Groundwater, And Subsurface Infrastructure Risks In Mega Cities. *Innovatech Engineering Journal*, *1*(01), 205-222. https://doi.org/10.70937/itej.v1i01.20

[12] Al-Arafat, M., Kabir, M. E., Dasgupta, A., & Nahid, O. F. (2024). Designing Earthquake-Resistant Foundations: A Geotechnical Perspective On Seismic Load Distribution And Soil-Structure Interaction. *Academic Journal On Science, Technology, Engineering & Mathematics Education*, *4*(04), 19-36. https://doi.org/10.69593/ajsteme.v4i04.119

[13] Al Chami, Z., Manier, H., Manier, M.-A., & Fitouri, C. (2017). A hybrid genetic algorithm to solve a multi-objective Pickup and Delivery Problem. *IFAC-PapersOnLine*, *50*(1), 14656-14661. https://doi.org/10.1016/j.ifacol.2017.08.1906

[14] Alam, M. A., Sohel, A., Hossain, A., Eshra, S. A., & Mahmud, S. (2023). Medical Imaging For Early Cancer Diagnosis And Epidemiology Using Artificial Intelligence: Strengthing National Healthcare Frameworks In The Usa. *American Journal of Scholarly Research and Innovation*, *2*(01), 24-49. https://doi.org/10.63125/matthh09

eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

[15] Alam, M. F. B., Hosen, M. I., Mridha, J. H., Chowdhury, S. E., & Rahman, M. A. (2023). Assessing the barriers of integrating technological innovations in textiles sector: Implications towards sustainable production. *Green Technologies and Sustainability*, *1*(3), 100039-100039. https://doi.org/10.1016/j.grets.2023.100039

[16] Alam, M. J., Rappenglueck, B., Retama, A., & Rivera-Hernández, O. (2024). Investigating the Complexities of VOC Sources in Mexico City in the Years 2016–2022. *Atmosphere*, *15*(2).

[17] Aleem Al Razee, T., Manam, A., & Md Rabbi, K. (2025). Precision Mechanical Systems In Semiconductor Lithography Equipment Design And Development. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 71-97. https://doi.org/10.63125/j6tn8727

[18] Ammar, B., Faria, J., Ishtiaque, A., & Noor Alam, S. (2024). A Systematic Literature Review On AI-Enabled Smart Building Management Systems For Energy Efficiency And Sustainability. *American Journal of Scholarly Research and Innovation*, *3*(02), 01-27. https://doi.org/10.63125/4sjfn272

[19] Arora, S., & Majumdar, A. (2022). Machine learning and soft computing applications in textile and clothing supply chain: Bibliometric and network analyses to delineate future research agenda. *Expert Systems with Applications*, *200*(NA), 117000-117000. https://doi.org/10.1016/j.eswa.2022.117000

[20] Arshad, M., Islam, S., & Khaliq, A. (2014). Fuzzy logic approach in power transformers management and decision making. *IEEE Transactions on Dielectrics and Electrical Insulation*, *21*(5), 2343-2354. https://doi.org/10.1109/tdei.2014.003859

[21] Augustine, V., Hudepohl, J. P., Marcinczak, P., & Snipes, W. (2018). Deploying Software Team Analytics in a Multinational Organization. *IEEE Software*, *35*(1), 72-76. https://doi.org/10.1109/ms.2017.4541044

[22] Avventuroso, G., Silvestri, M., & Pedrazzoli, P. (2017). A Networked Production System to Implement Virtual Enterprise and Product Lifecycle Information Loops. *IFAC-PapersOnLine*, *50*(1), 7964-7969. https://doi.org/10.1016/j.ifacol.2017.08.902

[23] Awan, U., Kanwal, N., Alawi, S., Huiskonen, J., & Dahanayake, A. (2021). Artificial Intelligence for Supply Chain Success in the Era of Data Analytics. In (Vol. NA, pp. 3-21). Springer International Publishing. https://doi.org/10.1007/978-3-030-62796-6_1

[24] Awasthi, A., & Kannan, G. (2016). Green supplier development program selection using NGT and VIKOR under fuzzy environment. *Computers & Industrial Engineering*, *91*(NA), 100-108. https://doi.org/10.1016/j.cie.2015.11.011

[25] Aydin, N. S., & Tirkolaee, E. B. (2022). A systematic review of aggregate production planning literature with an outlook for sustainability and circularity. *Environment, Development and Sustainability*. https://doi.org/10.1007/s10668-022-02304-8

[26] B S, S., & Suresh, M. (2023). A Comprehensive Analysis of Retail Sales Forecasting Using Machine Learning and Deep Learning Methods. *2023 International Conference on Data Science and Network Security (ICDSNS)*, *NA*(NA), 1-5. https://doi.org/10.1109/icdsns58469.2023.10245887

[27] Balaji, T. K., Annavarapu, C. S. R., & Bablani, A. (2021). Machine learning algorithms for social media analysis: A survey. *Computer Science Review*, *40*(NA), 100395-NA. https://doi.org/10.1016/j.cosrev.2021.100395

[28] Baykasoğlu, A., & Gölcük, İ. (2019). A dynamic multiple attribute decision making model with learning of fuzzy cognitive maps. *Computers & Industrial Engineering*, *135*(NA), 1063-1076. https://doi.org/10.1016/j.cie.2019.06.032

[29] Bhattacharyya, S. S., & Nair, S. (2019). Explicating the future of work: perspectives from India. *Journal of Management Development*, *38*(3), 175-194. https://doi.org/10.1108/jmd-01-2019-0032

[30] Bhowmick, D., & Shipu, I. U. (2024). Advances in nanofiber technology for biomedical application: A review. *World Journal of Advanced Research and Reviews*, *22*(1), 1908-1919.

[31] Bhuiyan, S. M. Y., Mostafa, T., Schoen, M. P., & Mahamud, R. (2024). Assessment of Machine Learning Approaches for the Predictive Modeling of Plasma-Assisted Ignition Kernel Growth. ASME 2024 International Mechanical Engineering Congress and Exposition,

[32] Bottani, E., Murino, T., Schiavo, M., & Akkerman, R. (2019). Resilient food supply chain design: Modelling framework and metaheuristic solution approach. *Computers & Industrial Engineering*, *135*(NA), 177-198. https://doi.org/10.1016/j.cie.2019.05.011

[33] Bousqaoui, H., Slimani, I., & Achchab, S. (2021). Comparative analysis of short-term demand predicting models using ARIMA and deep learning. *International Journal of Electrical and Computer Engineering (IJECE)*, *11*(4), 3319-3328. https://doi.org/10.11591/ijece.v11i4.pp3319-3328

[34] Brinch, M. (2018). Understanding the value of big data in supply chain management and its business processes: Towards a conceptual framework. *International Journal of Operations & Production Management*, *38*(7), 1589-1614. https://doi.org/10.1108/ijopm-05-2017-0268

[35] Butt, A. S. (2021). Mitigating the effects of COVID-19: an exploratory case study of the countermeasures taken by the manufacturing industry. *Journal of Business & Industrial Marketing*, *NA*(NA), NA-NA. https://doi.org/10.1108/jbim-04-2021-0236

[36] Cai, Y.-J., & Choi, T.-M. (2020). A United Nations' Sustainable Development Goals perspective for sustainable textile and apparel supply chain management. *Transportation research. Part E, Logistics and transportation review*, *141*(NA), 102010-102010. https://doi.org/10.1016/j.tre.2020.102010

[37] Camaréna, S. (2020). Artificial intelligence in the design of the transitions to sustainable food systems. *Journal of Cleaner Production*, *271*(NA), 122574-NA. https://doi.org/10.1016/j.jclepro.2020.122574

[38] Caniato, F., Henke, M., & Zsidisin, G. A. (2019). Supply chain finance: Historical foundations, current research, future developments. *Journal of Purchasing and Supply Management*, *25*(2), 99-104. https://doi.org/10.1016/j.pursup.2019.02.002

[39] Carrera, D. A., Mayorga, R. V., & Peng, W. (2020). A Soft Computing Approach for group decision making: A supply chain management application. *Applied Soft Computing*, *91*(NA), 106201-NA. https://doi.org/10.1016/j.asoc.2020.106201

[40] Castillo, O., Amador-Angulo, L., Castro, J. R., & García-Valdez, M. (2016). A comparative study of type-1 fuzzy logic systems, interval type-2 fuzzy logic systems and generalized type-2 fuzzy logic systems in control problems. *Information Sciences*, *354*(NA), 257-274. https://doi.org/10.1016/j.ins.2016.03.026

[41] Chari, A., Niedenzu, D., Despeisse, M., Machado, C. G., Azevedo, J. D., Boavida-Dias, R., & Johansson, B. (2022). Dynamic capabilities for circular manufacturing supply chains—Exploring the role of Industry 4.0 and resilience. *Business Strategy and the Environment*, *31*(5), 2500-2517. https://doi.org/10.1002/bse.3040

[42] Chaturvedi, I., Satapathy, R., Cavallari, S., & Cambria, E. (2019). Fuzzy commonsense reasoning for multimodal sentiment analysis. *Pattern Recognition Letters*, *125*(NA), 264-270. https://doi.org/10.1016/j.patrec.2019.04.024

[43] Chidepatil, A., Bindra, P., Kulkarni, D., Qazi, M., Kshirsagar, M., & Sankaran, K. (2020). From Trash to Cash: How Blockchain and Multi-Sensor-Driven Artificial Intelligence Can Transform Circular Economy of Plastic Waste? *Administrative Sciences*, *10*(2), 23-NA. https://doi.org/10.3390/admsci10020023

[44] Choi, T.-M. (2020). Supply chain financing using blockchain: impacts on supply chains selling fashionable products. *Annals of operations research*, *331*(1), 393-415. https://doi.org/10.1007/s10479-020-03615-7

[45] Chowdhury, A., Mobin, S. M., Hossain, M. S., Sikdar, M. S. H., & Bhuiyan, S. M. Y. (2023). Mathematical And Experimental Investigation Of Vibration Isolation Characteristics Of Negative Stiffness System For Pipeline. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology*, *2*(01), 15-32. https://doi.org/10.62304/jieet.v2i01.227

[46] Contreras-Bolton, C., Rey, C., Ramos-Cossio, S., Rodríguez, C., Gatica, F., & Parada, V. (2016). Automatically Produced Algorithms for the Generalized Minimum Spanning Tree Problem. *Scientific Programming*, *2016*(NA), 16-11. https://doi.org/10.1155/2016/1682925

[47] Dasgupta, A., & Islam, M. M., Nahid, Omar Faruq, Rahmatullah, Rafio, . (2024). Engineering Management Perspectives on Safety Culture in Chemical and Petrochemical Plants: A Systematic Review. *Academic Journal On Science, Technology, Engineering & Mathematics Education*, *1*(1), 10.69593.

[48] Demizu, T., Fukazawa, Y., & Morita, H. (2023). Inventory management of new products in retailers using model-based deep reinforcement learning. *Expert Systems with Applications*, *229*(NA), 120256-120256. https://doi.org/10.1016/j.eswa.2023.120256

[49] Dey, N. L., Chowdhury, S., Shipu, I. U., Rahim, M. I. I., Deb, D., & Hasan, M. R. (2024). Electrical properties of Yttrium (Y) doped LaTiO3. *International Journal of Science and Research Archive*, *12*(2), 744-767.

[50] Doyle-Kent, M., & Kopacek, P. (2019). Industry 5.0: Is the Manufacturing Industry on the Cusp of a New Revolution? In (Vol. NA, pp. 432-441). Springer International Publishing. https://doi.org/10.1007/978-3-030-31343-2_38

[51] Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D., Giannakis, M., Foropon, C., Roubaud, D., & Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational

performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *International Journal of Production Economics*, *226*(NA), 107599-NA. https://doi.org/10.1016/j.ijpe.2019.107599

[52] Dutta, P., Choi, T.-M., Somani, S., & Butala, R. (2020). Blockchain technology in supply chain operations: Applications, challenges and research opportunities. *Transportation research. Part E, Logistics and transportation review*, *142*(NA), 102067-NA. https://doi.org/10.1016/j.tre.2020.102067

[53] Dwivedi, S. K., Roy, P., Karda, C., Agrawal, S. L., & Amin, R. (2021). Blockchain-Based Internet of Things and Industrial IoT: A Comprehensive Survey. *Security and Communication Networks*, *2021*(NA), 1-21. https://doi.org/10.1155/2021/7142048

[54] Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J. S., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., . . . Williams, M. D. (2021). Artificial Intelligence (AI) : Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*(NA), 101994-NA. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

[55] Ebinger, F., & Omondi, B. (2020). Leveraging Digital Approaches for Transparency in Sustainable Supply Chains: A Conceptual Paper. *Sustainability*, *12*(15), 6129-NA. https://doi.org/10.3390/su12156129

[56] Erol, B., & Inkaya, T. (2023). Ensemble Deep Transfer Learning Approaches for Sales Forecasting. *Proceedings of the 7th International Conference on Algorithms, Computing and Systems*, *NA*(NA), 60-66. https://doi.org/10.1145/3631908.3631917

[57] Fahimnia, B., Luong, L., & Marian, R. (2011). Genetic algorithm optimisation of an integrated aggregate production–distribution plan in supply chains. *International Journal of Production Research*, *50*(1), 81-96. https://doi.org/10.1080/00207543.2011.571447

[58] Fan, B., & Cai, Y. (2019). AIAM - The Research of Forecasting Model of Automobile Parts Recycling Cost Based on Data Intelligence. *Proceedings of the 2019 International Conference on Artificial Intelligence and Advanced Manufacturing*, *NA*(NA), 1-7. https://doi.org/10.1145/3358331.3358355

[59] Faria, J., & Md Rashedul, I. (2025). Carbon Sequestration in Coastal Ecosystems: A Review of Modeling Techniques and Applications. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 41-70. https://doi.org/10.63125/4z73rb29

[60] Faroukhi, A. Z., Alaoui, I. E., Gahi, Y., & Amine, A. (2020). Big data monetization throughout Big Data Value Chain: a comprehensive review. *Journal of Big Data*, *7*(1), 1-22. https://doi.org/10.1186/s40537-019-0281-5

[61] Fathifazl, G., Razaqpur, A. G., Isgor, O. B., Abbas, A., Fournier, B., & Foo, S. (2011). Creep and drying shrinkage characteristics of concrete produced with coarse recycled concrete aggregate. *Cement and Concrete Composites*, *33*(10), 1026-1037. https://doi.org/10.1016/j.cemconcomp.2011.08.004

[62] Feizabadi, J. (2020). Machine learning demand forecasting and supply chain performance. *International Journal of Logistics Research and Applications*, *25*(2), 119-142. https://doi.org/10.1080/13675567.2020.1803246

[63] Filali, A., Benlahmar, E. H., Lahmer, B., Filali, S. E., Kasbouya, M., Ajouary, M., & Akantous, S. (2022). Machine Learning Applications in Supply Chain Management: A Deep Learning Model Using an Optimized LSTM Network for Demand Forecasting. *International Journal of Intelligent Engineering and Systems*, *15*(2), 464-478. https://doi.org/10.22266/ijies2022.0430.42

[64] Frederico, G. F., Kumar, V., Garza-Reyes, J. A., Kumar, A., & Agrawal, R. (2021). Impact of I4.0 technologies and their interoperability on performance: future pathways for supply chain resilience post-COVID-19. *The International Journal of Logistics Management*, *34*(4), 1020-1049. https://doi.org/10.1108/ijlm-03-2021-0181

[65] Galvez-Martos, J.-L., Styles, D., Schoenberger, H., & Zeschmar-Lahl, B. (2018). Construction and demolition waste best management practice in Europe. *Resources, Conservation and Recycling*, *136*(NA), 166-178. https://doi.org/10.1016/j.resconrec.2018.04.016

[66] Geerts, G. L., & O'Leary, D. E. (2014). A supply chain of things: The EAGLET ontology for highly visible supply chains. *Decision Support Systems*, *63*(NA), 3-22. https://doi.org/10.1016/j.dss.2013.09.007

[67] Ghazali, I., Abdul-Rashid, S. H., Dawal, S. Z. M., Aoyama, H., Sakundarini, N., Ho, F. H., & Herawan, S. G. (2021). Green product preferences considering cultural influences: a comparison study between Malaysia and Indonesia. *Management of Environmental Quality: An International Journal*, *32*(5), 1040-1063. https://doi.org/10.1108/meq-11-2020-0245

[68] Gonçalves, J. N. C., Cortez, P., Carvalho, M. S., & Frazão, N. M. (2021). A multivariate approach for multi-step demand forecasting in assembly industries: Empirical evidence from an automotive supply chain. *Decision Support Systems*, *142*(NA), 113452-NA. https://doi.org/10.1016/j.dss.2020.113452

[69] Govindan, K., Jafarian, A., Khodaverdi, R., & Devika, K. (2014). Two-echelon multiple-vehicle location-routing problem with time windows for optimization of sustainable supply chain network of perishable food. *International Journal of Production Economics*, *152*(152), 9-28. https://doi.org/10.1016/j.ijpe.2013.12.028

[70] Govindan, K., Khodaverdi, R., & Jafarian, A. (2013). A fuzzy multi criteria approach for measuring sustainability performance of a supplier based on triple bottom line approach. *Journal of Cleaner Production*, *47*(NA), 345-354. https://doi.org/10.1016/j.jclepro.2012.04.014

[71] Grover, P., Kar, A. K., & Dwivedi, Y. K. (2020). Understanding artificial intelligence adoption in operations management: insights from the review of academic literature and social media discussions. *Annals of operations research*, *308*(1-2), 177-213. https://doi.org/10.1007/s10479-020-03683-9

[72] Gupta, N., Tiwari, A., Bukkapatnam, S. T. S., & Karri, R. (2020). Additive Manufacturing Cyber-Physical System: Supply Chain Cybersecurity and Risks. *IEEE Access*, *8*(NA), 47322-47333. https://doi.org/10.1109/access.2020.2978815

[73] Hamdan, I. K. A., Aziguli, W., Zhang, D., & Sumarliah, E. (2023). Machine learning in supply chain: prediction of real-time e-order arrivals using ANFIS. *International Journal of System Assurance Engineering and Management*, *14*(S1), 549-568. https://doi.org/10.1007/s13198-022-01851-7

[74] Hannan, M. A., Begum, R. A., Al-Shetwi, A. Q., Ker, P. J., Al Mamun, A., Hussain, A., Basri, H., & Mahlia, T. M. I. (2020). Waste collection route optimisation model for linking cost saving and emission reduction to achieve sustainable development goals. *Sustainable Cities and Society*, *62*(NA), 102393-NA. https://doi.org/10.1016/j.scs.2020.102393

[75] Haoud, N. E., & Bachiri, Z. (2019). Stochastic Artificial Intelligence benefits and Supply Chain Management inventory prediction. *2019 International Colloquium on Logistics and Supply Chain Management (LOGISTIQUA)*, *NA*(NA), 1-5. https://doi.org/10.1109/logistiqua.2019.8907271

[76] Hasan, Z., Haque, E., Khan, M. A. M., & Khan, M. S. (2024). Smart Ventilation Systems For Real-Time Pollution Control: A Review Of Ai-Driven Technologies In Air Quality Management. *Frontiers in Applied Engineering and Technology*, *1*(01), 22-40. https://doi.org/10.70937/faet.v1i01.4

[77] Hayles, M., Sanchez, L. F. M., & Noël, M. (2018). Eco-efficient low cement recycled concrete aggregate mixtures for structural applications. *Construction and Building Materials*, *169*(NA), 724-732. https://doi.org/10.1016/j.conbuildmat.2018.02.127

[78] Helal, A. M. (2022). State Of Indigenous Cultural Practices And Role Of School Curriculum: A Case Study Of The Garo Community In Bangladesh. *Available at SSRN 5061810*.

[79] Helal, A. M. (2024). Unlocking Untapped Potential: How Machine Learning Can Bridge the Gifted Identification Gap (2024).

[80] Helal, A. M., Wai, J., Parra-Martinez, A., McKenzie, S., & Seaton, D. (2025). Widening the Net: How CogAT and ACT Aspire Compare in Gifted Identification.

[81] Hendrickson, B. A., Wang, W., Ball, G., Bennett, D., Bhattacharyya, A., Fries, M., Kuebler, J., Kurek, R., McShea, C., & Tremmel, L. (2021). Aggregate Safety Assessment Planning for the Drug Development Life-Cycle. *Therapeutic innovation & regulatory science*, *55*(4), 717-732. https://doi.org/10.1007/s43441-021-00271-2

[82] Hohn, M. M., & Durach, C. F. (2021). Additive manufacturing in the apparel supply chain — impact on supply chain governance and social sustainability. *International Journal of Operations & Production Management*, *41*(7), 1035-1059. https://doi.org/10.1108/ijopm-09-2020-0654

[83] Hong, J., Liao, Y., Zhang, Y., & Yu, Z. (2019). The effect of supply chain quality management practices and capabilities on operational and innovation performance: Evidence from Chinese manufacturers. *International Journal of Production Economics*, *212*(NA), 227-235. https://doi.org/10.1016/j.ijpe.2019.01.036

[84] Hossain, A., Khan, M. R., Islam, M. T., & Islam, K. S. (2024). Analyzing The Impact Of Combining Lean Six Sigma Methodologies With Sustainability Goals. *Journal of Science and Engineering Research*, *1*(01), 123-144. https://doi.org/10.70008/jeser.v1i01.57

[85] Hossain, M. R., Mahabub, S., & Das, B. C. (2024). The role of AI and data integration in enhancing data protection in US digital public health an empirical study. *Edelweiss Applied Science and Technology*, *8*(6), 8308-8321.

[86] Hsu, C.-H., Li, M.-G., Zhang, T.-Y., Chang, A.-Y., Shangguan, S.-Z., & Liu, W.-L. (2022). Deploying Big Data Enablers to Strengthen Supply Chain Resilience to Mitigate Sustainable Risks Based on

Integrated HOQ-MCDM Framework. *Mathematics*, *10*(8), 1233-1233. https://doi.org/10.3390/math10081233

[87] Islam, M. M., Prodhan, R. K., Shohel, M. S. H., & Morshed, A. S. M. (2025). Robotics and Automation in Construction Management Review Focus: The application of robotics and automation technologies in construction. *Journal of Next-Gen Engineering Systems*, *2*(01), 48-71. https://doi.org/10.70937/jnes.v2i01.63

[88] Islam, M. M., Shofiullah, S., Sumi, S. S., & Shamim, C. M. A. H. (2024). Optimizing HVAC Efficiency And Reliability: A Review Of Management Strategies For Commercial And Industrial Buildings. *Academic Journal On Science, Technology, Engineering & Mathematics Education*, *4*(04), 74-89. https://doi.org/10.69593/ajsteme.v4i04.129

[89] Islam, M. N., & Helal, A. M. (2018). Primary school governance in Bangladesh: A practical overview of national education policy-2010. *International Journal for Cross-Disciplinary Subjects in Education (IJCDSE)*, *9*(4).

[90] Islam, M. T. (2024). A Systematic Literature Review On Building Resilient Supply Chains Through Circular Economy And Digital Twin Integration. *Frontiers in Applied Engineering and Technology*, *1*(01), 304-324. https://doi.org/10.70937/faet.v1i01.44

[91] Islam, M. T., Islam, K. S., Hossain, A., & Khan, M. R. (2025). Reducing Operational Costs in U.S. Hospitals Through Lean Healthcare And Simulation-Driven Process Optimization. *Journal of Next-Gen Engineering Systems*, *2*(01), 11-28. https://doi.org/10.70937/jnes.v2i01.50

[92] Jahan, F. (2023). Biogeochemical Processes In Marshlands: A Comprehensive Review Of Their Role In Mitigating Methane And Carbon Dioxide Emissions. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology*, *2*(01), 33-59. https://doi.org/10.62304/jieet.v2i01.230

[93] Jahan, F. (2024). A Systematic Review Of Blue Carbon Potential in Coastal Marshlands: Opportunities For Climate Change Mitigation And Ecosystem Resilience. *Frontiers in Applied Engineering and Technology*, *2*(01), 40-57. https://doi.org/10.70937/faet.v2i01.52

[94] Jain, N. K., & Singh, A. R. (2020). Sustainable supplier selection under must-be criteria through Fuzzy inference system. *Journal of Cleaner Production*, *248*(NA), 119275-NA. https://doi.org/10.1016/j.jclepro.2019.119275

[95] Javaid, M., Haleem, A., Singh, R. P., Suman, R., & Gonzalez, E. S. (2022). Understanding the adoption of Industry 4.0 technologies in improving environmental sustainability. *Sustainable Operations and Computers*, *3*(NA), 203-217. https://doi.org/10.1016/j.susoc.2022.01.008

[96] Jia, T., Jing, Z., & Hong, M. (2019). A Genetic Algorithm for the Two-Echelon Vehicle Routing Problem with Simultaneous Pickup and Delivery. *2019 IEEE 1st International Conference on Civil Aviation Safety and Information Technology (ICCASIT)*, *NA*(NA), 283-287. https://doi.org/10.1109/iccasit48058.2019.8973006

[97] Jim, M. M. I., Hasan, M., & Munira, M. S. K. (2024). The Role Of AI In Strengthening Data Privacy For Cloud Banking. *Frontiers in Applied Engineering and Technology*, *1*(01), 252-268. https://doi.org/10.70937/faet.v1i01.39

[98] Joseph, R. V., Mohanty, A., Tyagi, S., Mishra, S., Satapathy, S. K., & Mohanty, S. N. (2022). A hybrid deep learning framework with CNN and Bi-directional LSTM for store item demand forecasting. *Computers and Electrical Engineering*, *103*(NA), 108358-108358. https://doi.org/10.1016/j.compeleceng.2022.108358

[99] Jung, H.-S., & Park, S. (2020). A Study on the Deep Learning based Prediction of Production Demand by using LSTM under the State of Data Sparsity. *IOP Conference Series: Materials Science and Engineering*, 926(1), 012031-NA. https://doi.org/10.1088/1757-899x/926/1/012031

[100] Kamal, E., Abdel-Gawad, A. F. A., Ibraheem, B., & Zaki, S. (2023). Machine Learning Fusion and Data Analytics Models for Demand Forecasting in the Automotive Industry: A Comparative Study. *Fusion: Practice and Applications*, *12*(1), 24-37. https://doi.org/10.54216/fpa.120102

[101] Kannan, G., Sasikumar, P., & Devika, K. (2010). A genetic algorithm approach for solving a closed loop supply chain model: A case of battery recycling. *Applied Mathematical Modelling*, *34*(3), 655-670. https://doi.org/10.1016/j.apm.2009.06.021

[102] Kantasa-ard, A., Bekrar, A., Cadi, A. A. E., & Sallez, Y. (2019). Artificial intelligence for forecasting in supply chain management: a case study of White Sugar consumption rate in Thailand. *IFAC-PapersOnLine*, *52*(13), 725-730. https://doi.org/10.1016/j.ifacol.2019.11.201

[103] Kargar, S., Paydar, M. M., & Safaei, A. S. (2020). A reverse supply chain for medical waste: A case study in Babol healthcare sector. *Waste management (New York, N.Y.)*, *113*(NA), 197-209. https://doi.org/10.1016/j.wasman.2020.05.052

[104] Katsaliaki, K., Galetsi, P., & Kumar, S. (2021). Supply chain disruptions and resilience: a major review and future research agenda. *Annals of operations research*, *319*(1), 1-38. https://doi.org/10.1007/s10479-020-03912-1

[105] Kazancoglu, I., Ozbiltekin-Pala, M., Mangla, S. K., Kumar, A., & Kazancoglu, Y. (2022). Using emerging technologies to improve the sustainability and resilience of supply chains in a fuzzy environment in the context of COVID-19. *Annals of operations research*, *322*(1), 217-240. https://doi.org/10.1007/s10479-022-04775-4

[106] Khan, M. A. M. (2025). AI And Machine Learning in Transformer Fault Diagnosis: A Systematic Review. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 290-318. https://doi.org/10.63125/sxb17553

[107] Khan, M. A. M., & Aleem Al Razee, T. (2024). Lean Six Sigma Applications In Electrical Equipment Manufacturing: A Systematic Literature Review. *American Journal of Interdisciplinary Studies*, *5*(02), 31- 63. https://doi.org/10.63125/hybvmw84

[108] Kim, J. (2021). Construction and demolition waste management in Korea: recycled aggregate and its application. *Clean Technologies and Environmental Policy*, *23*(8), 2223-2234. https://doi.org/10.1007/s10098-021-02177-x

[109] Klashanov, F. (2018). Fuzzy logic in construction management. *MATEC Web of Conferences*, *170*(NA), 01111-NA. https://doi.org/10.1051/matecconf/201817001111

[110] Koç, E., & Turkoglu, M. (2021). Forecasting of medical equipment demand and outbreak spreading based on deep long short-term memory network: the COVID-19 pandemic in Turkey. *Signal, image and video processing*, *16*(3), 1-9. https://doi.org/10.1007/s11760-020-01847-5

[111] Kumar, A., & Nayyar, A. (2019). si 3 -Industry: A Sustainable, Intelligent, Innovative, Internet-of-Things Industry. In (Vol. NA, pp. 1-21). Springer International Publishing. https://doi.org/10.1007/978-3-030-14544-6_1

[112] Kumar, S., Sharma, D., Rao, S., Lim, W. M., & Mangla, S. K. (2022). Past, present, and future of sustainable finance: insights from big data analytics through machine learning of scholarly research. *Annals of operations research*, *345*(2-3), 1-1104. https://doi.org/10.1007/s10479-021-04410-8

[113] Li, B., Wang, H., Yang, J.-B., & Guo, M. (2013). A belief-rule-based inference method for aggregate production planning under uncertainty. *International Journal of Production Research*, *51*(1), 83-105. https://doi.org/10.1080/00207543.2011.652262

[114] Li, G., Yuan, C., Kamarthi, S., Moghaddam, M. E., & Jin, X. (2021). Data science skills and domain knowledge requirements in the manufacturing industry: A gap analysis. *Journal of Manufacturing Systems*, *60*(NA), 692-706. https://doi.org/10.1016/j.jmsy.2021.07.007

[115] Liu, Y., Ma, X., Shu, L., Hancke, G. P., & Abu-Mahfouz, A. M. (2021). From Industry 4.0 to Agriculture 4.0: Current Status, Enabling Technologies, and Research Challenges. *IEEE Transactions on Industrial Informatics*, *17*(6), 4322-4334. https://doi.org/10.1109/tii.2020.3003910

[116] Liu, Z., Chua, D. K. H., & Yeoh, K.-W. (2011). Aggregate production planning for shipbuilding with variation-inventory trade-offs. *International Journal of Production Research*, *49*(20), 6249-6272. https://doi.org/10.1080/00207543.2010.527388

[117] Lu, W., & Yuan, H. (2010). Exploring critical success factors for waste management in construction projects of China. *Resources, Conservation and Recycling*, *55*(2), 201-208. https://doi.org/10.1016/j.resconrec.2010.09.010

[118] Lynch, P. C., Hasbrouck, C., Wilck, J., Kay, M. G., & Manogharan, G. (2020). Challenges and opportunities to integrate the oldest and newest manufacturing processes: metal casting and additive manufacturing. *Rapid Prototyping Journal*, *26*(6), 1145-1154. https://doi.org/10.1108/rpj-10-2019-0277

[119] Ma, X., Li, M., Tong, J., & Feng, X. (2023). Deep Learning Combinatorial Models for Intelligent Supply Chain Demand Forecasting. *Biomimetics (Basel, Switzerland)*, *8*(3), 312-312. https://doi.org/10.3390/biomimetics8030312

[120] Machado, C. G., Winroth, M., & da Silva, E. R. (2019). Sustainable manufacturing in Industry 4.0: an emerging research agenda. *International Journal of Production Research*, *58*(5), 1462-1484. https://doi.org/10.1080/00207543.2019.1652777

[121] Maddikunta, P. K. R., Pham, Q.-V., Prabadevi, B., Deepa, N., Dev, K., Gadekallu, T. R., Ruby, R., & Liyanage, M. (2022). Industry 5.0: A survey on enabling technologies and potential applications. *Journal of Industrial Information Integration*, *26*(NA), 100257-NA. https://doi.org/10.1016/j.jii.2021.100257

eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

[122] Mahabub, S., Das, B. C., & Hossain, M. R. (2024). Advancing healthcare transformation: AI-driven precision medicine and scalable innovations through data analytics. *Edelweiss Applied Science and Technology*, *8*(6), 8322-8332.

[123] Mahabub, S., Jahan, I., Hasan, M. N., Islam, M. S., Akter, L., Musfiqur, M., Foysal, R., & Onik, M. K. R. (2024). Efficient detection of tomato leaf diseases using optimized Compact Convolutional Transformers (CCT) Model.

[124] Mahabub, S., Jahan, I., Islam, M. N., & Das, B. C. (2024). The Impact of Wearable Technology on Health Monitoring: A Data-Driven Analysis with Real-World Case Studies and Innovations. *Journal of Electrical Systems*, *20*.

[125] Mahdy, I. H., Roy, P. P., & Sunny, M. A. U. (2023). Economic Optimization of Bio-Crude Isolation from Faecal Sludge Derivatives. *European Journal of Advances in Engineering and Technology*, *10*(10), 119-129.

[126] Malik, A., Budhwar, P., & Srikanth, N. R. (2020). Gig Economy, 4IR and Artificial Intelligence: Rethinking Strategic HRM. In (Vol. NA, pp. 75-88). Emerald Publishing Limited. https://doi.org/10.1108/978-1-83867-223-220201005

[127] Mamede, F. P., da Silva, R. F., de Brito Junior, I., Yoshizaki, H. T. Y., Hino, C. M., & Cugnasca, C. E. (2023). Deep Learning and Statistical Models for Forecasting Transportation Demand: A Case Study of Multiple Distribution Centers. *Logistics*, *7*(4), 86-86. https://doi.org/10.3390/logistics7040086

[128] Mandičák, T., Mésároš, P., Kanáliková, A., & Špak, M. (2021). Supply Chain Management and Big Data Concept Effects on Economic Sustainability of Building Design and Project Planning. *Applied Sciences*, *11*(23), 11512-11512. https://doi.org/10.3390/app112311512

[129] Maniruzzaman, B., Mohammad Anisur, R., Afrin Binta, H., Md, A., & Anisur, R. (2023). Advanced Analytics And Machine Learning For Revenue Optimization In The Hospitality Industry: A Comprehensive Review Of Frameworks. *American Journal of Scholarly Research and Innovation*, *2*(02), 52-74. https://doi.org/10.63125/8xbkma40

[130] Md Mahfuj, H., Md Rabbi, K., Mohammad Samiul, I., Faria, J., & Md Jakaria, T. (2022). Hybrid Renewable Energy Systems: Integrating Solar, Wind, And Biomass for Enhanced Sustainability And Performance. *American Journal of Scholarly Research and Innovation*, *1*(1), 1-24. https://doi.org/10.63125/8052hp43

[131] Md Takbir Hossen, S., Ishtiaque, A., & Md Atiqur, R. (2023). AI-Based Smart Textile Wearables For Remote Health Surveillance And Critical Emergency Alerts: A Systematic Literature Review. *American Journal of Scholarly Research and Innovation*, *2*(02), 1-29. https://doi.org/10.63125/ceqapd08

[132] Md, W., Md Zahin Hossain, G., Md Tarek, H., Md Khorshed, A., Mosa Sumaiya Khatun, M., & Noor Alam, S. (2025). Assessing The Influence of Cybersecurity Threats And Risks On The Adoption And Growth Of Digital Banking: A Systematic Literature Review. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 226-257. https://doi.org/10.63125/fh49gz18

[133] Md. Rafiqul Islam, R., Iva, M. J., Md Merajur, R., & Md Tanvir Hasan, S. (2024, 2024/01/25). Investigating Modern Slavery in the Post-Pandemic Textile and Apparel Supply Chain: An Exploratory Study. International Textile and Apparel Association Annual Conference Proceedings,

[134] Meherishi, L., Narayana, S. A., & Ranjani, K. S. (2019). Sustainable packaging for supply chain management in the circular economy: A review. *Journal of Cleaner Production*, *237*(NA), 117582-NA. https://doi.org/10.1016/j.jclepro.2019.07.057

[135] Mezghani, M., Loukil, T., & Aouni, B. (2012). Aggregate planning through the imprecise goal programming model: integration of the manager's preferences. *International Transactions in Operational Research*, *19*(4), 581-597. https://doi.org/10.1111/j.1475-3995.2012.00844.x

[136] Mobarakeh, N. A., Shahzad, M. K., Baboli, A., & Tonadre, R. (2017). Improved Forecasts for uncertain and unpredictable Spare Parts Demand in Business Aircraft's with Bootstrap Method. *IFAC-PapersOnLine*, *50*(1), 15241-15246. https://doi.org/10.1016/j.ifacol.2017.08.2379

[137] Mohammad Shahadat Hossain, S., Md Shahadat, H., Saleh Mohammad, M., Adar, C., & Sharif Md Yousuf, B. (2024). Advancements In Smart and Energy-Efficient HVAC Systems: A Prisma-Based Systematic Review. *American Journal of Scholarly Research and Innovation*, *3*(01), 1-19. https://doi.org/10.63125/ts16bd22

[138] Mohammadi, M., & Rezaei, J. (2020). Bayesian best-worst method: A probabilistic group decision making model. *Omega*, *96*(NA), 102075-NA. https://doi.org/10.1016/j.omega.2019.06.001

[139] Monteleone, G., Di Natale, R., Conca, P., Biondi, S. M., Intilisano, A. R., Catania, V., & Panno, D. (2015). DEXA (1) - A Decision Support System for Hotel Facilities Inventory Management. In (Vol. NA, pp. 460-470). Springer International Publishing. https://doi.org/10.1007/978-3-319-22849-5_31

[140] Moroff, N. U., Kurt, E., & Kamphues, J. (2021). Machine Learning and Statistics: A Study for assessing innovative Demand Forecasting Models. *Procedia Computer Science*, *180*(NA), 40-49. https://doi.org/10.1016/j.procs.2021.01.127

[141] Mosa Sumaiya Khatun, M., Shaharima, J., & Aklima, B. (2025). Artificial Intelligence in Financial Customer Relationship Management: A Systematic Review of AI-Driven Strategies in Banking and FinTech. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 20-40. https://doi.org/10.63125/gy32cz90

[142] Mridha Younus, S. H., amp, & Md Morshedul, I. (2024). Advanced Business Analytics in Textile & Fashion Industries: Driving Innovation And Sustainable Growth. *International Journal of Management Information Systems and Data Science*, *1*(2), 37-47. https://doi.org/10.62304/ijmisds.v1i2.143

[143] Mridha Younus, S. H. P. M. R. A. I. T., amp, & Rajae, O. (2024). Sustainable Fashion Analytics: Predicting The Future of Eco-Friendly Textile. *Global Mainstream Journal of Business, Economics, Development & Project Management*, *3*(03), 13-26. https://doi.org/10.62304/jbedpm.v3i03.85

[144] Muhammad Mohiul, I., Morshed, A. S. M., Md Enamul, K., & Md, A.-A. (2022). Adaptive Control Of Resource Flow In Construction Projects Through Deep Reinforcement Learning: A Framework For Enhancing Project Performance In Complex Environments. *American Journal of Scholarly Research and Innovation*, *1*(01), 76-107. https://doi.org/10.63125/gm77xp11

[145] Mukhopadhyay, S., Waterhouse, B., & Hartford, A. (2018). Bayesian detection of potential risk using inference on blinded safety data. *Pharmaceutical statistics*, *17*(6), 823-834. https://doi.org/10.1002/pst.1898

[146] Mukhuty, S., Upadhyay, A., & Rothwell, H. (2022). Strategic sustainable development of Industry 4.0 through the lens of social responsibility: The role of human resource practices. *Business Strategy and the Environment*, *31*(5), 2068-2081. https://doi.org/10.1002/bse.3008

[147] Munira, M. S. K. (2025). Digital Transformation in Banking: A Systematic Review Of Trends, Technologies, And Challenges. *Strategic Data Management and Innovation*, *2*(01), 78-95. https://doi.org/10.71292/sdmi.v2i01.12

[148] Mutalemwa, L. C., & Shin, S. (2020). A Classification of the Enabling Techniques for Low Latency and Reliable Communications in 5G and Beyond: AI-Enabled Edge Caching. *IEEE Access*, *8*(NA), 205502-205533. https://doi.org/10.1109/access.2020.3037357

[149] Nahid, O. F., Rahmatullah, R., Al-Arafat, M., Kabir, M. E., & Dasgupta, A. (2024). Risk mitigation strategies in large scale infrastructure project:a project management perspective. *Journal of Science and Engineering Research*, *1*(01), 21-37. https://doi.org/10.70008/jeser.v1i01.38

[150] Nassar, M., Salah, K., Rehman, M. H. u., & Svetinovic, D. (2019). Blockchain for explainable and trustworthy artificial intelligence. *WIREs Data Mining and Knowledge Discovery*, *10*(1), NA-NA. https://doi.org/10.1002/widm.1340

[151] Nasseri, M., Falatouri, T., Brandtner, P., & Darbanian, F. (2023). Applying Machine Learning in Retail Demand Prediction—A Comparison of Tree-Based Ensembles and Long Short-Term Memory-Based Deep Learning. *Applied Sciences*, *13*(19), 11112-11112. https://doi.org/10.3390/app131911112

[152] Nassibi, N., Fasihuddin, H., & Hsairi, L. (2023). Demand Forecasting Models for Food Industry by Utilizing Machine Learning Approaches. *International Journal of Advanced Computer Science and Applications*, *14*(3), NA-NA. https://doi.org/10.14569/ijacsa.2023.01403101

[153] Naz, F., Agrawal, R., Kumar, A., Gunasekaran, A., Majumdar, A., & Luthra, S. (2022). Reviewing the applications of artificial intelligence in sustainable supply chains: Exploring research propositions for future directions. *Business Strategy and the Environment*, *31*(5), 2400-2423. https://doi.org/10.1002/bse.3034

[154] Ni, D., Xiao, Z., & Lim, M. K. (2019). A systematic review of the research trends of machine learning in supply chain management. *International Journal of Machine Learning and Cybernetics*, *11*(7), 1463-1482. https://doi.org/10.1007/s13042-019-01050-0

[155] O'Sullivan, S., Nevejans, N., Allen, C., Blyth, A., Leonard, S., Pagallo, U., Holzinger, K., Holzinger, A., Sajid, M. I., & Ashrafian, H. (2019). Legal, regulatory, and ethical frameworks for development of standards in artificial intelligence (AI) and autonomous robotic surgery. *The international journal of medical robotics + computer assisted surgery : MRCAS*, *15*(1), e1968-NA. https://doi.org/10.1002/rcs.1968

eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

[156] Olan, F., Liu, S., Suklan, J., Jayawickrama, U., & Arakpogun, E. O. (2021). The role of Artificial Intelligence networks in sustainable supply chain finance for food<i>and drink industry</i>. *International Journal of Production Research*, *60*(14), 4418-4433. https://doi.org/10.1080/00207543.2021.1915510

[157] Oroojlooyjadid, A., Nazari, M., Snyder, L. V., & Takáč, M. (2022). A Deep Q-Network for the Beer Game: Deep Reinforcement Learning for Inventory Optimization. *Manufacturing & Service Operations Management*, *24*(1), 285-304. https://doi.org/10.1287/msom.2020.0939

[158] Özkan, G., & İnal, M. (2014). Comparison of neural network application for fuzzy and ANFIS approaches for multi-criteria decision making problems. *Applied Soft Computing*, *24*(NA), 232-238. https://doi.org/10.1016/j.asoc.2014.06.032

[159] Panda, S. K., & Mohanty, S. N. (2023). Time Series Forecasting and Modeling of Food Demand Supply Chain Based on Regressors Analysis. *IEEE Access*, *11*(NA), 42679-42700. https://doi.org/10.1109/access.2023.3266275

[160] Pandey, V. K., Bisoy, S., & Panda, S. (2023). Time Series Forecasting and Prediction of Walmart Data using Hybrid Machine Learning Techniques. *2023 1st International Conference on Circuits, Power and Intelligent Systems (CCPIS)*, *NA*(NA), 1-5. https://doi.org/10.1109/ccpis59145.2023.10291333

[161] Park, S.-W. (2017). Improvement of National Waste Statistics. *Journal of Korea Society of Waste Management*, *34*(5), 431-441. https://doi.org/10.9786/kswm.2017.34.5.431

[162] Patel, D., Shah, S., & Chhinkaniwala, H. (2019). Fuzzy logic based multi document summarization with improved sentence scoring and redundancy removal technique. *Expert Systems with Applications*, *134*(NA), 167-177. https://doi.org/10.1016/j.eswa.2019.05.045

[163] Peidro, D., Mula, J., Jiménez, M., & del Mar Botella, M. (2010). A fuzzy linear programming based approach for tactical supply chain planning in an uncertainty environment. *European Journal of Operational Research*, *205*(1), 65-80. https://doi.org/10.1016/j.ejor.2009.11.031

[164] Peres, R. S., Jia, X., Lee, J., Sun, K., Colombo, A. W., & Barata, J. (2020). Industrial Artificial Intelligence in Industry 4.0 - Systematic Review, Challenges and Outlook. *IEEE Access*, *8*(NA), 220121-220139. https://doi.org/10.1109/access.2020.3042874

[165] Pournader, M., Shi, Y., Seuring, S., & Koh, S. C. L. (2019). Blockchain applications in supply chains, transport and logistics : a systematic review of the literature. *International Journal of Production Research*, *58*(7), 2063-2081. https://doi.org/10.1080/00207543.2019.1650976

[166] Punia, S., Singh, S. P., & Madaan, J. (2020). A cross-temporal hierarchical framework and deep learning for supply chain forecasting. *Computers & Industrial Engineering*, *149*(NA), 106796-NA. https://doi.org/10.1016/j.cie.2020.106796

[167] R, K., Kayathwal, K., Dhama, G., & Arora, A. (2021). IJCNN - A Survey on Classical and Deep Learning based Intermittent Time Series Forecasting Methods. *2021 International Joint Conference on Neural Networks (IJCNN)*, *NA*(NA), 1-7. https://doi.org/10.1109/ijcnn52387.2021.9533963

[168] Rafiei, H., Rabbani, M., & Alimardani, M. (2013). Novel bi-level hierarchical production planning in hybrid MTS/MTO production contexts. *International Journal of Production Research*, *51*(5), 1331-1346. https://doi.org/10.1080/00207543.2012.661089

[169] Rasmi, S. A. B., Kazan, C., & Turkay, M. (2019). A multi-criteria decision analysis to include environmental, social, and cultural issues in the sustainable aggregate production plans. *Computers & Industrial Engineering*, *132*(NA), 348-360. https://doi.org/10.1016/j.cie.2019.04.036

[170] Raut, R. D., Gotmare, A., Narkhede, B. E., Govindarajan, U. H., & Bokade, S. U. (2020). Enabling Technologies for Industry 4.0 Manufacturing and Supply Chain: Concepts, Current Status, and Adoption Challenges. *IEEE Engineering Management Review*, *48*(2), 83-102. https://doi.org/10.1109/emr.2020.2987884

[171] Reyes, P. M., Visich, J. K., & Jaska, P. (2020). Managing the Dynamics of New Technologies in the Global Supply Chain. *IEEE Engineering Management Review*, *48*(1), 156-162. https://doi.org/10.1109/emr.2020.2968889

[172] Roh, S., Kim, R., Park, W.-J., & Ban, H. (2020). Environmental Evaluation of Concrete Containing Recycled and By-Product Aggregates Based on Life Cycle Assessment. *Applied Sciences*, *10*(21), 7503-NA. https://doi.org/10.3390/app10217503

[173] Roksana, H. (2023). Automation In Manufacturing: A Systematic Review Of Advanced Time Management Techniques To Boost Productivity. *American Journal of Scholarly Research and Innovation*, *2*(01), 50-78. https://doi.org/10.63125/z1wmcm42

Volume 01 Issue 01 (2025)
Page No: 382-437
eISSN: 3067-0470
DOI: 10.63125/3jdpkd14

[174] Roksana, H., Ammar, B., Noor Alam, S., & Ishtiaque, A. (2024). Predictive Maintenance in Industrial Automation: A Systematic Review Of IOT Sensor Technologies And AI Algorithms. *American Journal of Interdisciplinary Studies*, *5*(01), 01-30. https://doi.org/10.63125/hd2ac988

[175] Rolf, B., Jackson, I., Müller, M., Lang, S., Reggelin, T., & Ivanov, D. (2022). A review on reinforcement learning algorithms and applications in supply chain management. *International Journal of Production Research*, *61*(20), 7151-7179. https://doi.org/10.1080/00207543.2022.2140221

[176] Roy, P. P., Abdullah, M. S., & Sunny, M. A. U. (2024). Revolutionizing Structural Engineering: Innovations in Sustainable Design and Construction. *European Journal of Advances in Engineering and Technology*, *11*(5), 94-99.

[177] Rožanec, J. M., Kažič, B., Škrjanc, M., Fortuna, B., & Mladenic, D. (2021). Automotive OEM Demand Forecasting: A Comparative Study of Forecasting Algorithms and Strategies. *Applied Sciences*, *11*(15), 6787-NA. https://doi.org/10.3390/app11156787

[178] Sabid, A. M., & Kamrul, H. M. (2024). Computational And Theoretical Analysis On The Single Proton Transfer Process In Adenine Base By Using DFT Theory And Thermodynamics. *IOSR Journal of Applied Chemistry*.

[179] Salah, K., Rehman, M. H. U., Nizamuddin, N., & Al-Fuqaha, A. (2019). Blockchain for AI: Review and Open Research Challenges. *IEEE Access*, *7*(NA), 10127-10149. https://doi.org/10.1109/access.2018.2890507

[180] Sanayei, A., Mousavi, S. F., & Yazdankhah, A. (2010). Group decision making process for supplier selection with VIKOR under fuzzy environment. *Expert Systems with Applications*, *37*(1), 24-30. https://doi.org/10.1016/j.eswa.2009.04.063

[181] Sanders, N. R., Boone, T., Ganeshan, R., & Wood, J. D. (2019). Sustainable Supply Chains in the Age of AI and Digitization: Research Challenges and Opportunities. *Journal of Business Logistics*, *40*(3), 229-240. https://doi.org/10.1111/jbl.12224

[182] Sanjay Raja, S., Maurus Maria Rubenson, A., & Sankaradass, V. (2023). Evaluating the Effectiveness of Reinforcement Learning in Optimizing Supply Chain Management for Dynamic Demand Forecasting. *2023 International Conference on Data Science, Agents & Artificial Intelligence (ICDSAAI)*, *NA*(NA), 1-6. https://doi.org/10.1109/icdsaai59313.2023.10452542

[183] Sgantzos, K., & Grigg, I. (2019). Artificial Intelligence Implementations on the Blockchain. Use Cases and Future Applications. *Future Internet*, *11*(8), 170-NA. https://doi.org/10.3390/fi11080170

[184] Shahan, A., Anisur, R., & Md, A. (2023). A Systematic Review Of AI And Machine Learning-Driven IT Support Systems: Enhancing Efficiency And Automation In Technical Service Management. *American Journal of Scholarly Research and Innovation*, *2*(02), 75-101. https://doi.org/10.63125/fd34sr03

[185] Sharif, K. S., Uddin, M. M., & Abubakkar, M. (2024, 17-19 Dec. 2024). NeuroSignal Precision: A Hierarchical Approach for Enhanced Insights in Parkinson's Disease Classification. 2024 International Conference on Intelligent Cybernetics Technology & Applications (ICICyTA),

[186] Sharma, P. K., Kumar, N., & Park, J. H. (2019). Blockchain-Based Distributed Framework for Automotive Industry in a Smart City. *IEEE Transactions on Industrial Informatics*, *15*(7), 4197-4205. https://doi.org/10.1109/tii.2018.2887101

[187] Sharma, R., Shishodia, A., Gunasekaran, A., Min, H., & Munim, Z. H. (2022). The role of artificial intelligence in supply chain management: mapping the territory. *International Journal of Production Research*, *60*(24), 7527-7550. https://doi.org/10.1080/00207543.2022.2029611

[188] Shen, B., Dong, C., & Ng, C. T. (2021). Technology-Driven Supply Chain Management with OR Applications in Industrial 4.0 Era. *Asia-Pacific Journal of Operational Research*, 39(1), 2102003-NA. https://doi.org/10.1142/s0217595921020036

[189] Shimul, A. I., Haque, M. M., Ghosh, A., Sunny, M. A. U., Aljazzar, S. O., Al-Humaidi, J. Y., & Mukhrish, Y. E. (2025). Hydrostatic Pressure-Driven Insights into Structural, Electronic, Optical, and Mechanical Properties of A3PCl3 (A = Sr, Ba) Cubic Perovskites for Advanced Solar Cell Applications. *Journal of Inorganic and Organometallic Polymers and Materials*. https://doi.org/10.1007/s10904-025-03629-3

[190] Shipley, M. F., Johnson, M., Pointer, L., & Yankov, N. (2013). A fuzzy attractiveness of market entry (FAME) model for market selection decisions. *Journal of the Operational Research Society*, *64*(4), 597-610. https://doi.org/10.1057/jors.2012.59

[191] Shohel, M. S. H., Islam, M. M., Prodhan, R. K., & Morshed, A. S. M. (2024). Lifecycle Management Of Renewable Energy Systems In Residential Housing Construction. *Frontiers in Applied Engineering and Technology*, *1*(01), 124-138. https://doi.org/10.70937/faet.v1i01.23

[192] Sillekens, T., Koberstein, A., & Suhl, L. (2011). Aggregate production planning in the automotive industry with special consideration of workforce flexibility. *International Journal of Production Research*, *49*(17), 5055-5078. https://doi.org/10.1080/00207543.2010.524261

[193] Silva, R. V., de Brito, J., & Dhir, R. K. (2017). Availability and processing of recycled aggregates within the construction and demolition supply chain: A review. *Journal of Cleaner Production*, *143*(NA), 598-614. https://doi.org/10.1016/j.jclepro.2016.12.070

[194] Sobb, T. M., Turnbull, B., & Moustafa, N. (2020). Supply Chain 4.0: A Survey of Cyber Security Challenges, Solutions and Future Directions. *Electronics*, *9*(11), 1864-NA. https://doi.org/10.3390/electronics9111864

[195] Sodhi, M. S., Seyedghorban, Z., Tahernejad, H., & Samson, D. (2022). Why emerging supply chain technologies initially disappoint: Blockchain, IoT, and AI. *Production and Operations Management*, *31*(6), 2517-2537. https://doi.org/10.1111/poms.13694

[196] Sohel, A., Alam, M. A., Hossain, A., Mahmud, S., & Akter, S. (2022). Artificial Intelligence In Predictive Analytics For Next-Generation Cancer Treatment: A Systematic Literature Review Of Healthcare Innovations In The USA. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology*, *1*(01), 62-87. https://doi.org/10.62304/jieet.v1i01.229

[197] Sohel, R. (2025). AI-Driven Fault Detection and Predictive Maintenance In Electrical Power Systems: A Systematic Review Of Data-Driven Approaches, Digital Twins, And Self-Healing Grids. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 258-289. https://doi.org/10.63125/4p25x993

[198] Soofi, A. A., & Awan, A. (2017). Classification Techniques in Machine Learning: Applications and Issues. *Journal of Basic & Applied Sciences*, *13*(NA), 459-465. https://doi.org/10.6000/1927-5129.2017.13.76

[199] Sousa, M. J., & Wilks, D. C. (2018). Sustainable skills for the world of work in the digital age. *Systems Research and Behavioral Science*, *35*(4), 399-405. https://doi.org/10.1002/sres.2540

[200] Stadtler, H., & Kilger, C. (2010). *Supply Chain Management and Advanced Planning: Concepts, Models, Software, and Case Studies* (Vol. NA). NA. https://doi.org/NA

[201] Stanisławski, R., & Szymonik, A. (2021). Impact of Selected Intelligent Systems in Logistics on the Creation of a Sustainable Market Position of Manufacturing Companies in Poland in the Context of Industry 4.0. *Sustainability*, *13*(7), 3996-NA. https://doi.org/10.3390/su13073996

[202] Tam, V. W. Y., & Tam, C. M. (2007). Assessment of durability of recycled aggregate concrete produced by two-stage mixing approach. *Journal of Materials Science*, *42*(10), 3592-3602. https://doi.org/10.1007/s10853-006-0379-y

[203] Tao, F., Zuo, Y., Da Xu, L., & Zhang, L. (2014). IoT-Based Intelligent Perception and Access of Manufacturing Resource Toward Cloud Manufacturing. *IEEE Transactions on Industrial Informatics*, *10*(2), 1547-1557. https://doi.org/10.1109/tii.2014.2306397

[204] Thapa, C., & Camtepe, S. (2020). Precision health data: Requirements, challenges and existing techniques for data security and privacy. *Computers in biology and medicine*, *129*(NA), 104130-NA. https://doi.org/10.1016/j.compbiomed.2020.104130

[205] Tonoy, A. A. R. (2022). Mechanical Properties and Structural Stability of Semiconducting Electrides: Insights For Material. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology*, *1*(01), 18-35. https://doi.org/10.62304/jieet.v1i01.225

[206] Tonoy, A. A. R., & Khan, M. R. (2023). The Role of Semiconducting Electrides In Mechanical Energy Conversion And Piezoelectric Applications: A Systematic Literature Review. *American Journal of Scholarly Research and Innovation*, *2*(1), 01-23. https://doi.org/10.63125/patvqr38

[207] Torabi, S. A., Ebadian, M., & Tanha, R. (2010). Fuzzy hierarchical production planning (with a case study). *Fuzzy Sets and Systems*, *161*(11), 1511-1529. https://doi.org/10.1016/j.fss.2009.11.006

[208] Tran, T. X., Hajisami, A., Pandey, P., & Pompili, D. (2017). Collaborative Mobile Edge Computing in 5G Networks: New Paradigms, Scenarios, and Challenges. *IEEE Communications Magazine*, *55*(4), 54-61. https://doi.org/10.1109/mcom.2017.1600863

[209] Tsolakis, N., Keramydas, C., Toka, A., Aidonis, D., & Iakovou, E. (2014). Agrifood supply chain management: A comprehensive hierarchical decision-making framework and a critical taxonomy. *Biosystems Engineering*, *120*(NA), 47-64. https://doi.org/10.1016/j.biosystemseng.2013.10.014

[210] Tsolakis, N., Niedenzu, D., Simonetto, M., Dora, M., & Kumar, M. (2021). Supply Network Design to Address United Nations Sustainable Development Goals: A Case Study of Blockchain Implementation in Thai Fish Industry. *Journal of Business Research*, *131*(NA), 495-519. https://doi.org/10.1016/j.jbusres.2020.08.003

[211] Uddin Shipu, I., Bhowmick, D., & Lal Dey, N. (2024). Development and applications of flexible piezoelectric nanogenerators using BaTiO3, PDMS, and MWCNTs for energy harvesting and sensory integration in smart systems. *International Journal of Scientific and Research Publications*, *14*(6), 221.

[212] Vasili, M., Tang, S. H., & Vasili, M. (2012). Automated Storage and Retrieval Systems: A Review on Travel Time Models and Control Policies. In (Vol. NA, pp. 159-209). Springer London. https://doi.org/10.1007/978-1-4471-2274-6_8

[213] Venkatesh, V. G., Zhang, A., Deakins, E., Luthra, S., & Mangla, S. K. (2018). A fuzzy AHP-TOPSIS approach to supply partner selection in continuous aid humanitarian supply chains. *Annals of operations research*, *283*(1), 1517-1550. https://doi.org/10.1007/s10479-018-2981-1

[214] Villar, A., Paladini, S., & Buckley, O. (2023). Towards Supply Chain 5.0: Redesigning Supply Chains as Resilient, Sustainable, and Human-Centric Systems in a Post-pandemic World. *Operations Research Forum*, *4*(3), NA-NA. https://doi.org/10.1007/s43069-023-00234-3

[215] Wanchoo, K. (2019). Retail Demand Forecasting: a Comparison between Deep Neural Network and Gradient Boosting Method for Univariate Time Series. *2019 IEEE 5th International Conference for Convergence in Technology (I2CT)*, *NA*(NA), 1-5. https://doi.org/10.1109/i2ct45611.2019.9033651

[216] Wang, Y., Wang, X., & Liu, A. (2020). Digital Twin-driven Supply Chain Planning. *Procedia CIRP*, *93*(NA), 198-203. https://doi.org/10.1016/j.procir.2020.04.154

[217] Wen, R., & Yan, W. (2019). Supply–Demand Prediction for Agile Manufacturing with Deep Neural Network. *Smart and Sustainable Manufacturing Systems*, *3*(2), 95-105. https://doi.org/10.1520/ssms20190025

[218] Yakovleva, N., Sarkis, J., & Sloan, T. W. (2012). Sustainable benchmarking of supply chains: the case of the food industry. *International Journal of Production Research*, *50*(5), 1297-1317. https://doi.org/10.1080/00207543.2011.571926

[219] Yalcin Kavus, B., Ayyildiz, E., Gulum Tas, P., & Taskin, A. (2022). A hybrid Bayesian BWM and Pythagorean fuzzy WASPAS-based decision-making framework for parcel locker location selection problem. *Environmental science and pollution research international*, *30*(39), 90006-90023. https://doi.org/10.1007/s11356-022-23965-y

[220] Yan, E., & Ding, Y. (2012). Scholarly network similarities: How bibliographic coupling networks, citation networks, cocitation networks, topical networks, coauthorship networks, and coword networks relate to each other. *Journal of the American Society for Information Science and Technology*, *63*(7), 1313-1326. https://doi.org/10.1002/asi.22680

[221] Yang, W.-S., Park, J. K., Park, S.-W., & Seo, Y.-C. (2014). Past, present and future of waste management in Korea. *Journal of Material Cycles and Waste Management*, *17*(2), 207-217. https://doi.org/10.1007/s10163-014-0301-7

[222] Yeheyis, M., Hewage, K., Alam, M. S., Eskicioglu, C., & Sadiq, R. (2012). An overview of construction and demolition waste management in Canada: a lifecycle analysis approach to sustainability. *Clean Technologies and Environmental Policy*, *15*(1), 81-91. https://doi.org/10.1007/s10098-012-0481-6

[223] Younus, M. (2022). Reducing Carbon Emissions in The Fashion And Textile Industry Through Sustainable Practices and Recycling: A Path Towards A Circular, Low-Carbon Future. *Global Mainstream Journal of Business, Economics, Development & Project Management*, *1*(1), 57-76. https://doi.org/10.62304/jbedpm.v1i1.226

[224] Younus, M. (2025). The Economics of A Zero-Waste Fashion Industry: Strategies To Reduce Wastage, Minimize Clothing Costs, And Maximize & Sustainability. *Strategic Data Management and Innovation*, *2*(01), 116-137. https://doi.org/10.71292/sdmi.v2i01.15

[225] Yuan, W.-J., Chen, J.-H., Cao, J., & Jin, Z.-Y. (2018). ICMLC - Forecast Of Logistics Demand Based On Grey Deep Neural Network Model. *2018 International Conference on Machine Learning and Cybernetics (ICMLC)*, *1*(NA), 251-256. https://doi.org/10.1109/icmlc.2018.8527006

[226] Zawish, M., Ashraf, N., Ansari, R. I., & Davy, S. (2023). Energy-Aware AI-Driven Framework for Edge-Computing-Based IoT Applications. *IEEE Internet of Things Journal*, *10*(6), 5013-5023. https://doi.org/10.1109/jiot.2022.3219202

[227] Zawish, M., Ashraf, N., Ansari, R. I., Davy, S., Qureshi, H. K., Aslam, N., & Hassan, S. A. (2022). Toward On-Device AI and Blockchain for 6G-Enabled Agricultural Supply Chain Management. *IEEE Internet of Things Magazine*, *5*(2), 160-166. https://doi.org/10.1109/iotm.006.21000112

[228] Zhan, Y., & Tan, K. H. (2020). An analytic infrastructure for harvesting big data to enhance supply chain performance. *European Journal of Operational Research*, *281*(3), 559-574. https://doi.org/10.1016/j.ejor.2018.09.018

[229] Zhao, J., Zhao, W., Deng, B., Wang, Z., Zhang, F., Zheng, W., Cao, W., Nan, J., Lian, Y., & Burke, A. F. (2024). Autonomous driving system: A comprehensive survey. *Expert Systems with Applications*, *242*(NA), 122836-122836. https://doi.org/10.1016/j.eswa.2023.122836

[230] Zupic, I., & Čater, T. (2014). Bibliometric Methods in Management and Organization. *Organizational Research Methods*, *18*(3), 429-472. https://doi.org/10.1177/1094428114562629