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AI-Based Decision Support Systems in Industry 4.0, A Review

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Abstract: The development of modern technologies such as the Internet of Things (IoT), cloud computing, and artificial intelligence (AI) resulted in a new era of industrial automation and data interchange, which is known as Industry 4.0. AI-based decision support systems (DSS) play a crucial role in this paradigm by enhancing the integration and processing of IoT and sensor data to optimize operations, improve productivity, and enable predictive maintenance. Machine learning models analyze production data and visual inspections to identify defects and ensure product quality. This review paper explores the transformative role of AI in enhancing DSS within Industry 4.0, highlighting key technologies including machine learning, deep learning, and natural language processing. It explores a number of applications, including supply chain optimization, energy management, predictive maintenance, quality control, and production planning, showing how AI-driven DSS can significantly boost operational dependability, cut costs, and improve efficiency. The article also discusses the AI-based DSS's architecture and implementation, with a focus on data management, user interface design, and IoT integration. Furthermore, it examines the challenges related to data quality, technical integration, and human factors, offering potential solutions and strategies for effective deployment. The study highlights the continued development of AI technologies and their potential to support autonomous decision-making in industrial settings by identifying new trends and areas for further research. This comprehensive review aims to provide valuable insights for researchers and practitioners, fostering a deeper understanding of the capabilities and future potential of AI-based DSS in Industry 4.0.

Keywords: AI-Based Decision Support Systems, Industry 4.0

1. Introduction

The integration of cutting-edge digital technology into industrial processes heralds a disruptive age known as Industry 4.0, or the Fourth Industrial Revolution (Hassoun et al. 2023). The convergence of cyber-physical systems, cloud computing, artificial intelligence (AI), and the Internet of Things (IoT) is at the center of this transformation. These technologies are changing the face of supply chain management, manufacturing, and logistics. In this context, Artificial Intelligence (AI) has been used by Decision Support Systems (DSS) to improve decision-making across a range of industrial applications (Gupta et al. 2022). The idea of intelligent, networked systems with the ability to independently optimize supply chains, manufacturing procedures, and overall operational efficiency is at the core of this shift. AI in Decision DSS is one of the key technologies propelling this transformation. The significance of making intelligent judgments has grown due to the fast advancement of Industry 4.0, characterized by the amalgamation of digital and physical systems (Borangiu et al. 2020). AI-Based DSS have emerged as critical tools that aid organizations in making informed and strategic decisions. These systems harness the power of artificial intelligence to process large volumes of data, recognize patterns, and generate actionable insights, thus transforming the decision-making landscape across various industrial sectors (Braun et al. 2021). The integration of AI into DSS is central to this shift, providing previously unheard-of capacities for data analysis, significant insight extraction, and the facilitation of well-informed decision-making processes. Utilizing AI-based DSS becomes strategically imperative as companies navigate challenging operational challenges and seek to grasp novel opportunities in order to enhance competitiveness, efficacy, and flexibility (Perifanis and Kitsios 2023). AI-Based DDS represent a transformative force within Industry 4.0, offering unparalleled capabilities to enhance operational efficiency, quality control, supply chain management, and risk mitigation (Burggräf et al. 2020; Kasie, Bright, and Walker 2017). Despite the challenges, the continuous advancement of AI technologies promises to further revolutionize industrial decision-making processes (Kasie, Bright, and Walker 2017; Anbalagan and Moreno-Garcia 2021).

Industry 4.0's AI-based DSS are a major development as they give businesses sophisticated tools to evaluate enormous volumes of data, extract useful insights, and make choices quickly (Gupta et al. 2021). Traditional decision support systems sometimes find it difficult to handle the massive volumes of heterogeneous data streams and the dynamic character of modern industrial settings, even when they function effectively on their own (H. Wang et al. 2016). While still valuable, classic DSS occasionally rely on static models and pre-established rules that don't adapt to the complex and dynamic industrial environments of today (Raptis, Passarella, and Conti 2019; Srinivasan et al. 2024). On the other hand, AI-based DSS make use of Natural Language Processing (NLP), Machine Learning (ML), and Deep Learning (DL) to continually learn from data, forecast future trends, and improve processes with never-before-seen accuracy and efficiency (Demirkan and Delen 2013; D'Cruze et al. 2023). By automating complex decision-making tasks, AI-based DSS not only improve efficiency and productivity, but also adapt to changing conditions and learn from historical data to continuously refine their recommendations (Lebedev 2022; Nicodeme 2020).

Industry 4.0's AI-based DSS are transforming industries by fusing cutting-edge technology to improve decision-making. The Internet of Things (IoT), big data analytics, and cyber-physical systems are all integrated into manufacturing and industrial processes as part of Industry 4.0, or the fourth industrial revolution (Mehedi et al. 2024). Because AI-based DSS can handle large volumes of data and deliver insights that can be put to use, they are essential in this environment (Kaklauskas and Kaklauskas 2015). The incorporation of AI with DSS has the potential to revolutionize several industrial domains (S. Liu et al. 2010). In predictive maintenance, for example, AI systems may evaluate sensor data to anticipate equipment breakdowns, limiting downtime and lowering maintenance expenses. AI improves demand forecasting, inventory optimization, and logistics planning in supply chain management, creating more robust and effective supply networks (Nica and Stehel 2021). Moreover, real-time defect detection is possible with AI-powered quality control systems, guaranteeing improved product uniformity and quality (Khinvasara, Ness, and Shankar 2024). Supply chain data analysis powered by AI enhances logistical planning, inventory control, and demand forecasting. AI systems optimize utilization by analyzing trends in energy consumption, which helps save costs and promote sustainability (Pająk, Patalas-Maliszewska, and Pająk 2021).

AI-based decision support systems are intended to help human decision-makers by sifting through massive amounts of data, seeing trends, and offering useful insights (Antoniadi et al. 2021). These technologies are essential to Industry 4.0 in a number of areas, including supply chain management, production optimization, quality control, and predictive maintenance (Arunkumar 2024; Pejić Bach et al. 2023). AI can analyze massive amounts of data at very quick speeds, enabling timely analysis and the creation of insights in real time (Dingli, Haddod, and Klüver 2021). Ultimately, this leads to decision-making processes that are faster and more efficient, especially when many process elements are automatable (Bharadiya 2023). AI simplifies tedious and repetitive activities in decision-making processes, freeing up human capital to focus on more complex and strategic problems (Andargoli et al. 2024; Al-

Surmi, Bashiri, and Koliousis 2022). Moreover, AI's computational power allows for the exploration of complex interdependencies among various risk factors, providing a more comprehensive understanding of the overall risk landscape (Shah et al. 2023). By automating the analysis process, AI streamlines decision-making and helps prioritize actions based on the severity and likelihood of risks. Furthermore, AI's capabilities extend to predictive modeling, enabling organizations to anticipate future risks and proactively implement mitigation strategies (Skulimowski and Lydek 2022). In order to ensure business improvement and lessen the effect of possible threats during working conditions, a proactive strategy is essential. While human comprehension can be hindered by the complexities of data processing, AI streamlines this process by utilizing advanced algorithms and computational methods. (Leung et al. 2015). Through the integration of AI computer science methodologies, researchers and practitioners can unlock actionable insights from data that would otherwise remain hidden or overlooked (Srinivasan et al. 2024; Dilsizian and Siegel 2014).

Decision-makers can employ the updated information to evaluate risks, pinpoint weaknesses, create efficient mitigation plans, and reduce any potential drawbacks. AI technologies can help auditors and risk managers in ensuring that they are using more data than just the evidence that they have independently discovered (Council et al. 2006). By utilizing the power of data-driven insights, AI essentially enables decision-makers to make more strategic and informed decisions on risk management (Resende, Geraldes, and Junior 2021). By embracing AI technology in risk assessment and mitigation planning, organizations can enhance their resilience, agility, and ability to thrive in an ever-changing environment (Heilig and Scheer 2023). As industries increasingly adopt digital transformation strategies, it becomes essential for stakeholders to comprehend the role and potential of AI-based DSS. This understanding is critical for them to fully leverage the advantages offered by Industry 4.0 technologies, which integrate advanced automation, data exchange, and manufacturing technologies. By recognizing how AI-based DSS can optimize decision-making processes and improve operational efficiency, stakeholders can maximize the benefits of these cutting-edge technological advancements (Bhadra, Chakraborty, and Saha 2023; Felsberger, Oberegger, and Reiner 2016). Main components of a decision support system is shown in the figure 1 (Stanescu and Filip 2011).

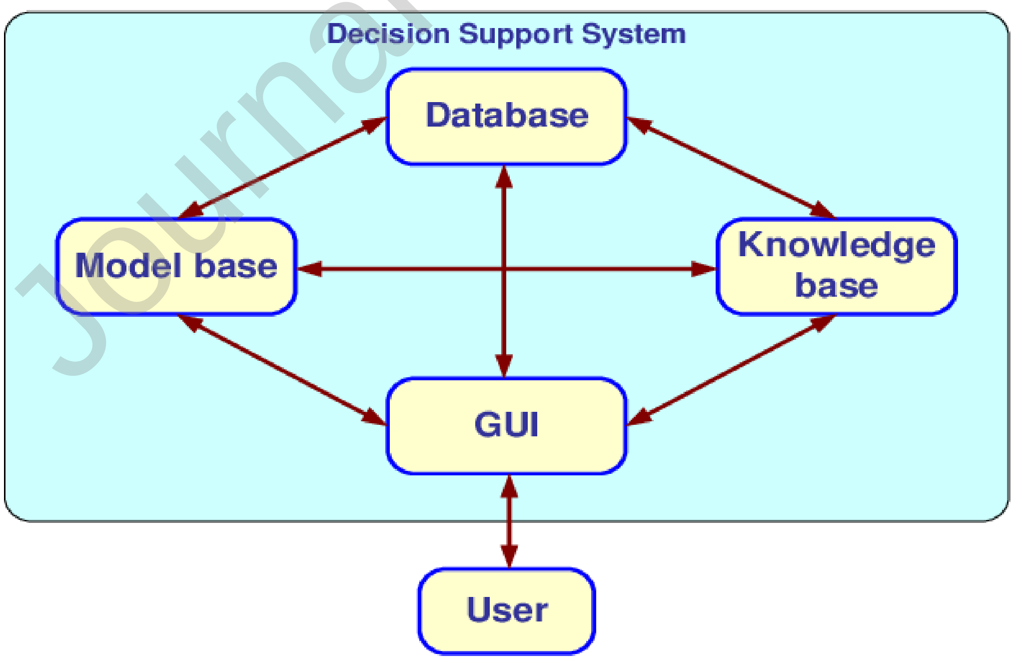

Fig. 1. Main components of a decision support system (Stanescu and Filip 2011).

Karimi Ghaleh Jough and Şensoy (Jough and Şensoy 2016) introduced meta-heuristic methods to estimate the bursting risk of mid-rise steel tension frame buildings, hence improving risk management in concrete moment frames. Using the FCM-PSO Method, Karimi Ghaleh Jough and Şensoy (Karimi Ghaleh Jough and Şensoy 2020) examined Steel Moment-Resisting Frame Dependability via Interval Analysis to improve accuracy and save execution time while computing siesmic fragility curves. With the aid of finite element models, Karimi Ghaleh Jough and Golhashem (Karimi Ghaleh Jough and Golhashem 2020) investigated the out-of-plane motion of ad hoc brick structures, and found that walls built with the lightest masonry components currently on the market had less self-weight axial distortion. Karimi Ghaleh Jough and Beheshti Aval (Karimi Ghaleh Jough and Beheshti Aval 2018) developed an adaptive neuro-fuzzy inference framework using the fuzzy C-means method to construct the seismic sensitivity curve for an SMRF structure. As a result, computation accuracy was raised and epistemic uncertainty was incorporated. Ghasemzadeh et al. (Ghasemzadeh et al. 2022) explored the characteristics that characterize and situate infrastructure projects in order to highlight and demonstrate the current drawbacks of employing BIM for infrastructure projects. Unlike the previously described methods, the unpredictable nature of epistemic knowledge employing a group-based data processing approach, Karimi Ghaleh Jough et al. (Karimi Ghaleh Jough, Veghar, and Beheshti-Aval 2021) exploited vulnerabilities in order to increase power and output precision while maintaining the same processing time. The goal of this inquiry was to use optimal fuzzy approaches, which were designed to decrease execution time and increase precision while driving the 3D-fragility curved. In order to reduce environmental contamination throughout the manufacturing process, sustainable CNC machining operations is studied by Soori et al. (Soori, Jough, et al. 2024b). Soori and Karimi Ghaleh Jough (Soori and Jough) assess the application of artificial intelligence to steel moment frame construction optimization to enhance these structures' operational performance. Karimi Ghaleh Jough and Ghasemzadeh (JOUGH and GHASEMZADEH) have developed SMRF reliability prediction, which is based on the integration of incremental dynamic analysis and neural networks, with the aim of enhancing performance through the reduction of random variability in steel structures. Karimi Ghaleh Jough (Karimi Ghaleh Jough 2023) examines the impact of steel wallposts on the out-of-plane behavior of non-structural concrete walls in an effort to create wallposts for masonry walls with fewer adjustment parts. Karimi Ghaleh Jough and Ghasemzadeh (Karimi Ghaleh Jough and Ghasemzadeh 2023) provided the foundation for constructing a 3D-fragility curvature in order to assess the unknown interval of steel at that instant. The goal of this inquiry was to use optimal fuzzy approaches, which were designed to decrease execution time and increase precision while driving the 3D-fragility curvature. Karimi Ghaleh Jough (Soori, Dastres, et al. 2024) utilizes a metaheuristic algorithm to predict the danger of seismic collapse in steel moment framed buildings, which improves the performance of these structures. In order to examine and assess the most current developments in artificial intelligence applications for the optimization of steel moment frame structures, a study of the modification of steel moment frame structures is offered by Soori and Karimi Ghaleh Jough (Soori and Jough 2024a; Jough 2016).

Soori et al. (Soori, Dastres, et al. 2024) examined ways to increase industrial productivity using smart robots systems 4.0. To increase performances of sustainable supply chain management of industry 4.0, applications of blockchains for industrial internet of things is reviewed by Soori et al. (Soori, Jough, et al. 2024a). To enhance productivity in CNC machining operations, Soori et al. (Soori et al. 2023) studied the applications of robotical automation.

Soori et al. (Soori, Arezoo, and Habibi 2017, 2014, 2013, 2016; Soori, Jough, and Arezoo 2024) recommended virtual machining methods for improving and assessing CNC machining in virtual settings. Soori et al. (Soori, Asmael, and Solyalı 2020) provided a summary of the most current developments in friction stir welding methods in order to assess and enhance welding process performance during component manufacturing. Soori (Soori 2019) offered virtual innovation in an effort to better understand and investigate the part creation process in virtual environments. In order to assess and eliminate surface roughness and residual stress during EDM machining processes, optimized machining parameters are obtained by Soori and Karimi Ghaleh Jough (Soori and Jough 2024b). Soori et al. (Soori, Arezoo, and Dastres 2023a) Explore recent advances in the literature to assess and improve how artificial intelligence, deep learning, and machine learning affect sophisticated robots. A survey of current developments from released works is carried out by Soori (Soori 2023a) to study and alter composite materials and structures. Soori et al. (Soori, Arezoo, and Dastres 2023b) are researching AI to develop supply chain management in high-tech manufacturing. In order to increase the lifespan of the cutters used in machining operations, Soori and Arezoo (Soori and Arezoo 2022) looked into an array of methods for predicting tool wear. To analyze and enhance the performances pf virtual machining systems in machining operations, different methods of virtual machining is reviewed by Soori and Arezoo

(Soori and Arezoo 2020). Virtual manufacturing in industry 4.0 is studied by Soori et al. (Soori, Arezoo, and Dastres 2023e) to enhance the performances of virtual simulation in advanced manufacturing process. To enhance the accuracy of five-axis milling operations for turbine blades, Soori (Soori 2023b) evaluates and rectifies deformation defects. Soori and Arezoo (Soori and Arezoo 2023d) looked at the application of the finite element approach in CNC machine tool modification in order to evaluate and enhance the accuracy of CNC machining processes and parts. To evaluate and enhance industrial robots' energy usage, several energy consumption optimization strategies were examined by Soori et al. Soori et al. (Soori, Arezoo, and Dastres 2023d).

Soori and Arezoo (Soori and Arezoo 2023b) examined the effects of coolant on the cutting the outside temperature, tool utilize, and roughness of the surface during the turning of Ti6Al4V material. Soori et al. (Soori, Arezoo, and Dastres 2023c) explored methods to increase industry quality control and optimize part production processes in smart factories of industry 4.0 with the application of IoT. In order to lessen the amount of damage that occurs on drilling instruments, Soori and Arezoo (Soori and Arezoo 2023a) proposed a virtual machining. Soori and Arezoo (Soori and Arezoo 2023c) decreased roughness of the surface and residual stress to improve the total quality of the product created by abrasive water jet cutting.

To enhance the battery management of the next generation of electric aircraft, Raoofi and Yildiz (Raoofi and Yildiz 2023) examined battery state estimation techniques using machine learning for airplane propulsion battery battery management systems. Raoofi and Yasar (Raoofi and Yasar 2023) examine cutting-edge digital technologies in ongoing airworthiness management frameworks and apps to provide light on the existing state of the interaction between maintenance procedures and the digital world, as well as to draw attention to the untapped potential for digital change in aviation maintenance.

While numerous studies discuss the benefits of AI-enhanced DSS, there is a lack of detailed analysis regarding the specific AI technologies (e.g., machine learning, natural language processing, reinforcement learning) that are most effective in different industrial contexts. This paper seeks to identify and categorize these technologies, linking them to specific decision-making processes within Industry 4.0. However, the integration of AI into DSS introduces several challenges, such as data quality issues, the complexity of AI models, and the need for real-time decision-making in dynamic industrial environments.

This paper explores the specific ways in which AI enhances DSS capabilities, such as predictive analytics, real-time decision-making, and autonomous systems management of DSS systems. However, it also delves into the unique challenges that arise in this context, including the need for handling vast amounts of heterogeneous data, ensuring system interoperability, managing AI-driven uncertainties, and addressing ethical concerns related to AI decision-making. The goal of this review article is to give a thorough overview of AI-based DSSs in the context of Industry 4.0. It will examine the AI-driven DSS's technological foundations, uses, advantages, and drawbacks while providing insights into its revolutionary potential and possible future paths. This study provides insight into the many functions of AI-based DSS in improving operational effectiveness, optimizing resource allocation, reducing risks, and stimulating innovation in a range of industrial sectors by analyzing key works, current breakthroughs, and emerging best practices. Moreover, it seeks to highlight the evolving nature of decision-making processes in the digital age, characterized by the fusion of human expertise with machine intelligence, and the imperative of designing decision support systems that are not only accurate and reliable but also transparent, interpretable, and ethically sound. Through this exploration, we seek to highlight how AI-based DSS are poised to revolutionize industrial decision-making, driving efficiency, innovation, and competitive advantage in the era of Industry 4.0. This study will be invaluable to scientists, developers, and decision-makers as they navigate the opportunities and difficulties associated with integrating AI into industrial decision support systems. Therefore, this research attempts to give a road map for organizations wishing to apply artificial intelligence (AI) to accomplish more intelligent, effective, and resilient operations in the era of Industry 4.0 by extensively assessing the challenges and potential solutions relevant to these systems.

2. **Data Integration and Processing**

AI-based DSS is capable of managing massive amounts of data from a variety of sources, such as business systems, sensors, and Internet of Things devices. Real-time processing of this data yields insights. These systems may automate decision-making and offer insightful analysis by efficiently integrating and processing data from IoT devices and sensors (Tien 2017). This can result in notable increases in productivity, quality, and cost effectiveness. To fully utilize the promise of these technologies, however, issues with data security, interoperability, scalability, and real-time processing must be resolved (Hu et al. 2014).

1. Data Collection and Integration: Deployments of IoT devices and sensors in industrial environments continuously collect vast amounts of data. These data streams can include information on machinery performance, environmental conditions, energy usage, and production processes (Zakizadeh and Zand 2024). AI-DSS utilizes data integration platforms to aggregate data from various sources, ensuring a unified and comprehensive dataset. This includes handling heterogeneous data types and formats, often employing edge computing to preprocess data at the source (D. Liu et al. 2019).
2. Real-time data processing and analysis: Artificial intelligence systems handle data instantly, providing quick insights and decision-making. This is important for applications like as predictive maintenance, where expensive downtime may be avoided with prompt intervention. These artificial intelligence methods look for trends, abnormalities, and correlations in both historical and current data. Machine learning models, for example, may improve quality control procedures, streamline supply chains, and forecast equipment breakdowns (Nathali Silva, Khan, and Han 2017).
3. Predictive Maintenance: AI-DSS systems monitor the condition of equipment using sensor data, predicting potential failures before they occur. This minimizes downtime and extends the lifespan of machinery. Also, based on predictive insights, AI-DSS can schedule maintenance activities during optimal times, reducing disruption to operations and improving resource utilization (Gupta et al. 2022).
4. Operational Optimization: AI-DSS continuously analyzes production processes, identifying inefficiencies and recommending improvements. This can lead to enhanced throughput, reduced waste, and lower operational costs. By analyzing data from energy consumption sensors, AI-DSS can optimize energy usage, reducing costs and environmental impact (Ananias et al. 2021).
5. Quality Control and Assurance: AI-DSS systems can detect defects in products early in the production process by analyzing sensor data, reducing waste and ensuring high quality. Based on quality data, AI-DSS can automatically adjust production parameters to maintain product standards (Simaei and Rahimifard 2024).
6. Supply Chain Management: AI models predict demand patterns using historical data and real-time market trends, helping in inventory management and reducing stockouts or overstock situations. AI-DSS optimizes logistics by analyzing transportation data, ensuring timely delivery and cost efficiency.
7. Human-Machine Collaboration: AI-DSS supports human operators by providing data-driven insights and recommendations, enhancing decision-making capabilities (Yuan et al. 2024; Heine et al. 2023). The Augmented Reality (AR) and Virtual Reality (VR) can be integrated with AI-DSS to provide immersive training and support for operators, improving their efficiency and safety (Zhang et al. 2022).

The Figure 2 depicts the theoretical structure of an examination of intelligent decision-making informed by big data-driven industrial technologies (C. Li, Chen, and Shang 2022).

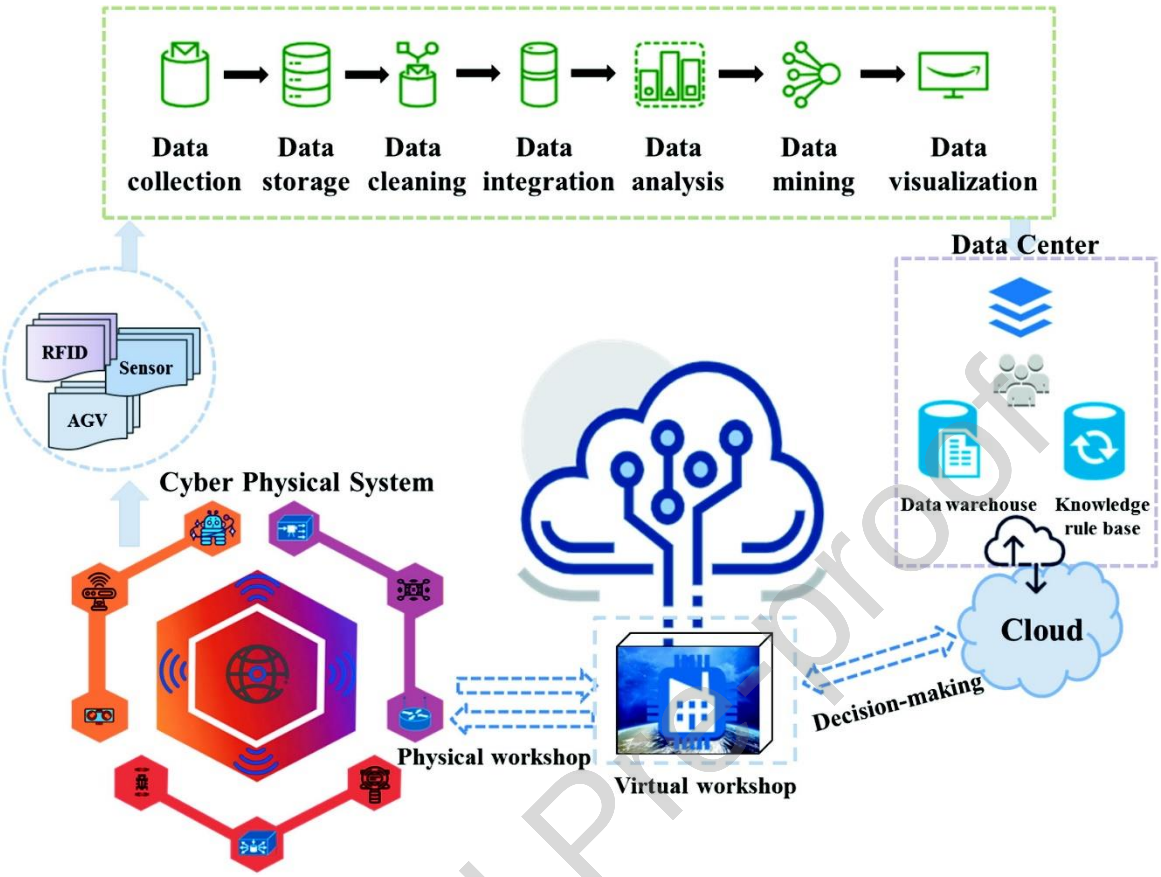

Fig. 2. The theoretical foundation for intelligent decision-making analysis of big data-driven industrial technologies (C. Li, Chen, and Shang 2022).

Technical challenges and actionable solutions in data integration and processing within AI-based DSS in Industry 4.0 can be presented as:

1. Data Heterogeneity: Industry 4.0 involves a variety of data sources, including IoT devices, sensors, enterprise systems, and external databases (Bousdekis and Mentzas 2021). These data sources often differ in structure, format, and semantics, making it difficult to integrate them seamlessly (Sun et al. 2020). In order to solve the challenges the Strategies can be presented as:
    - Data Wrangling and Transformation Tools: Tools like Apache NiFi and Talend can help preprocess and transform data from various sources into a common format.
    - Semantic Interoperability: Utilizing ontologies and semantic web technologies (e.g., OWL, RDF) can ensure consistent interpretation of data across different sources.
    - Middleware Solutions: Middleware platforms like Apache Kafka and Apache Flink can be used to handle data streams from heterogeneous sources, enabling real-time processing and integration (Pulivarthy 2023).
2. Real-Time Data Processing: In Industry 4.0, decisions often need to be made in real-time or near real-time, which requires processing large volumes of data swiftly. Delays in processing can lead to suboptimal decisions, reduced efficiency, or even operational failures (Kocsi et al. 2020). In order to solve the challenges the Strategies can be presented as:
    - Stream Processing Frameworks: The data analysis tool such as Apache Flink and Apache Storm offer low-latency processing capabilities for real-time analytics (Sharma and Jalota 2022).

   - In-Memory Computing: Technologies like Apache Ignite or Redis can be used for in-memory data grids, providing faster data access and processing capabilities.
   - Edge Computing: Implementing edge computing can reduce latency by processing data closer to where it is generated, minimizing the delay in decision-making processes (S. Hamdan, Ayyash, and Almajali 2020).
3. Scalability Issues: As Industry 4.0 systems grow, the volume of data and the number of connected devices increase exponentially. This requires the DSS to scale accordingly to maintain performance and reliability (J. Li et al. 2021). In order to solve the challenges the Strategies can be presented as:
   - Cloud-Based Solutions: Leveraging cloud computing platforms like AWS, Microsoft Azure, or Google Cloud can help scale resources dynamically based on demand, ensuring that the system can handle increased loads without performance degradation.
   - Microservices Architecture: Adopting a microservices architecture allows the DSS to scale individual components independently, improving system scalability and maintainability.
   - Distributed Databases: Utilizing distributed databases like Cassandra or MongoDB ensures that data storage and retrieval processes can scale horizontally across multiple servers (E.S. Kumar, Kesavan, and Naidu 2021).

In order to overcome challenges to implement the AI-based DSS in Industry 4, several integrated frameworks and best practices can be employed as:

- Data Lakes: Implementing data lakes can help in managing and integrating large volumes of heterogeneous data. Tools like Apache Hadoop and Azure Data Lake can be used to store and process structured, semi-structured, and unstructured data.
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- AI-Driven Automation: AI-based tools can automate data integration processes, using machine learning algorithms to identify patterns, map data across sources, and optimize processing workflows.
- Containerization and Orchestration: Using containerization technologies like Docker and Kubernetes can help in managing and scaling applications effectively. These tools also facilitate the deployment of micro services and ensure that the DSS remains agile and scalable (Carrión 2022).
- Standardization and Protocols: Establishing industry standards and protocols for data exchange (such as OPC UA in industrial automation) can simplify data integration and ensure that systems can communicate effectively (Coito et al. 2020).

3. Machine Learning (ML) in Decision Support Systems

AI-driven decision support systems are essential to Industry 4.0 development because they offer improved machine learning and data integration capabilities. The application of machine learning (ML) and sophisticated data analytics to streamline processes, boost productivity, and facilitate wise decision-making is at the heart of this transformation. (Javaid et al. 2022). AI-based Decision Support Systems (DSS) are pivotal in this context, leveraging ML to integrate and process vast amounts of data from various sources to provide actionable insights (Kaklauskas and Kaklauskas 2015; Caiazzo et al. 2023). Machine learning algorithms are pivotal in processing integrated data, offering the ability to learn from data patterns and make predictions or decisions (Jordan and Mitchell 2015). AI-based Decision Support

Systems, powered by machine learning, are transforming Industry 4.0 by enabling intelligent data integration and processing (J.C. Li et al. 2024). These systems enhance operational efficiency, predict and mitigate risks, and provide strategic insights, driving the future of smart manufacturing and industrial processes (Kasie, Bright, and Walker 2017). The main machine learning techniques used in Industry 4.0 include:

1. Supervised Learning: Used for predictive maintenance by training models on historical data to predict equipment failures.
2. Unsupervised Learning: Applied in anomaly detection to identify deviations in production processes (Krtalić, Kuveždić Divjak, and Miletić 2023).
3. Reinforcement Learning: Utilized for optimizing production schedules by learning the best actions through trial and error.
4. Deep Learning: Employed in image and video analysis for quality control and defect detection.
5. Preprocessing: Data cleaning, normalization, and transformation to prepare data for analysis.
6. Feature Extraction: Identifying and extracting relevant features from raw data to improve model performance (Sarker 2022).
7. Model Training and Validation: Using historical data to train ML models and validate their accuracy (Cheng et al. 2020).
8. Real-time Processing: Deploying models that can process and analyze data in real-time for immediate decision-making.

Figure 3 illustrates an Industry 4.0 predictive maintenance decision support system based on IoT and machine learning (Rosati et al. 2023).

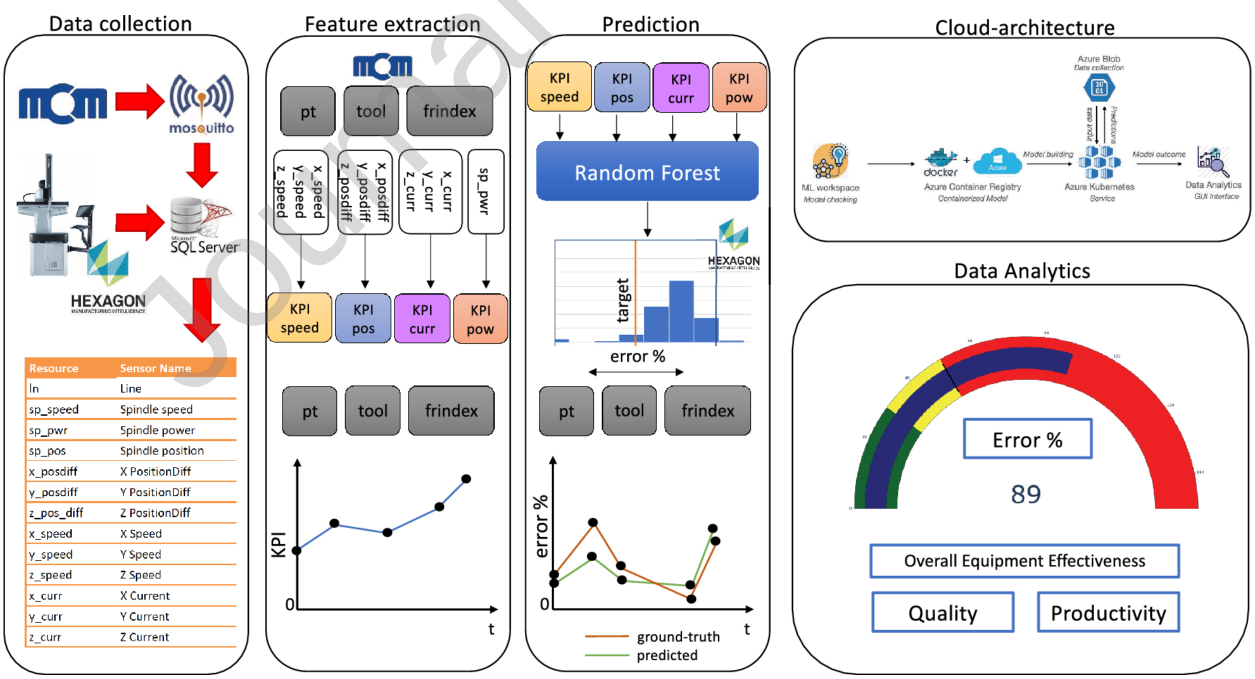

Fig. 3. An Industry 4.0 predictive maintenance decision support system based on IoT and machine learning (Rosati et al. 2023).

4. Deep Learning (DL) in Decision Support Systems

Within machine learning, deep learning is a field that excels in processing vast quantities of heterogeneous data with remarkable precision and efficacy. The design and functionality of the neural networks seen in the human brain served as inspiration (Kriegeskorte 2015). By leveraging multi-layered architectures and sophisticated algorithms, DL algorithms can autonomously extract intricate patterns, discern latent correlations, and derive actionable insights from diverse data sources—ranging from sensor data streams on the factory floor to enterprise-wide operational databases (Taleb et al. 2023). Industry 4.0's deep learning and decision support systems working together opens up a wide range of revolutionary possibilities in many industries (Zhou et al. 2021; Kocsi et al. 2020). AI-based DSS leverage the potential of DL to anticipate faults, improve processes, and boost productivity—all while avoiding downtime, lowering costs, and maximizing resource utilization—in anything from supply chain optimization and production scheduling to predictive maintenance and quality control (Mouzakitis et al. 2023). DL techniques, which can be used in advanced AI-based Decision Support Systems, can be classified as,

1. Convolutional Neural Networks (CNNs): Used for image and video analysis, useful in quality control and predictive maintenance.
2. Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs): Effective for time-series forecasting, critical for demand prediction and anomaly detection (Singh 2017).
3. Auto encoders: Employed for dimensionality reduction and anomaly detection.
4. Generative Adversarial Networks (GANs): Used for synthetic data generation to augment training datasets (Kornish, Ezekiel, and Cornacchia 2018).

Figure 4 illustrates an AI-based decision support system for production optimization and preventative maintenance in energy-intensive industrial facilities (Confalonieri et al. 2015).

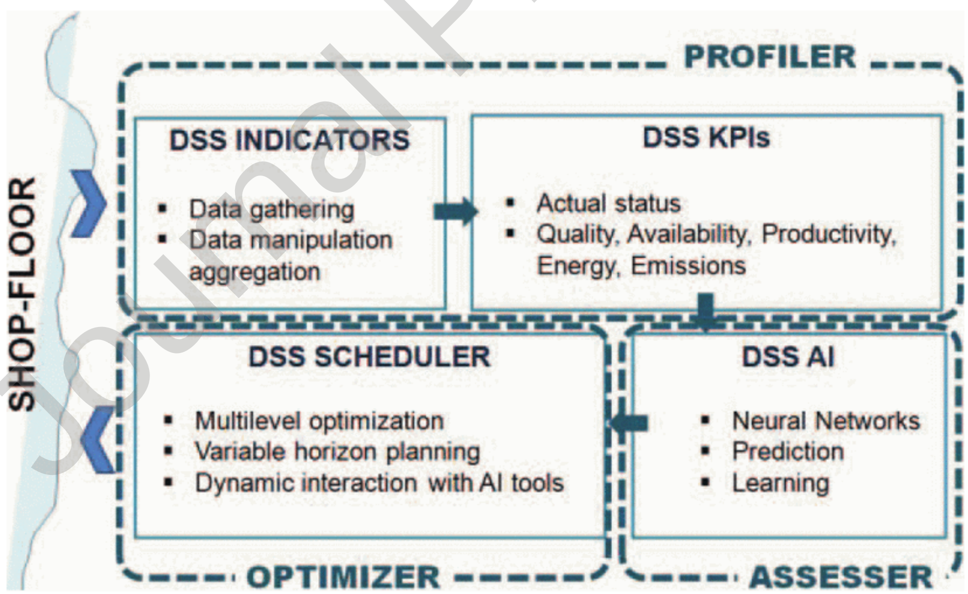

Fig. 4. AI-powered decision support solution for energy-intensive industrial facilities' preventative maintenance and production optimization (Confalonieri et al. 2015).

The integration of AI-based Decision Support Systems supported by Deep Learning capabilities is a strategic need for firms starting their Industry 4.0 journey. This revolutionary project is not without difficulties, though. Human-machine interface, scalability, model interpretability, data quality and availability, and these are some of the major factors that require careful thought and creative solutions. In conclusion, Industry 4.0 is being revolutionized by AI-based DSSs that use deep learning techniques to improve decision-making processes, save costs, and increase operational efficiency through automation and enhanced data analytics (Javaid et al. 2022). The continuous evolution of DL methodologies and their integration with industrial processes holds significant potential for further advancements in smart manufacturing.

5. Expert Systems and Knowledge-Based Systems in AI-based Decision Support Systems

Within the Industry 4.0 paradigm, Knowledge-Based Systems (KBS) and Expert Systems (ES) serve as a foundation for AI-based Decision Support Systems (DSS). In contrast to conventional rule-based systems, ES and KBS use sophisticated reasoning techniques to imitate domain knowledge and human skill, allowing for more intelligent decision-making (S.L. Kumar 2017). This subsection explores the principles, applications, and advancements of ES and KBS in Industry 4.0 DSS. Expert systems, rooted in the principles of knowledge representation and rule-based reasoning, encapsulate domain-specific expertise to emulate human decision-making processes. By encoding expert knowledge into a formalized structure, these systems enable automated inference and decision-making, empowering users with actionable insights and recommendations (Sarker 2022). Leveraging techniques such as rule-based reasoning, case-based reasoning, and knowledge graphs, expert systems excel in domains where well-defined rules and heuristics govern decision logic, offering robust support for complex problem-solving tasks.

Complementing expert systems, knowledge-based systems extend the scope of AI-driven decision support through the integration of diverse knowledge sources and reasoning mechanisms. These systems leverage ontologies, semantic models, and knowledge representation languages to capture and organize domain knowledge, facilitating advanced reasoning, inference, and decision synthesis (Nguyen et al. 2022). With the ability to integrate structured and unstructured data from disparate sources, knowledge-based systems empower decision-makers with comprehensive insights and holistic perspectives, fostering informed decision-making in dynamic industrial contexts.

In the context of Industry 4.0, Expert Systems find applications across various domains, including predictive maintenance, quality control, and production planning (Usuga Cadavid et al. 2020). For instance, in predictive maintenance, an ES can analyze sensor data to diagnose equipment faults and prescribe appropriate maintenance actions based on historical patterns and maintenance guidelines. Similarly, in quality control, an ES can interpret inspection results and recommend corrective measures based on predefined quality criteria and expert knowledge (Kirwan et al. 2022).

By leveraging techniques such as knowledge extraction from unstructured data or learning from expert demonstrations, ES/KBS can adapt and evolve over time, enhancing their effectiveness and applicability in dynamic industrial environments. However, challenges such as knowledge acquisition bottlenecks, rule maintenance overhead, and scalability limitations remain pertinent, necessitating ongoing research efforts. knowledge-based decision support systems design is shown in the figure 5 (Zaraté and Liu 2016).

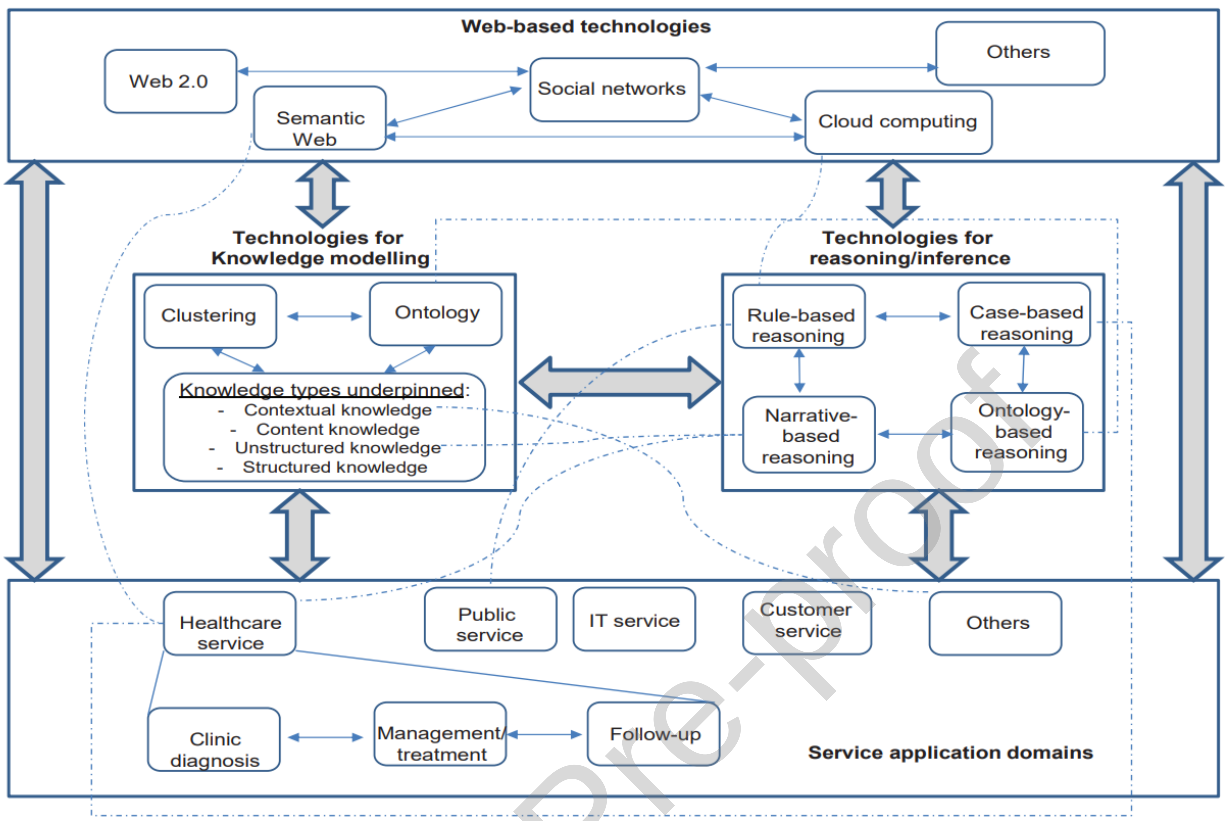

Fig. 5. Designing decision support systems based on knowledge (Zaraté and Liu 2016).

AI-based DSS in Industry 4.0 significantly outperform classic DSS models, particularly through the integration of advanced cloud algorithms. These cloud-based algorithms enable real-time data processing and analysis, providing rapid, scalable, and flexible decision-making capabilities that are crucial in dynamic industrial environments (Padmavathy, Muralidharan, and Sirajudeen 2022). Unlike classic DSS, which often relies on static data and predefined rules, AI-based systems leverage machine learning and predictive analytics to continuously adapt to new data and evolving scenarios. This adaptability enhances accuracy and allows for more informed, data-driven decisions, leading to optimized processes, reduced downtime, and increased efficiency in industrial operations (Gupta et al. 2022; Y. Liu et al. 2023). The seamless integration with IoT devices further amplifies these benefits by enabling real-time monitoring and decision-making across the entire supply chain.

To summarise, AI-based Decision Support Systems in Industry 4.0 are reliant on expert systems and knowledge-based systems, which utilise domain expertise and knowledge representation to facilitate intelligent decision-making in a variety of industrial domains. Despite challenges, ongoing research and technological innovations continue to propel the evolution of ES/KBS, opening avenues for enhanced decision support and operational efficiency in Industry 4.0 environments (Forgionne, Gupta, and Mora 2003).

6. Optimization of Resources by AI-based Decision Support Systems

AI-based DSS optimize the allocation of resources, including labor, materials, and energy, by analyzing production data and identifying areas for improvement, resulting in cost savings and increased productivity. AI-based Decision Support Systems (DSS) play a pivotal role in optimizing resources within the Industry 4.0 paradigm. By integrating advanced artificial intelligence techniques, these systems enhance the efficiency and effectiveness of resource management across various industrial processes (Vrontis et al. 2022).

1. Predictive Maintenance: Artificial intelligence (AI) systems use sensor data and maintenance history to forecast equipment faults before they happen. This makes proactive maintenance scheduling possible, which lowers downtime and increases machinery longevity. Consequently, businesses may maximize equipment use, save maintenance expenses, and avert expensive unscheduled disruptions (Abbas 2024).
2. Supply Chain Optimization: AI-based DSS analyze data across the supply chain to identify inefficiencies and bottlenecks. By predicting demand, optimizing inventory levels, and improving logistics, these systems ensure that resources are allocated effectively. This leads to reduced waste, lower inventory holding costs, and improved delivery performance (Kmiecik 2022).
3. Energy Management: AI systems monitor and analyze energy consumption patterns to identify opportunities for energy savings (Binyamin, Slama, and Zafar 2024). By optimizing energy usage, companies can reduce operational costs and minimize their environmental footprint. AI-driven energy management can involve adjusting machine operating schedules, optimizing HVAC systems, and integrating renewable energy sources (Muniandi et al. 2024).
4. Production Planning and Scheduling: AI-based DSS optimizes production schedules by taking into account a number of limitations, including personnel shifts, material supply, and equipment availability (Dickinson et al. 2024). These systems can dynamically adjust schedules in response to changes in demand or production conditions, ensuring that resources are used efficiently and production goals are met (Qiao, Liu, and Ma 2021).
5. Quality Control: AI-driven quality control systems analyze production data in real-time to detect defects and deviations from standards (Shafi et al. 2023). By identifying quality issues early, companies can reduce scrap rates and rework costs. This not only optimizes the use of raw materials but also enhances overall product quality.
6. Human Resource Management: AI-based DSS assist in workforce planning by analyzing employee performance, skill sets, and availability (A. Hamdan et al. 2024). These systems can optimize staffing levels, assign tasks based on skill matching, and predict future labor needs. This ensures that human resources are utilized effectively, improving productivity and job satisfaction (Garg et al. 2022).
7. Resource Allocation in Smart Manufacturing: AI enables the dynamic allocation of resources in smart factories. For instance, AI algorithms can determine the most efficient use of robotics and automated systems, adjusting operations in real-time based on production needs and resource availability. This flexibility leads to optimized use of both human and machine resources (Morariu et al. 2020).
8. Sustainability and Waste Reduction: AI helps identify opportunities for reducing waste and promoting sustainability. By analyzing production processes and material flows, AI-based DSS can suggest changes that lead to more efficient use of materials and reduce the generation of waste. This contributes to both cost savings and environmental sustainability (Simaei and Rahimifard 2024).

Decision support tools for managing water supplies is shown in the figure 6 (Giupponi and Sgobbi 2013).

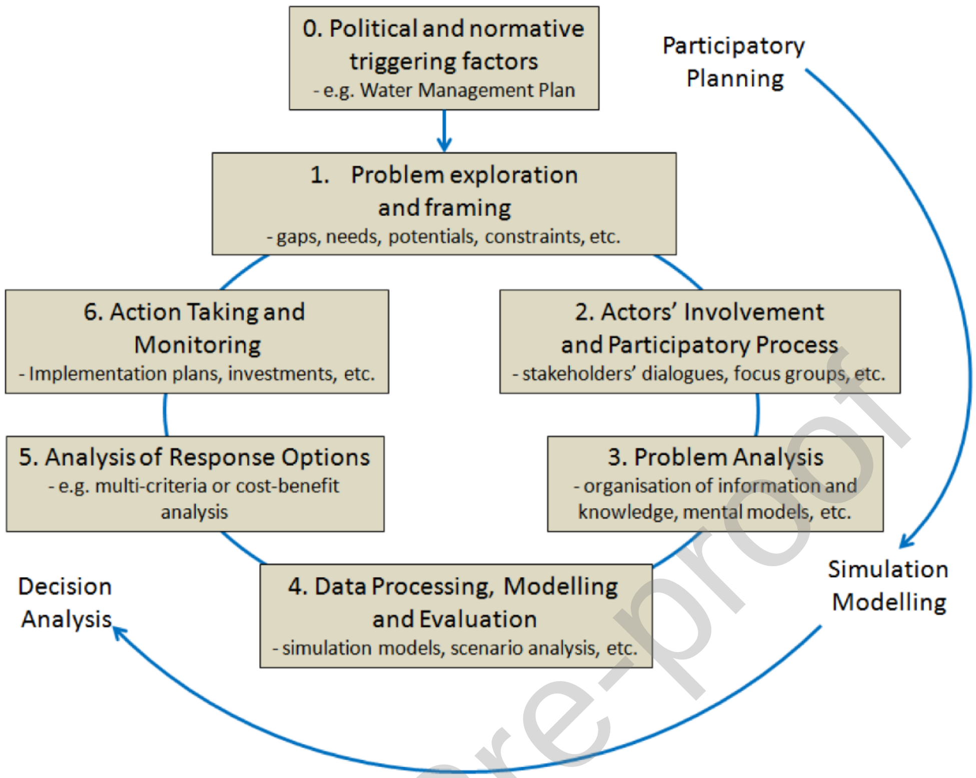

Fig. 6. Decision support tools for managing water supplies (Giupponi and Sgobbi 2013).

The integration of AI-based Decision Support Systems in Industry 4.0 represents a transformative approach to resource optimization. By leveraging AI's capabilities in predictive analytics, real-time monitoring, and dynamic adjustment, these systems ensure that resources—whether they be equipment, materials, energy, or human capital—are utilized in the most efficient and effective manner. As industries continue to evolve towards greater automation and intelligence, the role of AI-based DSS in optimizing resources will become increasingly crucial, driving both operational excellence and competitive advantage.

7. Continuous Learning and Improvement

AI-based DSS continuously learn and evolve from new data, improving their decision-making capabilities over time and staying relevant in dynamic industrial environments. AI-Based Decision Support Systems (DSS) in Industry 4.0 are not static tools; they thrive on continuous learning and improvement (Holsapple et al. 1993). This dynamic capability ensures that these systems remain effective, adaptive, and responsive to evolving industrial challenges and opportunities.

1. Adaptive Algorithms: AI-based DSS employ machine learning algorithms that can learn from new data, refining their models over time. This continuous learning process allows the systems to improve their accuracy and effectiveness in decision-making as more data becomes available.
2. Real-Time Data Integration: Industry 4.0 environments generate vast amounts of data in real-time through IoT devices, sensors, and other data sources. AI systems continuously ingest this data, updating their models to reflect the most current information and conditions (Duan, Edwards, and Dwivedi 2019).
3. Feedback Loops: Implementing feedback loops where the outcomes of decisions are monitored and evaluated enables AI systems to learn from their successes and failures. This iterative process helps in fine-tuning the algorithms for better performance in future scenarios (Retzlaff et al. 2024).

4. Transfer Learning: Leveraging transfer learning techniques, AI models can apply knowledge gained from one task or domain to another. This facilitates quicker adaptation to new contexts and reduces the need for extensive retraining.
5. Performance Monitoring: Regular monitoring of the AI-based DSS performance ensures that the systems are operating optimally. Key performance indicators (KPIs) and metrics are used to assess the efficacy of the decision support provided (Mtau and Rahul 2024).
6. Anomaly Detection and Correction: AI systems are equipped to detect anomalies or deviations from expected patterns, prompting investigations and corrections. This helps in maintaining the reliability and accuracy of the decision support provided (Rehman and Saba 2014).
7. User Feedback Integration: Incorporating feedback from users—such as operators, managers, and other stakeholders—into the system helps in identifying areas for improvement. User insights are invaluable for refining the system's functionality and usability (Carroll et al. 2002).
8. Updating Knowledge Bases: As industries evolve, so does the knowledge that drives decision-making. AI-based DSS must continuously update their knowledge bases to include new research, industry standards, regulatory changes, and best practices.

The continuous learning and improvement paradigm is crucial for AI-based Decision Support Systems in Industry 4.0. By embracing adaptive algorithms, real-time data integration, feedback loops, and transfer learning, these systems can stay ahead of the curve. Regular performance monitoring, anomaly detection, user feedback, and updating knowledge bases drive continuous improvement, ensuring that AI-based DSS remain relevant and effective. Implementing these strategies in a scalable, collaborative, and ethically sound manner will be key to maximizing the potential of AI in transforming industrial decision-making processes.

8. Architecture and Implementation of AI-Based Decision Support Systems

Data acquisition and preprocessing modules, pipelines for developing and deploying machine learning models, decision engines, user interfaces, and integration interfaces with other enterprise systems like Manufacturing Execution Systems (MES) and Enterprise Resource Planning (ERP) are examples of the interconnected components that typically make up an architecture (Sarker 2022; Malliaroudaki and Zoumas 2024).

1. Data Acquisition and Preprocessing: The foundation of an AI-based DSS is data. The gathering of data for this component comes from a variety of sources, including databases, sensors, Internet of Things devices, and external systems. The raw data is then cleaned, transformed, and organized using preprocessing procedures to create a format that can be used for analysis and model training (Çetin and Yıldız 2022).
2. AI Model Development and Training: In this component, AI models such as machine learning algorithms, deep learning networks, and expert systems are developed and trained using the preprocessed data. Model development involves selecting appropriate algorithms, defining features, and tuning hyper parameters to optimize performance. Training datasets are used to train the models, and techniques such as cross-validation and regularization are employed to prevent overfitting (Kaggwa et al. 2024).
3. Model Deployment and Integration: Trained AI models are deployed into the DSS environment, where they interact with real-time data streams to make predictions or generate insights (Hassija et al. 2024). Model deployment may involve deploying models to edge devices for low-latency processing or deploying them to cloud-based servers for scalability (Helenason et al. 2024). Integration with existing systems and workflows is crucial to ensure seamless operation and interoperability.
4. Model Selection and Evaluation: For the DSS to be successful, selecting the appropriate AI model for a particular problem domain is essential. Model selection is influenced by several factors, including the type of data, the intricacy of the problem, and the computational resources available. The performance of candidate models is evaluated using evaluation measures including accuracy, precision, recall, and F1 score in order to determine which performs the best.

5. Model Deployment Strategies: Deploying AI models into production environments requires careful planning and consideration of deployment strategies. Options include batch processing, real-time inference, and online learning approaches. Model deployment frameworks such as TensorFlow Serving, ONNX Runtime, and Kubernetes enable scalable and efficient deployment of AI models across different platforms and environments.

AI-Powered Real-Time Informational System for Decision Support is shown in the figure 7 (Islam and Chang 2021).

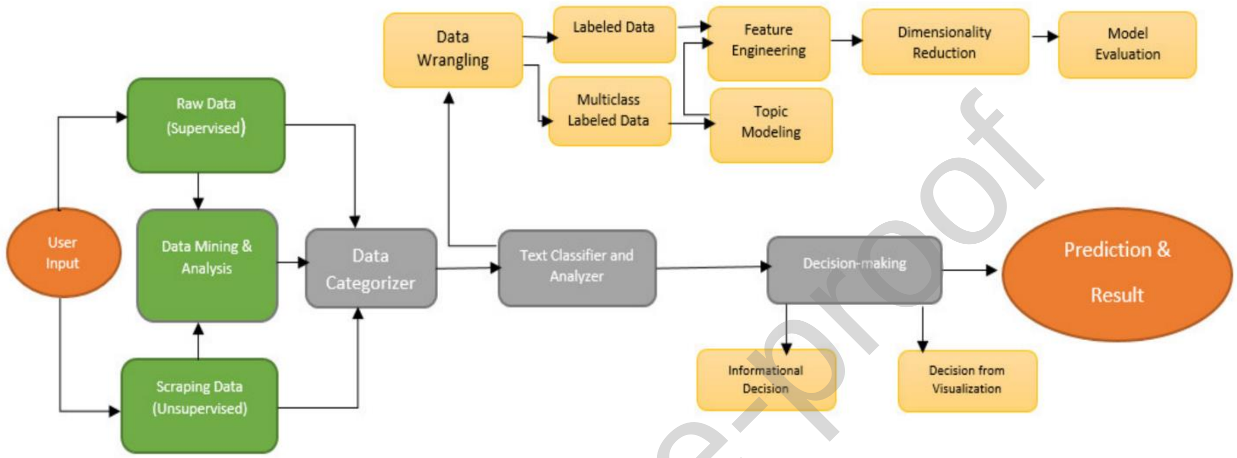

Fig. 7. AI-Powered Real-Time Informational System for Decision Support (Islam and Chang 2021).

In conclusion, Industry 4.0 relies heavily on the architecture and application of AI-based decision support systems to facilitate data-driven decision-making and maximize operational performance. Organizations may leverage AI to improve productivity, efficiency, and competitiveness in the Industry 4.0 era by using user-centered design concepts, a strong architecture, and efficient data management techniques.

9. Challenges and consideration of AI-based Decision Support Systems in Industry 4.0

There are difficulties in implementing AI-based DSS in Industry 4.0. Important factors to take into account include data quality, integration complexity, and the requirement for strong cybersecurity measures. The workforce's ability to adopt new technologies and the evolution of paradigms for decision-making are two other organizational and human factors that are critical to the effective implementation of these systems (Antoniadi et al. 2021; Dulebohn and Johnson 2013). While AI-based DSS offer significant benefits, several challenges need to be addressed:

1. Data-Related Challenges

- Data Quality and Accessibility: Industry 4.0 relies heavily on data-driven decision-making, but ensuring data quality and accessibility remains a challenge. In many cases, the data available may be incomplete, inconsistent, or biased, leading to suboptimal decisions (Angelopoulos et al. 2019). Additionally, accessing relevant data from disparate sources within the organization or across supply chains can be challenging (Sayogo et al. 2015).

- Data Privacy and Security: In the context of AI-based decision support systems in Industry 4.0, ethical and legal issues are of paramount importance, particularly regarding data privacy and protection. The vast amounts of data generated and utilized by these systems necessitate stringent measures to ensure that sensitive information is secured (Jagatheesaperumal et al. 2021). The general data protection regulation plays a crucial role in this regard, setting the standard for data handling practices within the European Union and influencing global norms (Kuner et al. 2020). Moreover, robust supervision mechanisms are needed to prevent misuse of AI systems, such as biased decision-making or unauthorized data access, thus ensuring that the benefits of AI are realized without compromising ethical standards. It is crucial to protect sensitive industrial data's privacy and security. Data security and privacy are critical issues in Industry 4.0 environments due to the widespread use of networked systems and data gathering devices (Sarker 2024). There are several obstacles in the way of facilitating data exchange for decision assistance while protecting sensitive information. Data management procedures become more sophisticated to comply with laws like GDPR (Ozkan-Ozay et al. 2024). Organizations implementing AI in Industry 4.0 must ensure compliance with GDPR by adopting transparent data practices, obtaining explicit consent for data usage, and ensuring individuals' rights to access, correct, or delete their data (Khan and Mer 2023).

- Data Governance and Compliance: Establishing robust data governance frameworks and ensuring compliance with industry regulations and standards are essential for AI-based DSS. However, achieving consensus on data ownership, usage rights, and accountability across organizational boundaries can be daunting (Dwivedi, Nerur, and Balijepally 2023). Harmonizing data governance practices with evolving regulatory requirements presents ongoing challenges (Martínez-García and Hernández-Lemus 2022).

2. Technical Challenges

- Scalability and Performance: It is developing scalable solutions that can handle the vast amounts of data generated in Industry 4.0. The scalability of AI-based DSS to handle large volumes of data and support real-time decision-making is critical. However, scaling AI models and infrastructure to meet increasing demands while maintaining performance levels can be technically challenging. Balancing computational resources, such as processing power and memory, with the complexity of AI algorithms is a continuous optimization task (Simaiya et al. 2024).

- Interoperability and Integration: Integrating AI-based DSS with existing IT systems, manufacturing equipment, and IoT devices requires seamless interoperability. However, disparate technologies, standards, and protocols often hinder smooth integration. Developing standardized interfaces and protocols for data exchange and communication between heterogeneous systems is a complex undertaking (Werbrouck et al. 2024).

- Model Interpretability and Transparency: Deep learning models in particular are frequently viewed as "black boxes" in decision support systems because of their intricate topologies. It can be difficult to understand and interpret the choices made by these models, particularly in regulated industries where openness is essential (C. Wang et al. 2024). Establishing confidence and promoting user adoption of AI-based DSS requires ensuring its interpretability and openness.

3. Human and Organizational Challenges: Enhancing the collaboration between human operators and AI systems to leverage the strengths of both.

- Resistance to Change: Introducing AI-based DSS into traditional manufacturing environments may face resistance from employees accustomed to manual decision-making processes. Fear of job displacement, lack of trust in AI technologies, and resistance to new ways of working are common barriers to adoption. To solve these issues, effective change management techniques including communication and training are required (Pillai et al. 2024).

- Skills Gap and Talent Shortage: To create and maintain AI capabilities, organizations require skilled workers with machine learning, data science, and domain-specific expertise (Rodríguez Aguilar, Cardiel, and Somolinos 2023). Unfortunately, there is a serious lack of expertise in these disciplines, which makes it challenging to retain qualified personnel (Weinzierl et al. 2024). Upskilling the present workforce and promoting interdisciplinary cooperation are essential strategies to narrow the skills gap (Berger and Frey 2016).

- Organizational Culture and Leadership: Cultivating a culture of data-driven decision-making and innovation is crucial for the successful implementation of AI-based DSS (Fosso Wamba et al. 2024). However, entrenched organizational cultures that resist change and hierarchical leadership structures may impede progress. Leadership commitment to fostering a culture of experimentation, learning, and agility is vital for driving organizational transformation (Patel et al. 2024).

Technical implications to solve the challenges in AI-Based DSS within Industry 4.0 can be presented as:

1. Data Quality and Availability: AI-based DSS systems rely heavily on large volumes of high-quality data. Poor data quality or incomplete datasets can lead to inaccurate decisions. To overcome this, organizations should invest in robust data governance frameworks that ensure data integrity, accuracy, and timeliness. Also, implementing advanced data cleaning and preprocessing techniques is essential (Ilori, Nwosu, and Naiho 2024).

2. System Integration: Integrating AI-based DSS with existing systems can be complex due to compatibility issues and the need for real-time processing. Adopting standardized protocols and leveraging middleware solutions can help in seamless integration. Additionally, designing AI models that are adaptable to different platforms and systems will enhance interoperability (Rasheed 2024).

3. Scalability and Computational Resources: The computational demand of AI algorithms can be high, especially when processing large datasets or running complex models. Organizations should explore cloud-based solutions or distributed computing to handle scalability challenges. Optimizing algorithms for efficiency can also reduce the computational load (Nithiyanandam et al. 2022).

4. Workforce Adaptation: The implementation of AI-based DSS may lead to job displacement or require significant upskilling of the workforce. Organizations should invest in continuous training programs to reskill employees and ensure they are equipped to work alongside AI technologies. Promoting a culture of innovation and adaptability within the organization will facilitate smoother transitions.

5. Change Management: Resistance to change is a common challenge when introducing new technologies. Effective communication strategies, involving stakeholders in the decision-making process, and demonstrating the tangible benefits of AI-based DSS can help in overcoming resistance. Leadership commitment and clear vision are crucial for successful implementation (Rane, Choudhary, and Rane 2024).

6. Bias and Fairness: AI systems can inherit biases present in the training data, leading to unfair decision-making. To mitigate this, organizations should implement fairness-aware algorithms and regularly audit AI models for bias. Transparency in AI decision-making processes and the inclusion of diverse perspectives during model development can also reduce bias.

7. Data Privacy and Security: The use of AI in DSS involves the processing of sensitive data, raising concerns about data privacy and security. Organizations should adhere to strict data protection regulations and implement robust cybersecurity measures to safeguard data. Ethical guidelines and frameworks should be established to ensure responsible AI use (Allahrakha 2023).

As a result, In order to effectively implement and utilize AI-based decision support systems in Industry 4.0 settings, a number of concerns and challenges need to be considered and solved. Enterprises can effectively utilize AI technology to boost operational effectiveness and achieve a competitive advantage by proactively identifying and mitigating these issues.

10. Sustainability and Environmental Impact

By streamlining processes, cutting waste, and lessening the environmental effect of industrial operations, AI-based DSS support sustainability initiatives. Within the Industry 4.0 paradigm, artificial intelligence (AI)-based Decision Support Systems (DSS) have the potential to greatly improve sustainability and reduce environmental impact (Bibri et al. 2024). By leveraging AI's capabilities in data analysis, pattern recognition, and predictive modeling, these systems can drive more efficient and environmentally friendly industrial processes (Smith and Wong 2022).

1. Optimized Resource Utilization: AI-based DSS can analyze production processes to identify inefficiencies and optimize the use of raw materials, energy, and water. By predicting the exact quantities needed and minimizing waste, these systems contribute to resource conservation and cost savings (Bhambri et al. 2024).
2. Energy Efficiency: AI algorithms can monitor and control energy consumption in real-time, identifying areas where energy use can be reduced without compromising production quality. This includes optimizing machinery operations, reducing idle times, and implementing smart energy management practices (Hanafi, Moawed, and Abdellatif 2024).
3. Predictive Maintenance: By predicting equipment failures before they occur, AI-based DSS can schedule maintenance activities at the most opportune times, reducing downtime and avoiding the environmental impact of unexpected breakdowns. This not only enhances operational efficiency but also extends the lifespan of machinery, reducing the need for replacements.
4. Supply Chain Optimization: AI-driven insights can streamline supply chains by optimizing logistics, reducing transportation emissions, and ensuring that inventory levels are maintained at optimal levels (Mahi 2024). This reduces the carbon footprint associated with excess inventory and transportation inefficiencies.

Figure 8 illustrates the decision support system for managing supply chain control choices and decision makers in the context of Industry 4.0 (Alahmadi and Jamjoom 2022).

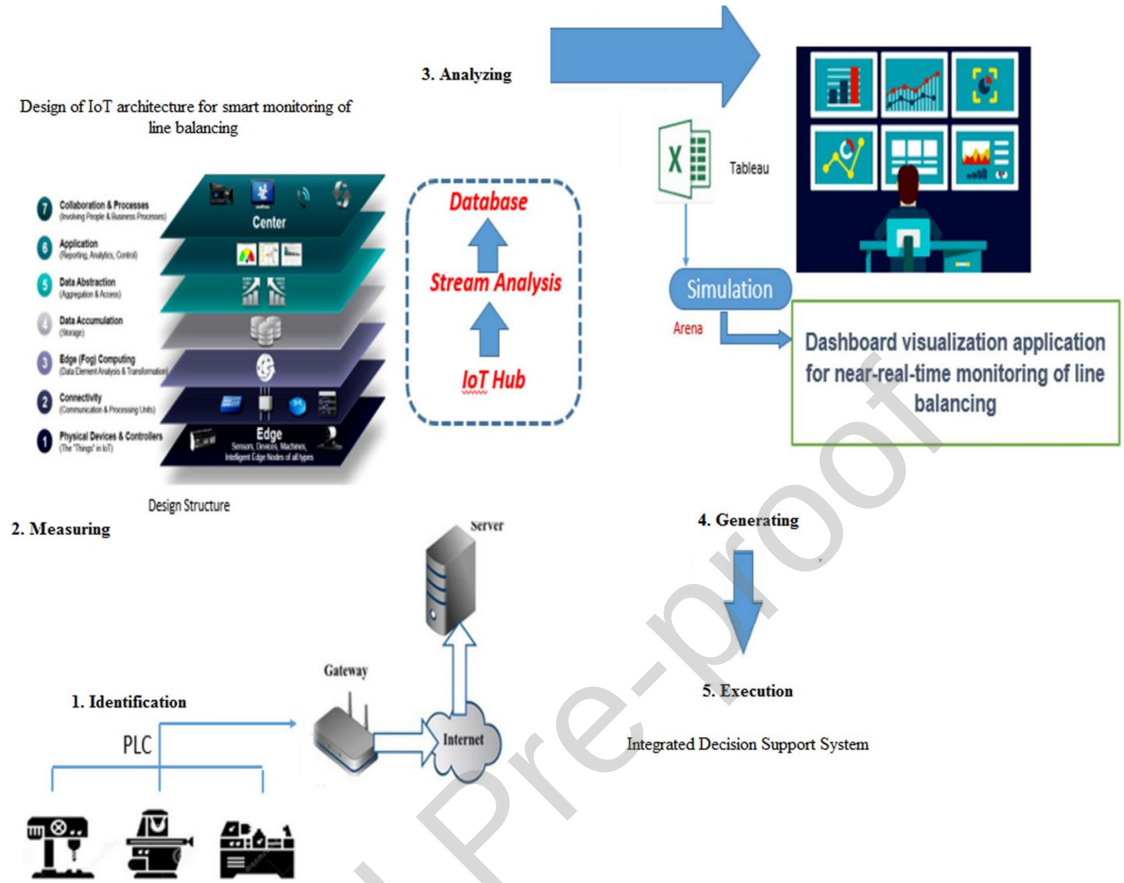

Fig. 8. Decision support system for managing supply chain control choices and decision makers in the context of Industry 4.0 (Alahmadi and Jamjoom 2022).

5. Waste Management: AI-based DSS can improve waste management practices by identifying patterns in waste generation and suggesting ways to reduce, reuse, and recycle materials. This contributes to a circular economy and minimizes the environmental impact of industrial waste.
6. Sustainable Product Design: AI can assist in designing products with sustainability in mind, from selecting eco-friendly materials to optimizing product lifecycles for minimal environmental impact. This includes considering end-of-life disposal and recycling options during the design phase (Delaney et al. 2022).

The integration of AI-based Decision Support Systems in Industry 4.0 offers a transformative approach to achieving sustainability and reducing environmental impact (Sadeghi et al. 2024). By optimizing resource use, enhancing energy efficiency, improving waste management, and ensuring regulatory compliance, these systems empower industries to operate more sustainably. As the technology continues to evolve, its potential to drive significant environmental benefits will only grow, making it an indispensable tool for the sustainable industrial landscape of the future.

Strategies for achieving environmental benefits in AI-Based DSS within Industry 4.0 cab be presented as:

1. Energy Optimization: AI-based DSS can optimize energy consumption in industrial processes by predicting demand and adjusting energy use accordingly. Implementing AI-driven predictive maintenance can also reduce energy wastage by identifying and rectifying inefficiencies in equipment performance. Organizations should invest in AI tools that monitor and analyze energy usage in real-time, enabling proactive adjustments to minimize consumption (Boza and Evgeniou 2021).

2. Resource Management: AI can optimize the use of raw materials by improving production planning and reducing waste. For example, AI-driven supply chain management systems can forecast demand more accurately, reducing overproduction and minimizing material waste (Shahin et al. 2024). Implementing AI-based systems that monitor and manage resource utilization throughout the production cycle will contribute to sustainable practices.

3. Emissions Reduction: AI can help reduce emissions by optimizing transportation routes, improving logistics, and enhancing the efficiency of industrial processes (Chung 2021). Organizations should deploy AI models that predict and minimize emissions by analyzing various factors such as fuel consumption, production schedules, and equipment efficiency. Additionally, integrating AI with IoT sensors can provide real-time feedback on emissions, enabling timely interventions (Nemitallah et al. 2023).

4. Increased Energy Consumption: The computational power required for AI models can lead to increased energy consumption, offsetting some of the environmental benefits. To mitigate this, organizations should focus on developing energy-efficient AI algorithms and explore the use of renewable energy sources to power AI systems. Additionally, implementing AI-driven energy management systems can help in balancing energy use across the organization.

5. Resource Depletion: The production and deployment of AI technologies may require significant resources, including rare earth metals and other non-renewable materials. To address this, organizations should explore the use of sustainable materials in AI hardware and promote the recycling and reuse of components. Developing AI solutions that optimize resource use and reduce waste in manufacturing processes can also mitigate this risk (Kshirsagar et al. 2022).

6. Environmental Impact of AI Infrastructure: The construction and maintenance of AI infrastructure, such as data centers, can have a significant environmental footprint. Data centers consume large amounts of energy and water, contributing to carbon emissions and resource depletion. Organizations should consider strategies such as adopting green data centers that use energy-efficient technologies, renewable energy sources, and innovative cooling methods to reduce environmental impact. Implementing AI-driven monitoring and optimization tools within data centers can further enhance their efficiency and sustainability.

7. Sustainability Audits: Conduct regular sustainability audits of AI infrastructure and processes to identify areas where environmental impact can be reduced. This includes evaluating the energy efficiency of AI algorithms, the environmental impact of hardware, and the overall carbon footprint of AI operations.

8. Lifecycle Assessment (LCA): Perform lifecycle assessments of AI-based DSS to understand the environmental impact from production to disposal. This will help in identifying critical areas for improvement and ensuring that AI deployments are aligned with sustainability goals (Ueda et al. 2024).

9. Cross-disciplinary Collaboration: Encourage collaboration between AI developers, environmental scientists, and industry experts to design AI systems that are not only effective but also environmentally sustainable. This interdisciplinary approach can lead to innovative solutions that balance technological advancements with environmental stewardship (Bibri et al. 2023).

By incorporating these detailed strategies and addressing potential trade-offs, your paper will provide a more comprehensive analysis of the environmental implications of AI-based DSS in Industry 4.0, offering actionable recommendations for organizations aiming to deploy AI technologies in a sustainable manner.

11. Conclusion

In conclusion, the review of AI-Based Decision Support Systems (DSS) within the context of Industry 4.0 underscores their pivotal role in revolutionizing decision-making processes across diverse industrial domains. Through the fusion of artificial intelligence, advanced analytics, and emerging technologies, these systems offer unprecedented capabilities to analyze vast volumes of data, extract actionable insights, and facilitate informed decision-making in real-time.

The synthesis of current research highlights the significant strides made in leveraging AI for optimizing operational efficiency, enhancing productivity, and driving innovation within Industry 4.0 ecosystems. From predictive maintenance and supply chain optimization to quality control and personalized manufacturing, AI-based DSS exemplify a transformative force reshaping the industrial landscape.

However, this review also underscores the evolving challenges and opportunities that lie ahead. As AI technologies continue to advance, there is a pressing need to address issues related to interpretability, transparency, and ethical use. Additionally, the integration of AI with other emerging technologies such as blockchain, IoT, and augmented reality presents exciting avenues for further exploration and innovation.

Artificial intelligence (AI) solutions can guarantee constant product quality and identify abnormalities in manufacturing data, which will increase customer satisfaction and save waste. Better demand forecasting, inventory control, and logistics planning are made possible by AI-driven insights, which also strengthen the supply chain's overall resilience. By evaluating client preferences and modifying manufacturing procedures to suit specific requirements, DSS enable bulk customisation. AI is capable of evaluating and analyzing a broad variety of risk indicators, which helps decision-makers spot possible threats and develop efficient mitigation strategies. AI-based DSS can foresee market trends, production bottlenecks, and equipment breakdowns by utilizing advanced predictive analytics. This allows for proactive maintenance and inventory management. Additionally, Industry 4.0 decision-making processes are greatly improved by AI-based decision support systems, which offer data-driven, real-time insights that maximize operational effectiveness and strategic planning.

In order to tackle difficult decision-making tasks in the future, research efforts should concentrate on maximizing the synergies between human expertise and AI capabilities. Scalability, resilience, and security should also be prioritized in order to guarantee the dependability and credibility of AI-based DSS in dynamic, networked industrial settings.

To put it simply, the path to achieving the full potential of AI-based DSS in Industry 4.0 is paved with constant innovation, teamwork, and a resolute dedication to tackling social issues while appreciating the transformational potential of technology. We must continue to be alert, flexible, and morally upright as we traverse this constantly changing environment. By doing so, we will be creating the foundation for a time in the future when wise choices are associated with both human and sustainable development.

12. Future research work directions

Future research directions in the realm of AI-based Decision Support Systems (DSS) within Industry 4.0 could explore several avenues to enhance efficiency, effectiveness, and adaptability. Here are some potential directions:

1. Integration of Emerging Technologies: Examine how to incorporate cutting-edge technologies like augmented reality (AR), blockchain, and the Internet of Things (IoT) with AI in DSS to produce more robust and comprehensive frameworks for decision-making.
2. Explainable AI (XAI): Develop methods for making AI-based decisions more transparent and interpretable, ensuring that decision-makers understand the rationale behind recommendations made by DSS. This is crucial for building trust and facilitating adoption, particularly in critical industries.

3. Personalization and Context-awareness: Explore techniques to personalize DSS outputs based on individual user preferences, roles, and contexts. Context-aware DSS can adapt recommendations to specific operational conditions or user requirements, enhancing their relevance and usability.

4. Real-time Decision Support: Investigate approaches to enable real-time decision support capabilities in DSS, leveraging advanced analytics and AI algorithms to process large volumes of streaming data and provide timely insights. This is especially relevant for dynamic and fast-paced environments where decisions need to be made rapidly.

5. Human-AI Collaboration: Examine the dynamics of cooperation between people and AI in decision-making processes, with an emphasis on how human and AI systems might enhance one another's advantages to produce superior results. Creating user interfaces and interaction systems that enable smooth cooperation between AI and humans falls under this category.

6. Robustness and Security: Discuss issues with data biases, privacy problems, and adversarial attack weaknesses as they pertain to the resilience and security of AI-based DSS. The goal of research should be to create methods for reducing these hazards and improving the dependability and credibility of DSS.

7. Scalability and Generalization: Explore methods for scaling AI-based DSS to handle increasingly complex and diverse decision-making scenarios across different domains and industries. This involves designing algorithms and architectures that can generalize well and adapt to new contexts without extensive retraining.

8. Ethical and Social Implications: Examine the moral and social ramifications of implementing AI-based DSS, taking into consideration concerns about responsibility, transparency, and justice. The goal of this research should be to provide frameworks and rules for the ethical use of AI in decision-making situations while taking into account the wider effects on society.

Scholars and practitioners can boost the current status of AI-based decision support systems and help to successfully deploy and adopt them in the Industry 4.0 environment by investigating these study directions.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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