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Data Mining Classification Techniques to Improve Decision-Making Processes

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Abstract. This study aims to enhance decision-making processes in dynamic organizational environments by integrating Artificial Intelligence (AI) techniques. It explores AI's potential to improve efficiency, accuracy, and predictability while addressing the ethical concerns, biases, and risks of over-reliance that accompany its implementation. We introduce a novel, domain-independent iterative methodology that leverages data mining classification techniques to analyze large datasets from information systems. This approach identifies specific situations where existing decision-making strategies yield suboptimal results and uses these insights to refine and improve the strategies employed. The methodology has proven effective in augmenting feedback control strategies by employing an inductive machine learning algorithm to uncover areas for enhancement. Our results indicate that initial strategies can be upgraded to achieve comparable levels of cost efficiency, even when accounting for the costs associated with evaluating potential strategies. This study recognizes limitations related to the variability of expert opinions in scenarios characterized by numerous components, which may constrain the optimization scope of the learning system. Future research should consider the application of advanced optimization techniques, such as genetic algorithms, to better establish optimal conditions for improvement. The findings suggest that this methodology can be readily applied within simulation frameworks, allowing organizations to assess changes in control strategies effectively. This facilitates informed resource allocation and improves operational efficiencies across diverse settings. As the adoption of AI in decision-making processes increases, attention to ethical considerations becomes crucial. Our methodology promotes transparency and addresses potential biases, fostering responsible AI use that mitigates negative societal impacts.

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1. Introduction

In the contemporary era of data abundance and technological advancements, the integration of artificial intelligence (AI) techniques into decision theory models has emerged as a critical strategy for enhancing decision-making processes across various industries. Decision-making plays a pivotal role in organizational success, influencing strategic directions, resource allocations, and competitive positioning. Traditional decision theory frameworks, while valuable, are often limited in their ability to effectively analyze large and complex datasets, leading to suboptimal decision outcomes in dynamic and uncertain environments.

The fusion of AI technologies with decision theory holds immense potential to revolutionize decision-making practices by empowering decision-makers with advanced analytical tools, predictive capabilities, and real-time insights. By leveraging AI algorithms such as machine learning, neural networks, and optimization techniques, organizations can extract valuable patterns and trends from vast amounts of data, enabling more informed and data-driven decision-making processes.

Numerous studies have highlighted the transformative impact of AI on decision theory and its applications across diverse domains. The work of Johnson et al. [30] showcased the benefits of neural networks in optimizing supply chain decision-making processes, leading to improved operational efficiency and cost savings.

This study builds upon the existing body of literature by presenting a comprehensive exploration of developing decision theory models based on AI techniques, with a focus on improving decision-making processes in complex and dynamic environments. Through a systematic review of decision theory frameworks, AI applications, and empirical analyses, this research aims to provide a roadmap for organizations to leverage AI-driven decision models to navigate uncertainty, mitigate risks, and capitalize on opportunities in a data-driven world.

By bridging the gap between traditional decision theory and AI technologies, this study seeks to contribute to the evolving landscape of decision science and empower organizations to embrace AI as a strategic enabler for enhanced decision-making capabilities. The insights and recommendations derived from this research are intended to guide decision-makers, researchers, and practitioners in adopting AI-driven decision theory models to drive organizational performance and competitiveness in an increasingly digital and dynamic business environment.

2. Background

The integration of artificial intelligence (AI) techniques into decision theory models has been a topic of increasing interest and research in recent years, with numerous studies highlighting the transformative impact of AI on decision-making processes. Yager, and Zadeh [71] utilized the integration of fuzzy logic and neural networks in decision-making and optimization processes. It discussed how combining these AI techniques can improve the handling of uncertainty and complexity in decision theory models, leading to more robust and efficient decision support systems. Jensen [29] explored the application of AI techniques in financial decision-making processes, such as neural networks and expert systems. Miller [47] examined the use of AI in medical decision-making models, focusing on expert systems and their role in diagnosis and treatment planning. Richeson et al. [58] focused on the application of neural networks in providing intelligent decision support in business contexts. It discussed the use of neural networks to analyze complex data and make accurate predictions, offering insights into how AI can enhance decision-making in business settings. Langley et al. [36] utilized the intersection of machine learning and decision-making processes. It discussed how AI algorithms can learn from data and make informed decisions, highlighting the importance of integrating machine learning techniques in decision theory models. Dutta [19] examined the theory and practical implementation of artificial intelligence techniques in decision support systems. It explored the challenges and opportunities of using AI in decision-making processes and discusses the gap between theoretical concepts and real-world applications. Wong and

Selvi [70] offered a comprehensive survey of expert systems and artificial intelligence techniques in decision support systems. It discusses the role of AI in enhancing decision-making processes and the applications of expert systems in various domains. Tah and Carr [64] investigated the integration of fuzzy logic in risk assessment models. The researchers showcased how fuzzy logic can handle uncertainties in risk analysis, assign degrees of membership to different risk factors, and aid in developing more accurate risk assessment methodologies. Edwards et al. [20] examined the usage of expert systems in providing strategic decision support to organizations. The study demonstrated how expert systems can analyze complex data, generate insights, and assist decision-makers in making informed and effective strategic choices. Fadlalla and Lin [21] explained the application of neural networks in financial decision-making processes. The researchers investigated how neural networks can be used to predict stock market trends, optimize investment strategies, and improve risk management in the financial industry. Chawla et al. [10] focused on the development of AI-powered risk assessment models for financial decision-making. The researchers showcased how AI algorithms, such as neural networks and decision trees, can analyze market data, evaluate risks, and support financial institutions in making more informed and reliable investment decisions. Chen [11] investigated the integration of fuzzy logic and neural networks to improve business decision-making. The authors propose a hybrid approach that combines the strengths of both AI techniques to handle uncertainty and complexity in decision theory models. Kuo and Chen [35] delved into the implementation of genetic algorithms to optimize supply chain decisions. By leveraging genetic algorithms, the study demonstrated how supply chain managers can efficiently solve complex optimization problems, such as inventory management, production scheduling, and logistics planning. Davenport, and Harris [13] explored the use of artificial intelligence in fraud detection. By analyzing different AI techniques, the researchers aimed to enhance fraud detection capabilities in financial transactions, demonstrating the effectiveness of AI in mitigating fraudulent activities. Yuangping et al. [72] examined AI-driven marketing strategies for customer acquisition. By leveraging AI technologies, the study aimed to optimize customer acquisition campaigns, enhance targeting strategies, and improve conversion rates, showcasing the role of AI in marketing effectiveness. Copeland and Proudfoot [12] provided a comprehensive literature review of the application of AI techniques in decision support systems. The authors explored how AI methods such as neural networks, fuzzy logic, and genetic algorithms have been used to enhance decision-making processes. Sahay [60] investigated the application of artificial intelligence for dynamic pricing strategies. By utilizing AI algorithms to analyze market dynamics and consumer behavior, the researchers aimed to optimize pricing decisions in real-time, showcasing the role of AI in pricing strategy development. Lawrynowicz [37] focused on supply chain optimization using artificial intelligence techniques. The researchers explored how AI methods could improve supply chain efficiency, reduce costs, and enhance decision-making processes, showcasing the potential of AI in optimizing supply chain operations. Mellit and Kalogirou [44]) provide a comprehensive overview of the use of artificial intelligence (AI) techniques in the field of photovoltaics. The authors highlight the importance of AI in optimizing the performance, efficiency, and reliability of photovoltaic systems. Various AI techniques such as artificial neural networks, genetic algorithms, fuzzy logic, and support vector machines are discussed in the article. The authors also present a detailed analysis of the applications of AI in photovoltaics, including solar forecasting, fault detection, monitoring, and control of photovoltaic systems. Overall, the article emphasizes the significant role of AI in advancing photovoltaic technology and improving its overall performance.

The study conducted by Ho et al. [26] explored the engine performance parameters and emission prediction of a hydrogen-powered car through the utilization of artificial intelligence. The research delved into optimizing the performance of the engine by analyzing various parameters. The use of hydrogen as a fuel source for vehicles is of particular interest due to its potential as a clean and sustainable energy alternative. Artificial intelligence techniques were implemented to predict emissions from the hydrogen-powered car, aiding in understanding the environmental impact of such vehicles. The findings of this study may contribute to the advancement of hydrogen fuel technology and the development of more environmentally friendly transportation options. Pedrycz et al. [55] provided an overview of computational intelligence techniques and their applications in decision-making processes. Authors discussed various computational intelligence methods such as neural networks, fuzzy logic, genetic algorithms, and expert systems, and how they can be employed to support decision-making in complex and uncertain environments. The authors may emphasize the role of computational intelligence in enhancing decision-making by processing large datasets, identifying patterns, and making predictions based on data-driven insights. The use of AI tools in decision-making support systems is reviewed in the article. Various applications and benefits of these tools are analyzed, highlighting their impact on enhancing decision-making processes. Recommendations are provided for the effective integration of AI in support systems to improve organizational efficiency [56].

Photovoltaic systems play a crucial role in renewable energy utilization, and optimizing the sizing of such systems is essential for maximizing their efficiency and performance. Mellit et al. [45] provides a comprehensive overview of the application of artificial intelligence techniques for sizing photovoltaic systems. The study explores various artificial intelligence methods employed for accurately determining the appropriate size and configuration of photovoltaic systems. By leveraging artificial intelligence, researchers aim to enhance the design and implementation of photovoltaic systems, ultimately fostering the adoption of solar energy as a sustainable power source. This review offers valuable insights into the innovative approaches and advancements in utilizing artificial intelligence for sizing photovoltaic systems.

Mellit et al. [46] focuses on the application of neural networks and genetic algorithms for the optimization of sizing photovoltaic systems. Neural networks aid in modeling complex relationships within the system, while genetic algorithms optimize the sizing process by mimicking natural selection mechanisms. By integrating these artificial intelligence methods, the researchers aim to enhance the efficiency and performance of photovoltaic systems, thereby promoting the widespread adoption of solar energy solutions. The findings of this study contribute to the ongoing efforts in advancing renewable energy technologies and optimizing the design of photovoltaic systems. Khanna [32] discussed the current landscape of AI applications in dentistry. They explore how AI is being utilized for tasks such as dental image analysis, treatment planning, and patient interaction in the dental industry. The authors may delve into the potential benefits of AI in improving diagnostic accuracy, treatment outcomes, and overall patient care within the dental field. Additionally, the article may touch upon the future prospects of AI in dentistry, including personalized treatment recommendations, robot-assisted surgeries, and disease prevention strategies. Ethical considerations around patient privacy, data security, and algorithm transparency are likely highlighted as essential factors to address in the integration of AI technologies in dental practices.

Tenório et al. [66] utilized artificial intelligence techniques to create a decision-support system for diagnosing celiac disease. The researchers likely explore the integration of AI algorithms for analyzing patient data, symptoms, and diagnostic tests to assist healthcare professionals in accurately identifying celiac disease in patients. The developed system may leverage machine learning algorithms to improve diagnostic accuracy, optimize treatment decisions, and enhance patient outcomes in the context of celiac disease diagnosis. The study likely highlights the potential of AI in transforming the diagnostic

process for celiac disease, offering a more efficient and effective approach for healthcare providers. Ethical considerations regarding patient data privacy, system transparency, and the validation of AI models are crucial aspects that may be addressed in the article.
Summary:
Omoteso [51] explored the use of artificial intelligence (AI) in the field of auditing. The study delved into the historical perspective and future potential of AI technologies in improving auditing processes. Through a comprehensive analysis, the author highlighted the benefits and challenges associated with implementing AI in auditing practices. The article underscored the significance of embracing AI tools to enhance efficiency, accuracy, and effectiveness in auditing procedures. Overall, Omoteso's research underscored the growing importance of AI in revolutionizing the auditing industry and emphasizes the need for further exploration and adoption of AI technologies in auditing practices.
Wren [56] conducted a comprehensive review of artificial intelligence tools utilized in decision-making support systems. The review may encompassed a range of AI techniques such as machine learning, expert systems, neural networks, and natural language processing, examining their applications and effectiveness in aiding decision-making processes. The author potentially analyzed the benefits of AI tools in enhancing decision accuracy, increasing efficiency, and facilitating complex decision tasks across various industries and domains. The scientific summary would likely highlighted the critical role of AI tools in decision support systems and their potential to deliver valuable insights, optimize decision outcomes, and drive intelligent decision-making practices in different organizational settings.
In 2013 Bennett and Hauser introduced a novel method for simulating clinical decision-making using Markov decision processes. This framework leveraged artificial intelligence techniques to model complex medical scenarios and improve the quality of healthcare delivery. By employing a Markov decision process approach, the researchers demonstrated how AI can be used to make informed decisions in clinical settings. Guo and Wong [25] explored the use of artificial intelligence in the context of apparel management. The authors discussed key AI techniques and their applications in optimizing decision-making processes within the apparel supply chain. By delving into the fundamentals of AI techniques and their specific relevance to apparel management, Guo and Wong offered a comprehensive overview of the opportunities and challenges associated with integrating AI into the apparel supply chain. Dobrzański et al. [17] delved into the application of neural networks and artificial intelligence tools in enhancing modeling, characterization, and forecasting activities within the field of material engineering. the authors explored how neural networks are leveraged to analyze complex material properties, predict material behavior, and optimize manufacturing processes and discussed the benefits of using AI tools for data-driven decision-making, improving material design, and enhancing performance evaluation in material engineering applications.

Stalidis et al. [62] explored the utilization of artificial intelligence and knowledge modeling techniques in the context of marketing decision-making for tourist destination management. The study delved into how AI tools and knowledge-based systems are applied to analyze consumer behavior, market trends, and tourism-related data to support strategic decision-making processes in the tourism industry. The authors discussed the integration of AI algorithms for personalized marketing strategies, customer segmentation, and targeted promotional campaigns to enhance tourist destination management practices. Trappey et al. [67] presented a comprehensive investigation into the utilization of collective intelligence approaches for enhancing decision-making processes in engineering. The study involved the development and application of models that integrate insights from diverse stakeholders, experts, and sources to facilitate innovative and informed engineering decision-making. The researchers discussed methodologies for analyzing collective intelligence data, synthesizing multiple perspectives, and deriving valuable insights to support complex engineering decisions. The article underscored the importance of leveraging collective intelligence techniques to harness the collective wisdom and expertise of groups in engineering domains, ultimately leading to more effective and innovative decision-making outcomes. A novel approach that incorporates artificial emotions into a decision-making system for the stock exchange market introduced by Cabrera-Paniagua et al. [7]. The study involved the development of a framework that integrates emotional intelligence principles and artificial intelligence techniques to enhance decision-making processes in stock trading. The researchers explored how artificial emotions are generated, represented, and utilized to analyze market trends, predict stock prices, and optimize trading strategies. The article discussed the impact of emotions on financial decision-making and the potential benefits of incorporating artificial emotions in stock market analysis and trading algorithms.

Klashanov [34] in their research, investigated the application of artificial intelligence in decision-making processes within the construction industry. The study focused on leveraging AI technologies to enhance the efficiency, accuracy, and effectiveness of organizing decisions in construction projects. The researcher explored how AI tools such as machine learning algorithms, expert systems, and data analytics can be utilized to optimize resource allocation, scheduling, risk management, and other aspects of decision-making in construction operations and discussed how AI contributes to improving project planning, monitoring, and control, ultimately leading to enhanced productivity and project outcomes in the construction sector. A novel application of artificial intelligence (AI) in clinical decision support systems to reduce medical errors presented by Buzaev et al. [6]. The authors developed a neural network model that integrates with multidisciplinary healthcare teams to provide accurate and timely diagnoses. The AI system was trained on a large dataset of medical records and was able to accurately identify patterns and relationships between patient symptoms, diagnoses, and treatment outcomes. The authors conducted a simulation study to evaluate the effectiveness of the AI system in reducing medical errors. The results showed that the AI system significantly improved diagnostic accuracy and reduced the likelihood of misdiagnosis compared to human clinicians. The study also demonstrated that the AI system was able to identify potential medical errors earlier than human clinicians, allowing for timely intervention and prevention of adverse outcomes. The findings of this study highlight the potential benefits of integrating AI into clinical decision support systems to improve patient outcomes and reduce medical errors. The authors suggest that the use of AI in healthcare may lead to more efficient and effective healthcare delivery, particularly in complex cases where human clinicians may be less likely to make accurate diagnoses. The potential application of artificial intelligence (AI) expert systems with neural network machine learning to assist decision-making for extractions in orthodontic treatment planning investigated by Takada [65]. The author proposed the development of an AI-based system that integrates clinical knowledge and patient data to provide personalized recommendations for extraction decisions. The author reviewed the current limitations of traditional orthodontic treatment planning methods, including the reliance on subjective clinical judgment and the lack of standardized decision-making protocols. The study highlighted the potential benefits of AI-based systems, including improved accuracy, reduced bias, and enhanced efficiency. in this research concluded that the integration of AI expert systems with neural network machine learning may improve the accuracy and efficiency of extraction decisions in orthodontic treatment planning. Marwala [43] explored the intersection of rational choice theory and artificial intelligence. The author argued that traditional rational choice models, which rely on human rationality, are limited in their ability to explain complex decision-making processes. In contrast, AI systems can process vast amounts of data and make decisions without being constrained by human biases. The paper discussed how AI can be used to improve decision-making in various fields, including economics, politics, and healthcare. The author also highlighted the potential risks and challenges associated with the increasing reliance on AI in decision-making. Specifically, the paper examined how AI systems can be designed to incorporate rational choice principles and how this can improve decision-making outcomes. The researcher concluded that a combination of human rationality and AI can lead to more effective decision-making. Paschek et al. [54] examined the impact of AI on decision-making processes in business. The authors argued that AI can revolutionize decision-making by providing faster and more accurate information, reducing human bias, and improving data analysis. They presented case studies and empirical evidence to illustrate how AI can be used to optimize business decisions, increase efficiency, and enhance competitiveness. The researchers concluded that AI has the potential to fundamentally change the way businesses make decisions, offering both opportunities and challenges for managers. Overall, this paper contributes to the ongoing debate about the role of AI in business decision-making. The integration of artificial intelligence (AI) technologies with rational and creative decision-making in quality management explored by Paliukas and Savanevičiene [52]. Optimal marketing strategies for a customer data intermediary are analyzed in the article. Insights are provided into effective approaches for leveraging customer data to enhance marketing efforts. Recommendations are offered for improving marketing performance and customer engagement through data-driven strategies [53]. The researchers proposed a harmonization framework that combines analytical and intuitive decision-making approaches to improve quality management and the potential benefits of AI in enhancing decision-making speed, accuracy, and transparency. The authors argued that AI can facilitate the integration of human creativity with data-driven analysis, leading to more effective quality management practices. A theoretical framework that examines the interplay between prediction, judgment, and complexity in decision-making and AI presented by Agrawal et al. [1]. They mentioned that AI systems can augment human judgment by providing accurate predictions, but also introduce new complexities that require human judgment to interpret and contextualize the outputs. They argue that this interplay between prediction and judgment is essential for effective decision-making in AI systems. Jarrahi [28] explored the impact of AI on organizational decision-making, arguing that a human-AI symbiosis is essential for effective decision-making. The impact of AI on decision-making, highlighting both its potential benefits and limitations examined by Dear [14] and he argued that AI can improve decision-making by providing accurate and timely data, but also notes that human judgment is still essential for contextualizing and interpreting AI outputs.

A novel conceptualization of patterns in decision-making with AI introduced by leyer et al. [39]. They showed that AI systems can uncover complex patterns in data, but human decision-makers must understand and interpret these patterns to make informed decisions. Trunk, Birkel, and Hartmann [67] examined the integration of human and artificial intelligence in strategic organizational decision-making. The study provides a comprehensive overview of the current landscape in this domain, highlighting the challenges and opportunities for leveraging both human expertise and AI capabilities. They emphasized the need for a balanced approach to harness the strengths of both human judgment and AI algorithms in order to enhance strategic decision-making processes within organizations. Främling [22] explored the intersection of decision theory and explainable AI (XAI), highlighting the need for transparent and interpretable AI systems. also researcher argued that XAI can facilitate human understanding and trust in AI-driven decision-making, while decision theory provides a framework for evaluating the rationality and robustness of AI-based decisions. The study by Gil et al. [24] highlighted how artificial intelligence can effectively model complex systems, enhancing decision-

making processes by simplifying intricate expert models. Their research focused on mitigating the challenges posed by complex systems through AI techniques, ultimately improving decision-making accuracy in varied domains.
The evolving role of artificial intelligence methods as innovative tools for decision-making processes is proposed by Lotfi and Bouhadi [41] . Their research underscored the potential of AI techniques in facilitating informed and efficient decision-making, signaling a paradigm shift towards advanced decision support systems in diverse domains. Al-Surmi, Bashiri, and Koliousis [3] elucidated the synergistic benefits of leveraging AI in decision making, emphasizing its role in enhancing operational performance. they showed the effectiveness of integrating diverse strategies with AI techniques to optimize decision-making processes, aimed at improving operational efficiency and productivity. The research conducted by Chatterjee and Satpathy [9] sheds light on the efficacy of integrating artificial intelligence in decision-making systems, showcasing improved decision accuracy and efficiency. The study emphasized AI's potential to enhance strategic decision-making processes within organizations, offering valuable insights for implementing AI-driven decision support systems. Dietzmann and Duan's [16] study delved into the application of artificial intelligence in aiding managerial information processing and decision-making amidst information overload. Their research showcased AI's capacity to assist managers in effectively navigating and analyzing vast amounts of information, thereby enhancing decision-making efficiency in the modern era characterized by information abundance. The role of artificial intelligence in decision-making and its impact on the future of work is explored in the article. Key insights are provided into how AI technologies are shaping workplace dynamics and enhancing organizational efficiency. Recommendations are offered for adapting to the changes brought about by AI in various professional settings [15]. A decision-making model that strengthens digital transformation strategies through the utilization of artificial intelligence technology proposed by Kim and Kim's [33]. They demonstrated the efficacy of integrating AI in enhancing strategic decision-making processes for optimizing digital transformation initiatives, contributing valuable insights to effective organizational strategy implementation.

Dennehy et al. [15] investigated the role of artificial intelligence in decision-making and its implications for the future of work. Through an analysis of AI's impact on decision processes and work dynamics, the research provided insights into the transformative potential of AI technologies in shaping future work environments. Shin et al. [61] explored how superhuman artificial intelligence enhances human decision-making by amplifying novelty in their study. The research illustrated the potential of integrating AI to augment decision-making processes by introducing novel perspectives, as documented in the Proceedings of the National Academy of Sciences, offering valuable insights into the collaborative capabilities of AI and human cognition. Venger and Dozortsev [69] focused on modeling trust in AI to understand human operators' decision-making in high-risk scenarios. This research in Mathematics offers insights into the dynamics of human-AI interaction, particularly in critical situations, shedding light on trust-building mechanisms for effective decision-making in hazardous environments. The impact of AI on human decision-making, work efficiency, and safety within the realm of education proposed by Ahmad et al. [2]. The study, delved into the implications of AI integration for reducing human error, enhancing productivity, and promoting safety protocols in educational settings. Steyvers and Kumar [63] addressed three key challenges related to AI-assisted decision-making. The research highlighted critical obstacles that arise in leveraging AI for decision support, offering valuable insights for enhancing the effectiveness and reliability of decision-making processes aided by artificial intelligence. Sadeghi et al. [59] explored the integration of explainable AI in supply chain cyber resilience to enhance agile decision-making. Their study delved into the synergy between

AI interpretability and adaptive strategies for bolstering cyber security measures in supply chain management. The research in Decision Support Systems highlighted the significance of transparency and flexibility in utilizing AI to fortify resilience against cyber threats in supply chains. Through the integration of intelligent systems, Mishra et al. [48] focused on optimizing decision-making processes in supply chain management, as discussed in Migration Letters. Their research highlighted the role of AI in enhancing efficiency and effectiveness in supply chain decision-making towards improved operational outcomes. The transformative effects of AI in the financial sector, focusing on its capacity to enhance decision-making and risk management practices with the goal of optimizing financial outcomes investigated by Balbaa and Abdurashidova [4]. This research showed the substantial impact of AI on reconfiguring traditional financial processes, leading to more efficient and effective strategies in the dynamic market environment of today. Furthermore, this work shaded light on the pivotal role AI plays in revolutionizing financial practices, thereby facilitating improved decision-making and risk mitigation. The application of AI in finance, exploring its potential to revolutionize decision-making and risk management practices investigated by Layn [38]. The study highlighted AI's ability to improve financial outcomes through enhanced predictive modeling, real-time monitoring, and optimized portfolio allocation. Lin [40] discussed the application of AI in Industrial Engineering . The paper explored how AI technologies are revolutionizing industrial processes and optimizing production outcomes, offering valuable insights into the integration of AI within the realm of industrial engineering. The transformative role of AI in reshaping business strategies through enhanced decision-making processes utilized by Kaggwa et al. [31]. The research underscored how AI technologies drive strategic innovation and improve decision outcomes, offering valuable insights into leveraging AI for business strategy development. BaniHani et al. [5] provided an in-depth examination of the role of AIin the decision-making process across healthcare, financial, and technology sectors. The review synthesized existing research on AI's applications in these domains, highlighting its potential to improve decision-making accuracy, efficiency, and effectiveness.

The potential of artificial intelligence (AI) as a catalyst for operational excellence in Iraqi industries was explored, specifically in the textile and food processing sectors. Significant improvements were demonstrated by the implementation of an AI model, resulting in increased production output and reduced defect and spoilage rates. It is suggested that AI can transform traditional manufacturing practices, fostering continuous improvement and enhancing competitiveness [50]. A novel framework integrating Multi-Criteria Decision Analysis (MCDA) with Deep Reinforcement Learning (DRL) is proposed to enhance decision-making in the Iraqi oil industry. Key criteria are considered for supplier selection, allowing for a systematic evaluation of potential suppliers and continuous improvement of strategies. It is aimed that this integrated approach will optimize procurement processes, reduce risks, and drive better outcomes in the sector [23].

The advent of AI in organizational decision-making presented an opportunity for enhanced efficiency and innovation. A growing body of research suggested that AI technologies are increasingly being integrated across various sectors, with the potential to augment human capabilities and judgments, thereby offering solutions to complex organizational challenges [18, 56, 27]. However, this integration also raised concerns regarding ethical considerations, potential biases, and the suitability of relying on AI recommendations [56]. This article assumed a comprehensive examination of the multifaceted role of AI in modern organizational strategies, critically evaluating its advantages and limitations to propose a balanced approach for future implementation. The limitations of AI in tasks requiring creativity and intuition underscore the difficulties encountered in promoting innovation and exploring novel solutions to complex problems

[42]. The determinism inherent in AI-generated decisions may pose a constraint on creative thinking, highlighting the necessity for incorporating human expertise in the decision-making process to mitigate the potential stifling of innovation. In order to optimize the benefits of AI while minimizing its limitations, a harmonious integration of AI and human expertise is essential [8]. This approach should facilitated synergy between humans and machines, thereby ensuring that AI tools augment human judgment rather than supplant it. The literature suggested that hybrid human-AI partnerships may offer a promising avenue for future development, underscoring the importance of ethical and responsible AI utilization.

3. Data Mining

In contemporary industrial contexts, the implementation of information systems has become a ubiquitous phenomenon. These systems generate vast quantities of data regarding process operations, often resulting in complex data sets that surpass human capabilities for analysis and interpretation. For instance, the incorporation of flight recorder devices on commercial aircraft enables the capture of comprehensive flight data, including audio recordings of cockpit conversations. Subsequent analysis of this information can facilitate the detection of process anomalies and inform corrective actions. However, the sheer magnitude of these data sets often renders traditional statistical methodologies, such as linear regression and t-tests, ineffective for meaningful interpretation.

This study endeavors to address a significant shortcoming of traditional control theory, namely its limitations in capturing complex patterns and relationships. By integrating control theory with a data mining paradigm, we seek to augment process control capabilities by incorporating a pattern recognition component. Specifically, our approach leverages data mining techniques to detect situations in which the controlled variables deviate from their desired states, thereby identifying instances of control failure.

This investigation employs established data mining methodologies to identify patterns indicative of control failure, characterized by suboptimal performance or excessive resource allocation. A crucial aspect of this study's approach is the development of a classification framework capable of distinguishing between successful and unsuccessful outcomes. Various classification techniques have been proposed in the literature, including artificial neural networks, support vector machines, naive Bayesian classifiers, and decision tree induction (Tan et al., 2006). Specifically, the algorithm proposed in this research is designed to generate a set of conditions under which control strategies can be refined to optimize their performance

4. A glimpse into our planned strategy

When dealing with complex situations, decision-making strategies may not always yield the desired results. Information systems often hold a wealth of data on such scenarios. By leveraging data mining techniques, we can uncover patterns that lead to optimal outcomes, allowing us to refine strategies for better results. Through our case studies in manufacturing, we demonstrate the practical application and effectiveness of this iterative approach in enhancing decision strategies. This method not only addresses specific issues in different domains but also highlights its potential for broader use in optimizing decision-making processes across various complex scenarios.

In this research presented a novel methodological framework for enhancing dynamic decision-making processes through the application of machine learning techniques. The study employed a mixed-methods approach, combining both qualitative and quantitative research methods to develop and evaluate a machine learning-based decision support system. Therefore, we commenced by identifying the limitations of traditional decision-making approaches, which are often hindered by incomplete or inaccurate information, cognitive biases, and the inability to adapt to changing environmental conditions. To address these limitations, proposed a machine learning-based framework that integrates multiple decision-making models and incorporates real-time data streams.

The methodological approach consists of three primary components:

1. Data Collection and Preprocessing
2. Machine Learning Model Development
3. Dynamic Decision Making

In this investigation, we have adopted a simulation-based approach to model the manufacturing process and estimate failure rates. The algorithm under consideration is not directly linked to the simulation, precluding its utilization for candidate evaluation purposes. Rather, a finite pool of exemplars is available, which are sequentially consumed by the manufacturing process. The algorithm learns from these consumed instances, employs means-end analysis to detect potential improvement opportunities, and subsequently consumes additional instances to validate these candidate strategies. The validated solutions are then integrated into the next iteration of the strategy.

This section delves into the methodology employed in the proposed machine learning approach for improving dynamic decision making. The hybrid architecture combines knowledge-based and machine learning techniques to effectively address the complexities of real-world decision-making problems. A dynamic data-driven process model is developed to generate predictions based on past data, while a knowledge-based system provides domain-specific rules and constraints. The machine learning component learns from historical data and updates the model in real-time, enabling the system to adapt to changing conditions. A framework is designed to integrate these components, ensuring seamless communication and cooperation between them. The system is trained on a large dataset of historical decision-making events, allowing it to learn from experience and refine its decision-making capabilities.

In the context of dynamic decision-making, consider a system that requires control, such as the assembly of an industrial part. This section explores the application of a newly introduced algorithm in addressing a specific manufacturing task in the automotive industry, where access to simulation models is unavailable. The variability in quality of industrial pieces poses a risk of failure during final assembly, prompting the need for reinforcement to strengthen vulnerable components. This selective reinforcement process incurs costs and influences the final product's attributes, with options such as component additions or material upgrades. While the initial quality of supplied parts impacts failure rates, it is the manipulable variables, like part dimensions and assembly methods, that are targeted for reinforcement efforts. Additionally, the decision-making context within this system highlights the complexity of managing industrial part assembly processes. By examining the introduced algorithm’s application in real-world manufacturing scenarios, we can better understand the challenges and opportunities in optimizing production processes. Effective reinforcement strategies for industrial pieces can significantly impact the overall quality and performance of the final product, emphasizing the importance of targeted interventions. As we delve deeper into the intricacies of this dynamic decision context, we recognize the significance of balancing cost-efficiency with quality enhancement to achieve optimal results in the automotive industry.

In this research, simulation is employed solely for modeling the manufacturing process and assessing failure probabilities. The algorithm under consideration is not permitted access to the simulation data for candidate evaluation. Instead, a finite supply of industrial pieces is utilized in the manufacturing process, serving as the algorithm's learning material. Through means-ends analysis, potential enhancements are identified, tested using additional instances, and integrated into iterative strategies for optimization.

Each industrial piece is characterized by k standardized attributes ($P_1, P_2, \dots, P_k$)representing its quality, with values ranging from 0 to 1. The attribute values are contingent upon the materials and assembly processes involved, as determined in collaboration with an expert in the manufacturing field. Furthermore, the failure mechanism of the industrial piece is also modeled in consultation with a manufacturing expert, with the failure function being a complex Boolean predicate involving nonlinear combinations of the k attributes. It is crucial to emphasize that the algorithm is not privy to this failure function; rather, it is utilized in experiments to emulate real-world manufacturing outcomes, which form the basis of the algorithm's decision-making.
At a certain moment t, the system's current condition is signified by $\Psi(S_{1,t}, S_{2,t}, S_{3,t})$. The effect of the execution process of this method as the algorithm implementation process is shown below:

Algorithm (Run-process)

$N = The\ total\ number\ of\ the\ community$
$T = A\ fixed\ number\ of\ products\ in\ each\ period\ that\ are\ reviewed\ by\ \Phi$
$K = A\ fixed\ number\ of\ products\ in\ each\ period\ that\ are\ reviewed\ by\ S_i$
$S_1:\ modifications\ involving\ enhancements\ and\ improvements\ in\ connections$
$S_2:\ modifications\ involving\ pre-purification\ of\ components$
$S_3:\ modifications\ through\ the\ reassembly\ method$
$\mu_1 = C \qquad (\mu_i: mean\ total\ cost,\quad C: average\ expected\ total\ cost)$
$for\ (i = 1\ to\ N)\ do$
$\quad While\ (\mu_i \geq C)\ do$
$\qquad N_1 \longleftarrow N - T$
$\qquad K_1 = The\ number\ of\ K\ pieces\ selected\ from\ the\ remaining\ N_1\ pieces$
$\qquad S_{1,i}(K_1)$
$\qquad N_2 \longleftarrow N_1 - K$
$\qquad K_2 = The\ number\ of\ K\ pieces\ selected\ from\ the\ remaining\ N_2\ pieces$
$\qquad S_{2,i}(K_2)$
$\qquad N_3 \longleftarrow N_2 - K$
$\qquad K_3 = The\ number\ of\ K\ pieces\ selected\ from\ the\ remaining\ N_3\ pieces$
$\qquad S_{3,i}(k_3)$
$\qquad N \leftarrow N_3 - k$
$\qquad T_i = The\ number\ of\ T\ pieces\ selected\ from\ the\ remaining\ N\ pieces$
$\qquad \Phi_i(T_i) \quad (\Phi_i\ :\ control-\ strategy\ for\ stage\ i)$
$\qquad \mu_i \leftarrow mean\ total\ cost\ in\ the\ results\ obtained\ from\ \Phi_i(T_i)$
$\quad end\ while$
$\quad \Phi(\mathrm{S_1, S_2, S_3})$
$end\ for$
$return\ \ Mean\ total\ cost$

5. Case study: Industrial environment

Suppose an industrial part is used to work with an industrial machine in a factory. This industrial part (from now on it will be displayed as Ψ) is made of 8 smaller pieces, ($P_1, P_2, \dots, P_8$) . Different pieces of Ψ are made in different industrial centers and assembled in a special company. Each piece has the necessary standards, but in terms of quality level, it chooses the real number belonging to the range $[0, 1]$, In other words: $\forall i,\ 1 \leq i \leq 8 \qquad 0 \leq v(P_i) \leq 1$. See Figure 1 for a better understanding of the topic.

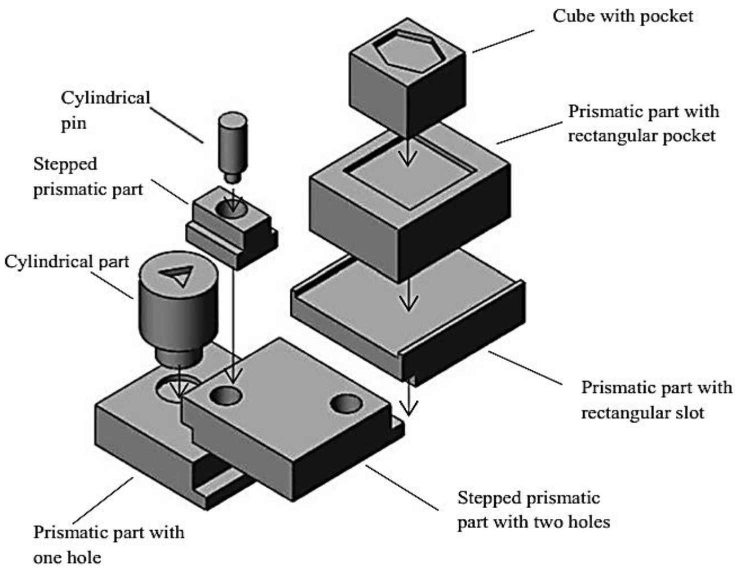

Figure 1. An eight-component assembly [49].

Not all pieces of an Ψ possess uniform quality. The quality of Ψ is different based on the quality of its components and assembly process. A deviation from the required standard in any part can significantly impact the overall performance of the main machine a, resulting in substantial losses for the company. Hence, prior to final installation in the car, stringent quality checks must be conducted to minimize the number of parts that do not meet the necessary standards. Experimental evidence demonstrates that reinforcing industrial parts lacking in quality (through additions and improve joins $\mathcal{S}_1$, pretreat components$\mathcal{S}_2$ or reassembly$\mathcal{S}_3$) can enhance their functionality for use in machines, while effectively managing production costs.

In order to establish the standard range of each component for achieving Ψ under specified standard conditions, engineers have delineated a range of values for each component and have formulated a Boolean linear combination to model the interrelationships among these variables. The forthcoming research will concentrate solely on enhancing system performance through training and will not involve an analysis of these interrelationships; rather, only the outcomes will be utilized.

In the initial phase of system training, an optimal volume recommended by consulting engineers is taken into account. Specifically, an initial set of 60,000 Ψ is designated for system training, followed by the implementation of the model on a dataset comprising a minimum of one million Ψ.

In this research approach, the following procedure is followed. Initially, without consideration of any specific model, an analysis is conducted on $T = 5000$ components to determine the quantity and proportion of parts necessitating removal from the cycle, along with an assessment of the resulting losses. Subsequently, the subsequent set of 6000 Ψ is divided into three groups as outlined below, with specific corrective measures implemented for each group:

The first group comprises 2000 Ψ, which undergo modifications involving enhancements and improvements in connections.

The second group consists of 2000 Ψ, which undergo modifications involving pre-purification of components. The third group includes 2000 Ψ, which undergo modifications through the reassembly method. Upon completion of these three phases, the system has undergone its initial learning process and is poised for enhanced improvements. Subsequently, an analysis is conducted on the next 5000 components, with the outcomes documented and presented in Table 1.

Moving on to the second phase, a similar approach is adopted as in the preceding method, whereby the remaining components are divided into three groups and analyzed in a manner consistent with the initial process. It is acknowledged that at this stage, the system benefits from its prior learnings, enabling it to make more informed decisions for further enhancements. (Results presented in Table 1) In the investigated problem, bringing the mean total cost below 6 dollars has been the main goal. The training process of the system iterates through the established methodology up to five sequential steps. Following the completion of these five iterations, as depicted in Table 1, the results indicate that the system has attained the necessary readiness to operate effectively across all components. The predominance of performance significantly influenced the overall averages. Implicitly, an assumption was made concerning the existence of a substantially extensive total production capacity (1,000,000 units) in comparison to the relatively smaller scale required for refining and evaluating the production processes (e.g., 6,000 units). This proposition is consistent with common observations in various industrial settings. Noteworthy, conventional process control analyses often amplify this assumption, hypothesizing perpetual operation of the processes with an infinite timeline. As a result, the total cost per unit gradually converges towards the mean total cost associated with the final strategy.

Table 1. Enhancement of Components through Decision-Maker System Training.

Strategy		Number	Ψ remaining	Failures %	Mean Cost of Modification	Mean Cost of Failure	Mean total cost
Initial Group (Ψ_0)		5000	55000	17.3	0.00	21.8	21.8
First Step	$\mathcal{S}_1$	2000	53000	11.3	1.02	14.23	15.25
	$\mathcal{S}_2$	2000	51000	16.5	2.03	15.20	17.23
	$\mathcal{S}_3$	2000	49000	15.8	3.52	14.97	18.49
First Strategy (Ψ_1)		5000	44000	11.2	1.05	12.17	13.22
Second Step	$\mathcal{S}_1$	2000	42000	7.2	1.53	7.40	8.93
	$\mathcal{S}_2$	2000	40000	8.4	1.78	7.03	8.81
	$\mathcal{S}_3$	2000	38000	7.8	1.43	6.93	8.37
Second Strategy (Ψ_2)		5000	33000	8.93	1.48	8.76	10.24
Third Step	$\mathcal{S}_1$	2000	31000	4.3	1.79	5.64	7.43
	$\mathcal{S}_2$	2000	29000	3.8	2.88	6.02	8.91
	$\mathcal{S}_3$	2000	27000	5.8	2.17	7.91	10.08
The third Strategy (Ψ_3)		5000	22000	5.01	2.21	5.37	7.09
Fourth Step	$\mathcal{S}_1$	2000	20000	3.14	3.38	3.23	6.61
	$\mathcal{S}_2$	2000	18000	2.18	3.08	3.18	6.26
	$\mathcal{S}_3$	2000	16000	3.28	3.38	3.07	6.45
The Fourth Strategy (Ψ_4)		5000	11000	3.11	4.01	2.98	6.72
Fifth Step	$\mathcal{S}_1$	2000	9000	2.51	3.44	2.01	5.45
	$\mathcal{S}_2$	2000	7000	2.01	3.50	2.18	5.68
	$\mathcal{S}_3$	2000	5000	2.62	3.37	2.26	5.63
The Fifth Strategy (Ψ_5)		5000	0	2.83	3.98	1.97	5.95
Total Ψ		1000,000	0	2.71	3.88	2.31	5.98

6. Conclusions and future work

The study presents a novel machine learning system designed to enhance feedback control strategies through the utilization of principles and established theory to inform decision-making in complicated and organized dynamic environments. The recommended approach employs an inductive machine learning algorithm to pinpoint areas for enhancement and discern optimal iterative enhancements, thereby molding a control strategy that is more economically advantageous or demands diminished supplementary resources to attain the targeted objective. Modification can be achieved through a reduction in resource consumption if a given strategy performs more efficiently. As long as the monitored system presents observable variables and chances to fortify or attenuate the control strategy, the training and operational frameworks can be effectively applied within dynamic environments.

Commencing from diverse performance baselines, all three initial strategies(S_1, S_2, S_3) were elevated to an enhanced and comparable level of cost efficiency. In scenarios where the evaluation of potential strategies incurs costs, the suggested approach succeeded in enhancing the cost-effectiveness of the control strategy post-comprehension of strategy exploration and assessment expenses. These outcomes validate the applicability of the proposed method as a versatile solution for identifying areas that warrant enhancement and subsequently prioritizing these enhancements to allocate resources in a cost-efficient manner.

Utilizing the structured delineation expounded within the context of this study, the suggested technique may be readily executed within simulation frameworks to assess prospective alterations in control methodologies and facilitate process structuring. As evidenced by a practical illustration grounded in an industrial setting, the advocated method seamlessly integrates with simulation tools to simulate enhancements in process control. The benefits of this integration encompass a consistent repository of process data devoid of any gaps, the capacity to scrutinize and enhance counterfactual scenarios for the revelation of novel strategies, as well as the accelerated progression of investigations. Within the study, expert viewpoints were leveraged to establish selection criteria. In instances where the abundance of components within an industrial package leads to expert opinions being disparate, there exists a limitation in the improvement scope targeted by the learning and implementation system. In such scenarios, the recommendation is to employ methodologies like genetic algorithms to initially ascertain optimal conditions and consequently employ them as constraints for further progression.

References

[1] A. Agrawal, J. Gans and A. Goldfarb, Prediction, judgment, and complexity: a theory of decision-making and artificial intelligence. In The economics of artificial intelligence: An agenda (2018) 89-110. University of Chicago Press.

[2] S. F. Ahmad, H. Han, M. M. Alam, M. K. Rehmat, M. Irshad, M. Arraño-Muñoz and A. Ariza-Montes, Impact of artificial intelligence on human loss in decision making, laziness and safety in education. Humanities and Social Sciences Communications, **10 (1)** (2023)1–14. DOI: 10.1057/s41599-023-01787-8.

[3] A. Al-Surmi, M. Bashiri and I. Koliousis, AI based decision making: combining strategies to improve operational performance. International Journal of Production Research, **60(14)** (2022) 4464-4486. https://doi.org/10.1080/00207543.2021.1966540.

[4] M. E. Balbaa and M. S. Abdurashidova, The Impact of Artifical Inteligent in Decisomn Making a Comprehensive Review EPRA International Journal of Economics, Business and Management Studies (EBMS), **11(2)** (2024). 27-38. DOI: 10.36713/epra15747.

[5] I. BaniHani, S. Alawadi and N. Elmrayyan, AI and the decision-making process: a literature review in healthcare, financial, and technology sectors. Journal of Decision Systems, (2024) 1-11, https://doi.org/10.1080/12460125.2024.2349425.

[6] I. V. Buzaev, V. V. Plechev, I. E. Nikolaeva, R. M. Galimova, Artificial intelligence: Neural network model as the multidisciplinary team member in clinical decision support to avoid medical mistakes, Chronic Diseases and Translational Medicine, **2(3)** (2016) 166-172. https://doi.org/10.1016/j.cdtm.2016.09.007.

[7] D. Cabrera-Paniagua, C. Vicari, E. Urra, Decision-making system for stock exchange market using artificial

emotions, Expert Systems with Applications, **42 (20)** (2015) 7070-7083, https://doi.org/10.1016/j.eswa.2015.05.004.

[8] S. Cao, A. Liu and CM. Huang, Designing for Appropriate Reliance: The Roles of AI Uncertainty Presentation, Initial User Decision, and User Demographics in AI-Assisted Decision-Making. arXiv:2401.05612, (2024), https://arxiv.org/abs/2401.05612.

[9] S. Chatterjee and S. Satpathy, Artificial Intelligence in Decision Making System. In ACI@ ISIC (2022) 96-107. https://doi.org/10.1007/11893004_69.

[10] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, SMOTE: synthetic minority over-sampling technique. Journal of artificial intelligence research **16** (2002), 321–357. https://doi.org/10.1613/jair.953

[11] T. Chen, A fuzzy mid-term single-fab production planning model. Journal of Intelligent Manufacturing **14 (3)** (2003) 273–285. https://doi.org/10.1023/A:1024641507765.

[12] B. J. Copeland and D. Proudfoot, The History and Development of Artificial Intelligence. In P. Thagard (Ed.), Philosophy of Psychology and Cognitive Science, (2006). https://doi.org/10.1016/B978-044451540-7/50032-3

[13] T. H. Davenport, and J. G. Harris, Automated decision making comes of age. MIT Sloan Management Review, **46(4)** (2005). 83.

[14] K. Dear, Artificial intelligence and decision-making. The RUSI Journal, **164(5)** (2019) 18-25. https://doi.org/10.1080/03071847.2019.1693801.

[15] D. Dennehy, A. Griva, N. Pouloudi, M. Mäntymäki and I. Pappas, Artificial intelligence for decision-making and the future of work, (2023). DOI: 10.1016/j.ijinfomgt. (2022).102574.

[16] C. Dietzmann, Y. Duan, Artificial intelligence for managerial information processing and decision-making in the era of information overload, (2022). DOI: 10.24251/HICSS.2022.720.

[17] L. A. Dobrzański, J. Trzaska, A.D. Dobrzańska-Danikiewicz, (2014). 2.09 - Use of Neural Networks and Artificial Intelligence Tools for Modeling, Characterization, and Forecasting in Material Engineering, Editor(s): Saleem Hashmi, Gilmar Ferreira Batalha, Chester J. Van Tyne, Bekir Yilbas, Comprehensive Materials Processing, Elsevier, 2014, Pages 161-198, https://doi.org/10.1016/B978-0-08-096532-1.00215-6.

[18] R. Douglas, J. Karwowski, C. Bae, A. Draguns and V. Krakovna, Limitations of Agents Simulated by Predictive Models. (2024). arXiv:2402.05829. https://doi.org/10.48550/arXiv.2402.05829A.

[19] A. Dutta, Integrating AI and optimization for decision support: A survey. Decision Support Systems, (1996) 217–226. https://doi.org/10.1016/S0167-9236(96)80001-7.

[20] J. S. Edwards, Y. Duan and P. C. Robins, An analysis of expert systems for business decision making at different levels and in different roles. European Journal of Information Systems, **9(1)** (2000). 36–46. https://doi.org/10.1057/palgrave.ejis.3000344.

[21] A. Fadlalla, C. L. Lin, An analysis of the applications of neural networks in finance, Interfaces **31 (4)** (2001) 112 – 122. https://doi.org/10.1287/inte.31.4.112.9662.

[22] K. Främling, Decision theory meets explainable AI. In International workshop on explainable, transparent autonomous agents and multi-agent systems (2020) 57-74. Cham: Springer International Publishing.

[23] A.Ghani Nori Alsaedi, M. Jalali Varnamkhasti, H. Jasim Mohammed, M. Aghajani, Integrating Multi-Criteria Decision Analysis with Deep Reinforcement Learning: A Novel Framework for Intelligent Decision-Making in Iraqi Industries, International Journal of Mathematical Modeling & Computations, 2(14) (2024) 171-186

[24] Y. Gil, D. Garijo, D. Khider, C. A. Knoblock, V. Ratnakar, M. Osorio, ... and L. Shu, Artificial intelligence for modeling complex systems: taming the complexity of expert models to improve decision making. ACM Transactions on Interactive Intelligent Systems, **11(2)** (2021) 1-49.https://doi.org/10.1145/3453172.

[25] Z. Guo, X. Wong, W.K. Fundamentals of artificial intelligence techniques for apparel management applications, Editor(s): W.K. Wong, Z.X. Guo, S.Y.S. Leung, In Woodhead Publishing Series in Textiles, Optimizing Decision Making in the Apparel Supply Chain Using Artificial Intelligence (AI), Woodhead Publishing, (2013) 13-40, https://doi.org/10.1533/9780857097842.13.

[26] T. Ho, V. Karri, D. Lim, D. Barret, An investigation of engine performance parameters and artificial intelligent emission prediction of hydrogen powered car. Int. J. Hydrogen Energy **33** (2008) 3837–3846. https://doi.org/10.1016/j.ijhydene.2008.04.037.

[27] J. Hullman, A. Kaleand J. Hartline, Decision Theoretic Foundations for Experiments Evaluating Human Decisions. arXiv:2401.15106, (2024). https://arxiv.org/abs/2401.15106.

[28] M. J. Jarrahi, Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making, Business Horizons, Volume **61 (4)** (2018) 577-586.

[29] H. Jensen, Using neural network for credit scoring. Managerial Finance **18(6)** (1992) 15–26. https://doi.org/10.1108/eb013696.

[30] R.D. Johnson, D.L. Stone, and K.M. Lukaszewski, The benefits of eHRM and AI for talent acquisition", Journal of Tourism Futures, **7 (1)** (2021) 40-52, https://doi.org/10.1108/JTF-02-2020-0013.

[31] S. Kaggwa, T. F. Eleogu, F. Okonkwo, O. A. Farayola, P. U. Uwaoma and A. Akinoso, AI in decision making: transforming business strategies. International Journal of Research and Scientific Innovation, **10(12)** (2024) 423-444. DOI: 10.51244/IJRSI.2023.1012032.

[32] S. Khanna, Artificial intelligence: contemporary applications and future compass, International Dental Journal, **60 (4)** (2010) 269-272, https://doi.org/10.1922/IDJ_2422Khanna04.

[33] K. Kim and B. Kim, Decision-making model for reinforcing digital transformation strategies based on artificial intelligence technology. Information,**13(5)** (2022) 253. https://doi.org/10.3390/info13050253.

[34] F. Klashanov, Artificial Intelligence and Organizing Decision in Construction, Procedia Engineering, **165** (2016)

1016-1020, https://doi.org/10.1016/j.proeng.2016.11.813.
[35] R.J. Kuo, and J.A. Chen, A decision support system for order selection in electronic commerce based on fuzzy neural network supported by real-coded genetic algorithm', Expert Systems with Applications, **26(2)** (2004)141–154. https://doi.org/10.1016/S0957-4174(03)00115-5.
[36] P. Langley, Simon H. A. Applications of machine learning and rule induction, Communications of the ACM **38 (11)** (1995) 54–64. https://doi.org/10.1145/219717.219768.
[37] A. Lawrynowicz, Production planning and control with outsourcing using artificial intelligence. International Journal of Services and Operations Management, **3 (2**) 2007. 193–209, https://doi.org/10.1504/IJSOM.2007.012137.
[38] B. Layn, Artificial Intelligence in Finance: Transforming Decision-Making and Risk Management for Enhanced Financial Outcomes (2024).
[39] M. Leyer, A. Oberlaender, P. Dootson and M. Kowalkiewicz, Decision-making with artificial intelligence: Towards a novel conceptualization of patterns. In PACIS (2020) 224.
[40] X. Lin, Artificial Intelligence in the Industrial Engineering. Advances in Operation Research and Production Management, **1**(2024) 1-6. DOI: 10.54254/3006-1210/direct/0106
[41] I. Lotfi and, A. El Bouhadi, Artificial Intelligence methods: toward a new decision-making tool. Applied Artificial Intelligence, **36(1)** (2022) 1992141. https://doi.org/10.1080/08839514.2021.1992141
[42] Z. Lu, D. Wang and M. Yin, Does More Advice Help? The Effects of Second Opinions in AI-Assisted Decision Making. arXiv:2401.07058, (2024). https://arxiv.org/abs/2401.07058.
[43] T. Marwala, Rational choice and artificial intelligence (2017). arXiv preprint arXiv:1703.10098.
[44] A. Mellit, S.A. Kalogirou, Artificial intelligence techniques for photovoltaic applications: A review. Prog. Energy Combust. Sci. **34** (2008) 574–632. https://doi.org/10.1016/j.pecs.2008.01.001.
[45] A. Mellit, S.A. Kalogirou, L. Hontoria, S. Shaari, Artificial intelligence techniques for sizing photovoltaic systems: A review. Renew. Sustain. Energy Rev. **13** (2009) 406–419. https://doi.org/10.1016/j.rser.2008.01.006.
A. Mellit, S.A. Kalogirou, M. Drif, Application of neural networks and genetic algorithms for sizing of photovoltaic systems. Renew. Energy **35** (2010) 2881–2893, https://doi.org/10.1016/j.renene.2010.04.017.
[46] R. A. Miller, Medical Diagnostic Decision Support Systems-Past, Present, And Future: A Threaded Bibliography and Brief Commentary, J. Am. Med. Informatics Assoc., **1(1)** 1994 8–27. doi: 10.1136/jamia.1994.95236141.
[47] M. K. Mishra, A., Muthulakshnmi, B. R. Mishra and J. M. Sasikala, Optimizing Decision-Making Process In Supply Chain Management Through Intelligent Systems. Migration Letters, **21(6)** (2024) 1107-1113. https://doi.org/10.59670/ml.v21iS6.8164.
[48] A. Mishra, , I. A. Sainul, S. Bhuyan, S Deb., D. Sen, and A. K. Deb, (2018). Development of a flexible assembly system using industrial robot with machine vision guidance and dexterous multi-finger gripper. In Precision Product-Process Design and Optimization: Select Papers from AIMTDR (2016) 31-71. Springer Singapore.
[49] M. Mohammed Ridha Naser , M. Jalali Varnamkhasti, H. Jasim Mohammed, M. Aghajani, Artificial Intelligence as a Catalyst for Operational Excellence in Iraqi Industries: Implementation of a Proposed Model, International Journal of Mathematical Modeling & Computations, 2(14) (2024) 101-117
[50] K. Omoteso, The application of artificial intelligence in auditing: Looking back to the future, Expert Systems with Applications, **39 (9)** (2012) 8490-8495, https://doi.org/10.1016/j.eswa.2012.01.098.
V. Paliukas, and A. Savanevičiene, Harmonization of rational and creative ˙ decisions in quality management using AI technologies,'' Econ. Bus., **32(1)** (2018) 195–208. https://doi.org/10.2478/eb-2018-0016.
[51] J. Pancras, and K. Sudhir, Optimal marketing strategies for a customer data intermediary. Journal of Marketing Research, **44** (2007) 560–578. https://doi.org/10.1509/jmkr.44.4.560.
[52] D. Paschek, C.T. Luminosu, A. Draghici and A. Mateescu, Artificial intelligence and the way of changing decision-making for business. Management, (2018) 16, 18.
[53] W. Pedrycz, N. Ichalkaranje, G. Phillips-Wren, L.C. Jain, Introduction to computational intelligence for decision making. Intell Decis Mak AI-Based Approach Springe (2008) 97. https://doi.org/10.1007/978-3-540-76829-6_3.
[54] G. Phillips-Wren, AI tools in decision making support systems: a review. International Journal on Artificial Intelligence Tools, **21(2)** (2012) 1240005.
[55] T. D. Pilditch, The Reasoning Under Uncertainty Trap: A Structural AI Risk. arXiv:2402.01743. (2024). https://arxiv.org/abs/2402.01743.
[56] L. Richeson, R.A. Zimmermann, K.G. Barnett, Predicting consumer credit performance: can neural networks outperform traditional statistical methods? In: Trippi RR, Turban E (eds) Neural networks in finance and investing. IRWIN, Chicago, (1994) 45–70 https://doi.org/10.1007/s00521-010-0362-z
[57] K. Sadeghi,, D. Ojha, P. Kaur, R. V. Mahto and A. Dhir, Explainable artificial intelligence and agile decision-making in supply chain cyber resilience. Decision Support Systems, **180** (2024) 114194. DOI: 10.1016/j.dss.2024.114194.
[58] A. Sahay, How to reap Higher profits with Dynamic Pricing. MIT Sloan Management Review (2007).
[59] M. Shin, J. Kim, B Opheusden and T. L. Griffiths, Superhuman artificial intelligence can improve human decision-making by increasing novelty. Proceedings of the National Academy of Sciences, **120(12)** (2023). e2214840120. https://doi.org/10.1073/pnas.2214840120.
[60] G. Stalidis, D. Karapistolis, A. Vafeiadis, Marketing Decision Support Using Artificial Intelligence and Knowledge Modeling: Application to Tourist Destination Management, Procedia - Social and Behavioral Sciences, **175** (2015)

106-113. https://doi.org/10.1016/j.sbspro.2015.01.1180.

[61] M. Steyvers, A. Kumar, Three challenges for AI-assisted decision-making. Perspectives on Psychological Science, (2023), 17456916231181102. https://doi.org/10.1177/17456916231181102.

JHM. Tah and V. A. Carr, Proposal for construction project risk assessment using fuzzy logic. Construction Management and Economics, **18(4)** (2000) 491–500. https://doi.org/10.1080/01446190050024905

[62] K. Takada, Artificial intelligence expert systems with neural network machine learning may assist decision-making for extractions in orthodontic treatment planning. Journal of Evidence-Based Dental Practice, **16(3)** (2016) 190-192. doi: 10.1016/j.jebdp.2016.07.002.

[63] J. M. Tenório, A. D. Hummel, F. M. Cohrs, V. L. Sdepanian, I. T. Pisa, H. de F. Marin, Artificial intelligence techniques applied to the development of a decision–support system for diagnosing celiac disease, International Journal of Medical Informatics, **(80) (11)** (2011) 793-802, https://doi.org/10.1016/j.ijmedinf.2011.08.001.

[64] J.C. Trappey, J.L. Hou, K. Hiekata, Collective intelligence modeling, analysis, and synthesis for innovative engineering decision making, Advanced Engineering Informatics, **29 (4)** (2015) 757-758, https://doi.org/10.1016/j.aei.2015.09.007.

[65] A. Trunk, H. Birkel and E. Hartmann, On the current state of combining human and artificial intelligence for strategic organizational decision making. Business Research, **13(3)** (2020) 875-919. https://doi.org/10.1007/s40685-020-00133-x.

[66] A. L. Venger and V. M. Dozortsev, Trust in Artificial Intelligence: Modeling the Decision Making of Human Operators in Highly Dangerous Situations. Mathematics, **11(24)** (2023) 4956. https://doi.org/10.3390/math11244956.

[67] BK. Wong, Y. Selvi, Neural network applications in finance: a review and analysis of literature (1990–1996). Information Manage, **34(3**) (1998) 129–139. https://doi.org/10.1016/S0378-7206(98)00050-0

[68] R. Yager, Zadeh, L. An Introduction to Fuzzy Logic Applications in Intelligent Systems (1992). https://doi.org/10.1007/978-1-4615-3640-6.

[69] Y. Yuangping, F. Fred, and W. Michel, Leveraging Missing Ratings to Improve Online Recommendation Systems, Journal of Marketing Research, **43** (2006), 355–65. https://doi.org/10.1509/jmkr.43.3.355.