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ARTIFICIAL INTELLIGENCE IN INDUSTRIAL DECISION-MAKING: A SYSTEMATIC LITERATURE REVIEW

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Abstract –
This article undertakes a systematic literature review on the applications of artificial intelligence (AI) in manufacturing, specifically focusing on its role in industrial decision-making. The review highlights AI's critical contribution to optimizing processes, thereby enabling manufacturers to maintain competitiveness in an increasingly dynamic market. The paper focuses on recent research that integrates advanced technologies and well-developed techniques, providing insights into the utilization of AI for industrial decision-making and evaluating their readiness for application in the real world. Thus, this study identifies existing gaps in the literature and offers a foundation for future research, aiding in the development of robust and mature AI solutions that are ready for real-world implementation.

Index Terms - *About four, alphabetical order, key words or phrases, separated by commas (e.g., Camera-ready, FIE format, Preparation of papers, Two-column format).*

INTRODUCTION

The current industrial landscape is marked by the inability of conventional decision-making processes to ensure rapid and accurate decision-making, as digital progress swiftly transformed industrial processes into more complicated ones requiring advanced strategic reasoning and analysis of massive volumes of data to overcome the challenges they face. Hence the necessity to adopt new reliable decision-support systems that have evolved from computer-based systems to artificial intelligence (AI) powered systems which were been shown to outperform human decision-making [1–3]

Indeed, the necessity of decision-making in the industrial framework is evident, since management choices cannot rely on cleverness, instinct, or subjective judgments, but must be based on rigorous and statistical analysis. A genuine option requires timely and exact knowledge, which DSS assists managers with. As a result, decision support systems are extremely adaptable and dynamic computational structures that offer decision-making the ability to handle large amounts of data and utilize them freely in the appropriate frameworks to acquire the necessary and sufficient knowledge ensuring more effective, agile, inventive, and credible decision-making [1, 4–6]

Artificial intelligence's fast growth has created a plethora of opportunities for enhancing decision-making processes across sectors.[7–9] This paper studies current research projects introducing applications of AI's within industrial decision-making contexts using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Statement which was issued a decade ago and has since had several extensions, which are evidence-based baseline standards intended to foster accountable and comprehensive presentation of systematic reviews[10–12], to consolidate the findings, identify gaps and create a richer picture of the subject while informing and shaping the direction of ongoing and future research by offering a holistic overview of the state of the art and underlining the opportunities and challenges that lie ahead of AI-driven decision-making tools and strategies by answering the following questions:

1- How artificial intelligence is used for decision-making?
2- Do present artificial intelligence application frameworks adequately satisfy industrial needs?
3- What benefits have artificial intelligence applications in decision-making brought to the industry?

DECISION-MAKING IN INDUSTRIAL PERFORMANCE

Decision-making in industrial performance presents a multifaceted challenge shaped by several critical factors. The inherent uncertainty and volatility of markets create an environment where predicting future conditions becomes intricate, impacting strategic planning.

The integration of advanced technologies introduces a layer of complexity, demanding careful consideration of costs, benefits, and potential disruptions to existing systems. Additionally, the abundance of data in industrial settings can lead to analysis paralysis, hindering timely and effective decision-making. Navigating the ever-changing landscape of regulatory compliance further complicates the decision-making process, requiring constant vigilance and adaptation. Finally, optimizing the allocation of resources, encompassing labor, materials, and energy, remains an ongoing challenge, necessitating a delicate balance between meeting short-term operational needs and achieving long-term sustainability objectives.

Overall, the challenges in industrial decision-making include integrating multi-dimensional issues, developing consistent indicators, and strengthening the infrastructure for data collection and analysis. Addressing these challenges is imperative for industrial decision-makers to foster resilience, innovation, and sustained performance [13, 14]

METHODOLOGY

The PRISMA approach was used to conduct this literature review, which looked at two databases: SCOPUS, Web of Science, and Science Directe, where the following keywords were used to guarantee that the analysis stays well-framed in the contribution of artificial intelligence in industrial decision-making: Decision making, artificial intelligence, and manufacturing. Given that the field of artificial intelligence (AI) is experiencing a rapid growth [15, 16], we restricted our study's scope to the last five years, focusing on research articles available in English in both fields of engineering and decision science. As a result, the query has been structured as follows:

TITLE-ABS-KEY("DECISION MAKING" AND "ARTIFICIAL INTELLIGENCE" AND "MANUFACTURING") AND (LIMIT-TO (DOCTYPE,"AR")) AND (LIMIT-TO (SUBJAREA,"ENGI") OR LIMIT-TO (SUBJAREA,"COMP") OR LIMIT-TO (SUBJAREA,"DECI") OR EXCLUDE (SUBJAREA,"ENGI")) AND (LIMIT-TO (PUBYEAR,2023) OR LIMIT-TO (PUBYEAR,2022) OR LIMIT-TO (PUBYEAR,2021) OR LIMIT-TO (PUBYEAR,2020) OR LIMIT-TO (PUBYEAR,2019)) AND (LIMIT-TO (LANGUAGE,"ENGLISH")) AND (LIMIT-TO (OA,"ALL"))

The search initially yielded a total of 3280 items. Upon focusing our query to encompass solely open-access papers, we were able to whittle down the results to 952 items. Subsequently, a detailed examination of the titles and keywords allowed us to further narrow down our selection to 44 articles. We specifically chose articles that included the term "decision-making," an AI method, and a manufacturing-related word in their titles or keywords. After this, we thoroughly evaluated the full texts of the remaining 9 articles that prominently showcase the application of AI for inclusion in this comprehensive literature review.

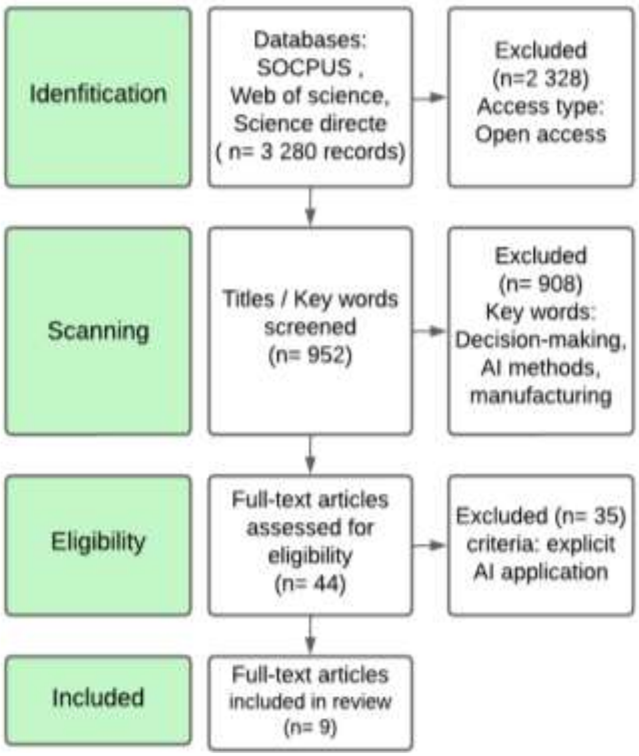

FIGURE 1 PRISMA flowchart for the keywords used

RESULTS

TABLE I OVERVIEW OF ARTICLES REVIEWED IN THE CURRENT LITERATURE STUDY

ID	Article	Journal	Year	Problematic	Authors
1	A decision support system for classifying supplier selection criteria using machine learning and random forest approach	Decision analytics journal	2023	Supplier selection	Md. Ramjan Ali, Shah Md. Ashiquzzaman Nipu Sharfuddin Ahmed Khan
2	A deep learning approach for anomaly detection with industrial time series	29th International Conference on Flexible	2019	anomaly detection	Mattia Carlettia, Chiara Masierob Alessandro Beghia, Gian Antonio Sustoa

	data: a refrigerators manufacturing case study	Automation and Intelligent Manufacturing (FAIM2019)			
3	AI based combined scheduling and motion planning in flexible robotic assembly lines	7th CIRP Global Web Conference: "Towards shifted production value stream patterns through inference of data, models, and technology"	2019	tasks scheduling and motion planning	Niki Kousia, Dimosthenis Dimosthenopoulosa Aleksandros-Stereos Matthaiakisa George Michalosa, Sotiris Makrisa
4	Human-centric artificial intelligence architecture for industry 5.0 applications	International Journal of Production Research	2022	Demand forecasting model	Jože M. Rožanec, Inna Novalija, Patrik Zajec, Klemen Kenda, Hooman Tavakoli Ghinani, Sungho Suh, Entso Veliou, Dimitrios Papamartzivanos, Thanassis Giannetsos, Sofia Anna Menesidou, Ruben Alonso, Nino Cauli, Antonello Meloni, Diego Reforgiato Recupero, Dimosthenis Kyriazis ,Georgios Sofianidis , Spyros Theodoropoulos, Blaž Fortuna, Dunja Mladenić, John Soldatos
5	Interactive knowledge discovery and knowledge visualization for decision support in multi-objective optimization	European Journal of Operational Research	2022	Multi-objective optimization	Henrik Smedberg, Sunith Bandaru
6	Toward zero -defect manufacturing with the support of artificial intelligence-insights from an industrial application	Computers in Industry	2023	anomaly detection	Nicolas Leberruyer, Jessica Bruch Mats Ahlskog, Sara Afshar
7	Predicting performance indicators with ANNs for AI-based online scheduling in dynamically	Production Engineering	2021	Tasks scheduling	Amon Göppert, Leon Mohring, Robert H. Schmitt

	interconnected assembly systems				
8	Performance assessment methodology for AI-supported decision-making in production management	53rd CIRP Conference on Manufacturing Systems	2020	Accuracy evaluation of decision-making in production management	Peter Burggräfa, Johannes Wagnera Benjamin Kokea, Milan Bamberga
9	A meta-learning classification model for supporting decisions on energy efficiency investments	Energy & Buildings	2022	Efficient investments selection	Elissaios Sarmas, Evangelos Spiliotis Vangelis Marinakis, Themistoklis Koutselis Haris Doukas

The literature review revealed that the engineering of decision support systems is particularly centered on the problem or problems to be handled where artificial intelligence is seen to be particularly used to compromise partially or totally the cognitive burden, especially in the complex stages of the decision-making process thus its contribution varies depending on the context between the construction of the decision-making framework, the suggestion of alternatives and taking the role of the decision-making brain

For instance, when it comes to supplier selection, defining a set of selection criteria is particularly challenging and extremely important as it closely conditions the relevance of the result. In this regard, [17] combines RF classifiers and RF feature selection to generate an extensive sorted criteria listing that ought to be considered when choosing suppliers. as a starting point of the process potential criteria are obtained from the literature via the PRISMA technique, and the random forest algorithm is subsequently utilized to preserve the most relevant criteria which were next prioritized using the random forest classifier , the ranked shortlist turned out to be as follow: Quality, On-Time Delivery, Material Price, Information sharing, after sales service, lead time, quantity discount, occupational health and safety system and transportation cost.

In addition, Meta-learning classifiers have also been introduced in the categorization of alternatives, indeed, [18] introduced the approach for categorizing energy investments according to their potential in terms of the following metrics: implementation expense and achieved savings in energy post-implementation. The model has two distinct layers, the first of which is a stacked ensemble of five different methods namely: the KNN classifier, the Random Forest classifiers, the SVM classifiers, the naive Bayes, and the XGBoost, while the second level includes the logistic regression technique chosen to serve as the application's meta-learner. The results show that the stacking ensemble model surpasses all baseline machine learning classification methods, efficiently recognizing projects with high and medium investment levels.

Another application of artificial intelligence supporting the construction of a human-operated decision support system was introduced by [19]where a decision support system for multi-objective optimization, that allows solutions evaluation in both objective and decision space using Interactive knowledge discovery and knowledge visualization, is introduced. The first step of the process consists of visualizing solutions using an appropriate approach that ranges from 2D scatter plot to PCPs, RadViz, t-SNE to UMAP capable of clearly emphasizing the clusters in the objective space, followed by decision maker's preferences elicitation using Lasso-based selection, Sliders on PCPs or reference point method. Flexible Pattern Mining (FPM) and Simulation-Based Innovization (SBI) are then used for generating if-then decision rules which are subsequently represented as nodes in an interactive graph displaying the significance of rules in the preferred solutions, the significance of rules in the remaining solutions, the significance ratio between the selected and unselected sets, and the level of rule-interactions that can be adjusted by the decision maker.

In the same context [20] proposes a demand forecasting model that employs statistical and machine learning models to anticipate future consumer demand based on historical data and other information sources that takes into account various sorts of demand patterns, and delivers explainable insights to enhance industrial decision-making with the goal of reducing operational ineffectiveness and allowing improved supply chain decision-making. The model adopts the approach of pooling product demand time series based on previous demand magnitude with two-step technique that addresses Stock-keeping-oriented Prediction Error Costs and delivers considerable increases in anticipating demand occurrence for items with lumpy and intermittent demand. Explainable Artificial Intelligence (XAI) is also used in the demand forecasting model to give an understanding of the model's reasoning underlying the prediction. Proxy algorithms are applied to figure out the most significant aspects of a specific forecast, and a bespoke ontology model translates relevant concepts to these features. Clarifications are supplemented by offering press-release information about previous events that may have affected demand, as well as looking for available datasets to enhance future findings.

In the context of manufacturing, anomalies recognition decision-making is an endeavor that entails assessing complex unstructured multimodal data involving natural variances. [21] propose an AI-based defect detection model that functions by analyzing vibration data from transmission axles using machine learning algorithms that utilizes random forest for classification and extreme gradient boosting for regression. The model required a feature selection phase where a label data set segregating approved from defective products was prepared, after which the random forest classifier was trained to capture important features on defects and approved labels which were next reduced to two dimensions using the principal component analysis displaying defective and approved products. While the extreme gradient boosting (XGBoost) was used to estimate the defect similarity ratio between training set and recently manufactured products metric that was used to evaluate model accuracy which turned out reasonable.

On the other hand, [22] introduced a method without an explicit feature engineering. This study describes BINN (Bayesian Inference Neural Network), a deep learning technique for detecting anomalies in industrial time series data that was tested on real industrial data consisting of pressure profiles measured after the vacuum creation process for thousands of refrigerators. The model contains a pair of convolutional layers subsequent to a pair of dense layers trained and tested considering dropout to induce a Bayesian variational inference interpretation with the purpose of computing an overall model uncertainty measure of each time series considered as an anomaly score to detect abnormal profiles. The introduced Deep Learning-based Anomaly Detection approach turned out to outperform the Isolation Forest, One-Class SVM, and Principal Component Analysis algorithms as well as a Deep learning-based solution using a fully-connected autoencoder in terms of precision, recall, and F1 score (harmonic mean of precision and recall)

Moreover, real-time autonomous decision-making solutions complement the substantial benefits in automation, efficiency, and production that the deployment of robots in Industry 4.0 provides. In fact, [23] presents two decision-making frameworks integrating artificial intelligence for both line level and resource level decision making which communicate with one another ensuring an optimal task scheduling and motion planning for robotic assembly line. the model relies on a Digital Twin providing real-time data and a conceptual overview of the processes and resources, as well as collision-free trajectories of alternative tasks developed by MRP motion planners, in addition to a rule-based resource suitability calculation classifying appropriate resources for each operation evaluating its characteristics and task requirements to operate a multi-criteria decision-making module that determines alternatives by assigning an assembly operation to one of the available resources and evaluating it based on Robot motion planning where execution is simulated creating the robot behavior template that provides data for operations evaluation done in terms of Part Flowtime, Payload handled by the human, Distance covered by the mobile robots and Resource Utilization while considering their weights determined in accordance to the production and end user objectives, the high-scoring alternative is chosen and efficient schedule is thus built and dispatched to MRP controllers and Human Machine Interfaces (HMIs).

In the same context, [24] discusses the use of artificial neural networks (ANNs) for predicting performance indicators in online scheduling for dynamically interconnected assembly systems where an assembly control system way created based on Google DeepMind's AlphaZero algorithm to train an ANN of multiple blocks of batch normalization, dense layers with ReLU activation functions, and dropout featuring vector and legal actions to suggest favorable job routing decisions and predict the value of actions. The results show that the trained network can predict favorable actions with high accuracy and estimate the makespan with low error.

Finally, [25] proposes a performance assessment methodology using item response theory to compare human decision-making to AI decision-making in production management, the comparison was performed for a low-complexity production task, specifically static, non-reactive, single-agent job-shop scheduling problems (JSSP) with perfect information and a relatively small solution space in form of two academic scheduling problems, namely a 5x1 job-shop scheduling problem (Case A) and a 5x3 Flow Shop Scheduling Problem (Case B), where the decision-making model was designed using reinforcement learning (RL) and trained to find the best policy of action was proved to outperforms human decision-making.

CONCLUSION AND FUTURE WORK

Artificial intelligence is used for decision-making in various ways within the industrial context, spanning tasks like supplier selection, optimization, forecasting, anomaly detection, real-time automation, and performance assessment. the wide range of applications can be categorized into three main groups by examining the human involvement that underlies in model operation : self-sufficient decision-making systems that are intended to substitute the conventional decision-making process, the collaborative systems offering recommendations based on integrating experienced knowledge and work as a hand in hand with human-driven decision-making, and decision-making models that contextualize and support human-centric decision-making for increased accuracy These categories help us understand how AI impacts decision-making in different industrial contexts.

Considering the various applications presented, it appears that AI has made significant strides in addressing industrial decision-making needs. AI is being used in diverse contexts such as supplier selection, demand forecasting, anomaly detection, and real-time decision-making, and it is shown to outperform traditional methods in some cases. This suggests that AI applications are increasingly meeting industrial needs by enhancing efficiency, accuracy, and the overall decision-making process.

However, it's important to note that the effectiveness of AI applications can vary depending on the specific industrial context and the quality of data and models. Continuous advancements in AI and machine learning will likely further improve the satisfaction of industrial needs in decision-making.

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