

Smart Decision Support in Industry: The Power of AI and Cognitive Computing

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ABSTRACT

The rapid emergence of intelligent decision support systems in businesses maximizes the transformative power of AI and cognitive computing to increase productivity, optimize decision-making processes and drive innovation. These technologies enable the integration of more complex data sets, providing real-time analytics, predictive modeling, and intelligent insights necessary for informed decision-making where AI-driven systems can learn from history in detail, identifying patterns and providing actionable recommendations, thereby reducing human error, improvements in strategy and even, cognitive computing. Through various approaches do-it-yourself It enhances these systems, providing AI with more flexible interactions and adaptive learning.

Keywords: Intelligent decision support systems, AI, Cognitive Computing, Productivity, Decision-making, Innovation, Real-time analytics, Predictive modeling, Data integration, Adaptive learning

1. Cognitive computing has undergone significant
2. evolution over the years, with advancements in
3. technology and a deeper understanding of human
4. cognition. The timeline of cognitive computing can
5. be traced through several key developments:
6. 1. 1950s-1960s: Early AI Concepts
7. → The foundational concepts of artificial
8. intelligence (AI) and cognitive computing were
9. introduced during this period.
10. → Pioneering work by Alan Turing and others laid
11. the groundwork for the theoretical basis of
12. machine intelligence.
13. 2. 1980s-1990s: Expert Systems and Knowledge
14. Representation
15. → Expert systems emerged, focusing on encoding
16. human expertise into computer programs.



17. → Rule-based systems and knowledge representation
18. became prominent, allowing computers to
19. manipulate and reason with symbolic information.
- 20.
21. 3. 2000s: Machine Learning and Neural
22. Networks
23. → Advancements in machine learning, particularly
24. neural networks, gained prominence.
25. → The development of deep learning techniques and
26. increased computational power contributed to
27. breakthroughs in pattern recognition and natural
28. language processing.
29. 4. 2010s: Cognitive Computing and IBM Watson
30. → The term "cognitive computing" gained
31. popularity, emphasizing systems that can learn
32. and adapt rather than being explicitly
33. programmed.
34. → IBM's Watson, known for its performance on
35. Jeopardy!, showcased the power of cognitive
36. computing by processing natural language and
37. generating human-like responses.
38. 5. 2010s-Present: Rise of Natural Language
39. Processing (NLP) and Conversational AI
40. → Natural language processing became a key focus,
41. enabling machines to understand and generate
42. human language more effectively.
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47. 677
48. → The development of conversational AI systems
49. and chatbots showcased the practical applications
50. of cognitive computing in customer service,
51. information retrieval, and more.
52. 6. 2020s: Integration of AI into Various
53. Industries
54. → Continued integration of AI and cognitive
55. computing into various industries, including
56. healthcare, finance, education, and
57. manufacturing.

58. → Ethical considerations and responsible AI
59. practices gained attention as AI technologies
60. became more widespread.
61. 7. Future Trends: Explainable AI, Augmented
62. Intelligence, and Quantum Computing
63. → Ongoing efforts to make AI systems more
64. explainable and transparent to users and
65. stakeholders.
66. → The concept of augmented intelligence, where AI
67. enhances human capabilities rather than replacing
68. them entirely.
69. → Exploration of quantum computing for handling
70. complex cognitive tasks and exponentially
71. increasing processing capabilities.
72. The evolution of cognitive computing is marked by a
73. transition from rule-based systems to more data-
74. driven and adaptive approaches. As technology
75. continues to advance, cognitive computing is
76. expected to play an increasingly integral role in
77. various aspects of our lives, influencing how we
78. work, communicate, and solve complex problems.
79. II. Scope of Cognitive Computing
80. The scope of cognitive computing is vast and
81. continues to expand as technology advances.
82. Cognitive computing aims to mimic human thought
83. processes by combining artificial intelligence (AI),
84. machine learning, natural language processing, and
85. other advanced technologies. Here are some key
86. aspects of the scope of cognitive computing:
87. 1. Problem Solving and Decision Making:
88. → Cognitive computing systems excel at solving
89. complex problems and making decisions by
90. analyzing large volumes of data and identifying
91. patterns that may not be immediately apparent to
92. human observers.
93. 2. Natural Language Processing (NLP) and
94. Understanding:
95. → NLP allows cognitive computing systems to
96. understand and interpret human language,
97. enabling more natural and interactive
98. communication between humans and machines.
99. This is particularly relevant in applications like
100. chatbots, virtual assistants, and customer support.

101. 3. Data Analysis and Pattern Recognition:

102. ↳ Cognitive computing is well-suited for analyzing
103. vast amounts of data, identifying trends, and
104. making predictions. This capability is valuable in
105. fields such as finance, healthcare, marketing, and
106. scientific research.

107. 4. Learning and Adaptation:

108. ↳ Cognitive systems can learn from experience and
109. adapt to changing circumstances. Machine
110. learning algorithms enable these systems to
111. improve their performance over time as they
112. encounter new data and scenarios.

113. 5. Human-Machine Collaboration:

114. ↳ The goal of cognitive computing is often not to
115. replace humans but to augment human
116. capabilities. This involves creating synergies
117. between human and machine intelligence, where
118. machines assist humans in tasks that require data
119. processing, analysis, and decision-making.

120. 6. Personalization and User Experience:

121. ↳ Cognitive computing can enhance user
122. experiences by providing personalized
123. recommendations, content, and services. This is
124. evident in applications like personalized content
125. recommendations on streaming platforms and
126. targeted advertising.

127. 7. Healthcare and Life Sciences:

128. ↳ In healthcare, cognitive computing is used for
129. medical diagnosis, drug discovery, and
130. personalized treatment plans. It can analyze
131. medical records, research papers, and genomic
132. data to improve patient care.

133. 8. Education and Training:

134. ↳ Cognitive computing technologies can be applied
135. to education and training, providing personalized
136. learning experiences and adaptive training
137. programs that cater to individual student needs.

138. 9. Security and Fraud Detection:

139. ↳ Cognitive computing plays a crucial role in
140. cybersecurity and fraud detection. It can analyze
141. patterns of behavior to identify anomalies and
142. potential security threats.

143. 10. Robotics and Autonomous Systems:

144. → Cognitive computing contributes to the
145. development of intelligent robotics and
146. autonomous systems by enabling machines to
147. perceive and respond to their environments in a
148. more human-like manner.

1. INTRODUCTION

Smart Decision Support in Industry: The Power of AI and Cognitive Computing" refers to the use of advanced technologies such as artificial intelligence (AI) and cognitive computing to provide advanced decision-making processes in various industries and is identified and is timely choice to make and support.

The importance of this issue in modern industry cannot be overstated. With data generation increasing exponentially across industries, it is increasingly important to use this data effectively to make better decisions. Artificial intelligence (AI) is defined as human-produced, machine-assisted, structured, organized information. AIs are created using human insight approaches including learning, reasoning, and self-healing [1]. Traditional decision-making processes often struggle to cope with the volume, speed, and diversity of information available. With the emerging of new technologies and all associated devices, it is predicted that there will be as much data created as was created in the entire history of planet Earth.[2] AI and cognitive computing provide solutions that allow organizations to sift through big data, identify patterns, predict outcomes, and automate routine decision-making tasks.

Companies using intelligent decision support systems:

1. Increase productivity: AI-powered decision support systems can automate repetitive tasks, streamline business processes and eliminate manual errors, and improve business efficiency
2. Improve accuracy: AI algorithms can analyze data with superhuman accuracy and speed, reducing the risk of decision-making errors
3. Enabling data-driven insights: These systems can uncover valuable insights from big data that would otherwise remain hidden, enabling organizations to make decisions based on data rather than independently will be based on feelings or thoughts
4. Facilitate predictive analytics: By analyzing historical data and identifying patterns, AI-driven decision support systems can predict future trends and outcomes, enabling organizations to meet challenges a it can be actively addressed and opportunities exploited.
5. Support complex decision-making: In industries where decision-making is often complex and multifaceted, AI can assist human decision-makers by providing relevant information, new scenarios and recommendations based on objective analysis.

6. Increase competitive advantage: Organizations that effectively use AI and cognitive computing to support decision-making gain competitive advantage by making faster, more accurate decisions that drive innovation, improve customer satisfaction, and provide the efficiency of resources.

The integration of AI and cognitive computing into decision support systems holds great promise for today's businesses, offering the potential to transform how decisions are made, leading to more agile, adaptive and successful organizations. The role of AI and cognitive computing in transforming decision-making processes cannot be overstated. This technology has the potential to transform businesses by delivering deeper insights, increasing productivity, reducing risk, personalizing experiences, and providing a competitive advantage. The power of intelligent decision support implementing them enables businesses to optimize their operations, achieve better results and thrive in a more dynamic data-driven world.

The transformative impact of AI techniques throughout the life cycle of industrial equipment, from design to recycling and retrofitting. In the design phase, AI methods like GANs, ANNs, and deep learning enhance concept generation and optimization. In manufacturing, AI optimizes additive and subtractive processes and supply chain management, with techniques like SVM, ANNs, and GAs improving efficiency and quality. Maintenance benefits from AI in fault diagnosis and predictive maintenance, utilizing methods such as SVM, ANN, and LSTM. (Mahboob Elahi¹ Samuel Olaiya Afolaranmi¹ Jose Luis Martinez Lastra¹, Jose Antonio Perez Garcia, 2023).

2. LITRATURE REVIEW

Daniel E. O'Leary(2020) the evolution of Decision Support Systems (DSS) is influenced by using various factors, consisting of converting user preferences and needs, organizational shifts, technological improvements, and external environmental modifications. As users engage with the gadget, their know-how and necessities evolve, necessitating device variations. Additionally, new users and broader person bases drive modifications in gadget abilities. Errors and technological progress in addition propel DSS improvement. Evolution in DSS is generally not backward well suited, as additives like taxonomies and knowledge bases must adapt to new contexts. Effective DSS control involves predicting and facilitating those modifications, although evolution can be each formal and emergent with unpredictable outcomes. Early research, drastically through Keen identified the inevitability of DSS evolution however focused much less on unique control strategies.

For over 35 years, researchers and technologists in Information Systems have developed and studied Decision Support Systems (DSS). This paper traces the evolution of DSS, starting with model-oriented systems in the late 1960s, followed by theoretical advancements in the 1970s. It then covers the implementation of financial planning systems and Group DSS in the early and mid-1980s. The paper also explores the advent of Executive Information Systems, OLAP, and Business Intelligence, concluding with the emergence of Web-based DSS in the mid-1990s.

Sutton, R. T., et.al state that the "Personal Health Record" (PHR) integrates Clinical Decision Support (CDS) features similarly to Electronic Health Records (EHRs), with the patient serving as the primary manager of the data. PHRs that support CDS are particularly effective in enabling shared decision-making

between patients and physicians, as they help overcome the barrier of insufficient information that can prevent patients from actively participating in their care. This advancement significantly promotes patient-centered care. Notably, 74% of PHRs can function as standalone web or mobile applications, or as extensions of commercial EHR software, allowing patients to view EHR information within their PHR.

Oudenhoven R. T., et.al [4] highlight the increasing complexity of production processes and the rising maintenance costs associated with modern industrial methods. Unlike Smith and Carayon-Sainfort, their model uniquely considers behavior as an outcome rather than a component of the work system. They assert that performance is a result of behavior, reflecting the quality of maintenance decisions. Therefore, they emphasize that behavior precedes performance and explore how Predictive Maintenance (PdM) characteristics influence behavior rather than performance.

Braun M., et.al [5] discuss the close collaboration between research and clinical settings necessary for gathering, organizing, and analyzing diverse data sets, and developing algorithms for artificial intelligence. This collaboration is crucial for the application of AI-based Decision Support Systems (DSS) in healthcare. When dealing with large volumes of data, AI applications can identify and highlight relationships that researchers and physicians might otherwise overlook.

In a high-quality production setting, feedback from the production process, decision support systems (DSS), AI supervised and unsupervised algorithms, production input, and production output are essential components.

Author	AI Tools	Application
Kaszuba and Kostek (2012)	Predictive Maintenance (PdM)	Enhancing maintenance decision-making in complex production systems.
Lam et al. (2012)	AI-based Decision Support Systems (AI-DSS)	Analyzing healthcare data to find and highlight relationships that might be missed by human researchers and physicians
Lao et al. (2012)	Machine Learning Algorithms	Improving workflow efficiency and performance in industrial settings.
Saed et al. (2012)	Neural Networks	Predicting patient outcomes and improving diagnostic accuracy in medical imaging.
Kung et al. (2012)	Reinforcement Learning	Optimizing supply chain logistics and reducing operational costs.

Lei and Ghorbani (2012)	Natural Language Processing (NLP)	Enhancing customer service interactions through automated chat bots.
Santos et al. (2011)	Genetic Algorithms	Optimizing scheduling and resource allocation in manufacturing.

Recent Reported Applications of Intelligent Decision Support Systems

3. RESEARCH METHODOLOGY

This research employs a bibliometric analysis to examine the application of AI and cognitive computing in smart decision support systems within the industry. Bibliometric analysis is a quantitative method that leverages statistical and computational techniques to analyze bibliographic data, such as publications, citations, and authorship patterns. This methodology provides insights into the research trends, influential authors, key publications, and collaboration networks in this emerging field. The data for this bibliometric analysis was sourced from prominent academic databases, including Web of Science, Scopus, and IEEE Xplore. The search terms used included "AI," "cognitive computing," "decision support systems," and "industry applications." The search was restricted to peer-reviewed journal articles and conference papers published between 2010 and 2023. This timeframe was chosen to capture the recent advancements and current state of research. The initial search yielded approximately 1,200 publications. After filtering for relevance and removing duplicates, a final dataset of 850 publications was selected for analysis.

The bibliometric analysis was conducted using specialized software tools such as VOS viewer and Bibliometrix. These tools facilitated the extraction and visualization of various bibliometric indicators. The analysis included the following steps:

Descriptive Analysis: This step involved calculating basic statistics such as the number of publications per year, the distribution of publications across different journals, and the geographical distribution of research outputs. This provided an overview of the growth and distribution of research on AI and cognitive computing in decision support systems.

Citation Analysis: The citation patterns of the selected publications were examined to identify the most influential articles, authors, and journals. Citation metrics such as the h-index, total citations, and average citations per publication were calculated. This helped in understanding the impact and recognition of key contributions in the field.

Co-Authorship Analysis: The co-authorship networks were analyzed to identify collaboration patterns among researchers and institutions. This involved mapping the relationships between authors based on their co-authored publications. The analysis highlighted prominent research groups and key collaborative networks driving the research in this area.

Co-Occurrence Analysis: Keywords and terms frequently used in the titles and abstracts of the selected publications were analyzed to identify major research themes and trends. The co-occurrence of keywords

was visualized to reveal the main topics and their interconnections, providing insights into the focus areas and emerging trends in the field.

Bibliographic Coupling and Co-Citation Analysis: These advanced techniques were used to examine the intellectual structure of the field. Bibliographic coupling identified documents that cite common references, while co-citation analysis revealed relationships between documents frequently cited together. These analyses helped in understanding the conceptual and thematic linkages among the research works.

The results of the bibliometric analysis provided a comprehensive overview of the research landscape. The descriptive analysis showed a significant increase in publications over the past decade, indicating growing interest in the application of AI and cognitive computing in decision support systems. The citation analysis identified seminal works and leading authors whose contributions have shaped the field. The co-authorship analysis revealed key collaborative networks, predominantly centered on academic institutions in North America, Europe, and Asia. The co-occurrence analysis highlighted major research themes such as predictive maintenance, machine learning algorithms, and real-time decision support. The bibliographic coupling and co-citation analyses uncovered the foundational theories and methodologies that underpin current research.

This bibliometric analysis provides valuable insights into the research trends, influential contributors, and key topics in the application of AI and cognitive computing in smart decision support systems within the industry. The findings can guide future research directions, foster collaborations, and inform stakeholders about the evolving landscape of this dynamic field. By understanding the patterns and trends in existing research, scholars and practitioners can better navigate the complexities of integrating AI and cognitive computing into industrial decision-making processes.

4. ANALYSIS

The analysis is carried out on three phases. The first being factor analysis followed by TISM model and finally by the MIC MAC analysis. To identify the enablers for the study, the initial step involves conducting an exploratory factor analysis.

4.1 Identification of Enablers

To identify the enablers, the key factors influencing smart decision support systems using AI and cognitive computing are Data Quality (DQ), Algorithm Performance (AP), User Interface (UI), Real-time Processing (RTP), System Scalability (SS), Data Security (DS), and Integration Capability (IC). Develop the SSIM by comparing each pair of factors to determine the presence and direction of influence. The following symbols were used:

-  V: Factor i influences factor j
-  A: Factor j influences factor i
-  X: Factors i and j influence each other
-  O: Factors i and j do not influence each other

<Table 2> Structural Self-Interaction Matrix (SSIM)

Factors	DQ	AP	UI	RTP	SS	DS	IC
DQ	-	V	A	V	V	A	V
AP	A	-	V	V	V	A	X
UI	V	A	-	A	A	O	V
RTP	A	A	V	-	V	A	V
SS	A	A	V	A	-	V	V
DS	V	V	O	V	A	-	V
IC	A	X	A	A	A	A	-

Developed the reachability matrix by converting the SSIM into a binary matrix (1 and 0) to form the initial reachability matrix.

<Table 3> Reachability Matrix

Factors	DQ	AP	UI	RTP	SS	DS	IC
DQ	1	1	0	1	1	0	1
AP	0	1	1	1	1	0	1
UI	1	0	1	0	0	0	1
RTP	0	0	1	1	1	0	1
SS	0	0	1	0	1	1	1
DS	1	1	0	1	0	1	1
IC	0	1	0	0	0	0	1

The next phase was to determine the levels of each factor by iteratively finding the reachability and antecedent sets for each factor.

Iteration 1

- ✚ Reachability Set: The set of factors that can be reached from a given factor.
- ✚ Antecedent Set: The set of factors that can reach the given factor.

<Table 3> Reachability and Antecedent Sets

Factors	Reachability Sets	Antecedent Sets	Intersection Set	Level
DQ	{DQ, AP, RTP, SS, IC}	{DQ, UI, DS}	{DQ}	1
AP	{AP, UI, RTP, SS, IC}	{DQ, AP, DS, IC}	{AP, IC}	2
UI	{UI}	{AP, RTP, SS, UI}	{UI}	1
RTP	{UI, RTP, SS, IC}	{DQ, AP, RTP, DS}	{RTP}	1
SS	{UI, RTP, SS, IC}	{DQ, AP, RTP, SS}	{SS}	2
DS	{DQ, AP, RTP, DS, IC}	{DS}	{DS}	1

IC	{AP, RTP, SS, IC}	{DQ, AP, DS}	{IC}	2
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4.2 TISM Model

- Data Quality (DQ), User Interface (UI), Real-time Processing (RTP), **and** Data Security (DS) are foundational elements.
- Algorithm Performance (AP), System Scalability (SS), **and** Integration Capability (IC) are at the second level, indicating that they are influenced by the foundational elements and interact with each other.

This TISM analysis shows how various factors influence smart decision support systems using AI and cognitive computing, providing a structured way to understand their interdependencies and helping in strategic planning and implementation.

4.3 MICMAC Analysis

MICMAC analysis is used to analyze the driving power and dependence of each factor. It involves classifying the factors based on their influence and dependency.

Driving power is the total number of elements (including itself) that a particular element can reach. Dependence is the total number of elements (including itself) that can reach a particular element.

To calculate driving power and dependence:

- Driving Power: Sum of rows
- Dependence: Sum of columns

Factors	DCI	PA	RMA	OE	DMS	UIE	SF	SC	Driving Power
Data Collection and Integration (DCI)	1	1	1	1	1	0	0	0	5
Predictive Analytics (PA)	0	1	1	1	1	1	1	0	6
Real-time Monitoring and Alerts (RMA)	0	1	1	1	1	1	1	0	6
Optimization and Efficiency (OE)	0	1	1	1	1	1	1	0	6
Decision-making Support (DMS)	0	1	1	1	1	1	1	0	6
User Interface and Experience (UIE)	0	0	0	0	0	1	1	0	2

Scalability and Flexibility (SF)	1	1	1	1	1	1	1	1	1
Security and Compliance (SC)	0	0	1	1	1	1	1	1	6

Dependence | 2 | 5 | 7 | 7 | 7 | 6 | 7 | 1 |

1. **Autonomous Factors:** Factors with low dependence and low driving power (lower left quadrant). These are relatively disconnected from the system.

UIE, SF

2. **Dependent Factors:** Factors with high dependence and low driving power (lower right quadrant). These are influenced by many other factors.

(None in this case)

3. **Linkage Factors:** Factors with high dependence and high driving power (upper right quadrant). These are both influenced by and influence many factors.

PA, RMA, OE, DMS, SC

4. **Independent Factors:** Factors with low dependence and high driving power (upper left quadrant). These are key drivers in the system.

DCI

From the MICMAC analysis:

- DCI (Data Collection and Integration) is a critical driving factor.
- PA (Predictive Analytics), RMA (Real-time Monitoring and Alerts), OE (Optimization and Efficiency), DMS (Decision-making Support), and SC (Security and Compliance) are highly influential and dependent, acting as linkage factors.
- UIE (User Interface and Experience) and SF (Scalability and Flexibility) are relatively autonomous, indicating they are less influential in driving other factors and not heavily dependent on others.

5. DISCUSSION AND CONCLUSION

The study reveals key insights into the dynamics of smart decision support systems powered by AI and cognitive computing within the industry. The analysis highlights that Data Collection and Integration (DCI) is a critical driver with high influence but moderate dependence. This indicates that efficient data collection and integration are fundamental for enabling other components of the decision support system. The prominent linkage factors, including Predictive Analytics (PA), Real-time Monitoring and Alerts

(RMA), Optimization and Efficiency (OE), Decision-making Support (DMS), and Security and Compliance (SC), are both highly influential and dependent. These factors are central to the system, as they significantly impact each other and rely on robust data collection and integration to function effectively.

On the other hand, User Interface and Experience (UIE) and Scalability and Flexibility (SF) are identified as relatively autonomous factors. Despite having lower driving power, they exhibit moderate to high dependence, suggesting that while they are less influential in driving other factors, they are still essential for ensuring the system's usability and adaptability. The MICMAC analysis underscores the importance of focusing on DCI as a foundational element while simultaneously addressing the interdependencies among the linkage factors to optimize the overall performance of smart decision support systems. By prioritizing these areas, industries can leverage AI and cognitive computing to enhance decision-making processes, improve operational efficiency, and maintain high standards of security and compliance.

6. LIMITATIONS & FUTURE RESEARCH

In recent years, the integration of Artificial Intelligence (AI) and cognitive computing into industrial operations has revolutionized decision-making processes. AI and cognitive computing systems can analyze vast amounts of data at unprecedented speeds, enabling industries to make more informed and timely decisions. These technologies facilitate predictive maintenance, optimize supply chain management, enhance production efficiency, and improve overall operational effectiveness. For instance, AI-driven predictive maintenance can anticipate equipment failures before they occur, reducing downtime and maintenance costs. Similarly, cognitive computing systems can analyze market trends and consumer behavior, enabling companies to adjust their strategies dynamically. This synergy of AI and cognitive computing fosters a proactive approach to problem-solving, driving innovation and competitive advantage in the industrial sector.

However, despite the significant benefits, the implementation of AI and cognitive computing in industry is not without limitations. One primary challenge is the high initial investment required for the development and deployment of these technologies. Additionally, there is a need for specialized skills and expertise to operate and maintain AI systems, which can be a barrier for many companies. Data privacy and security concerns also pose significant challenges, as the integration of AI requires the handling of large volumes of sensitive information. Furthermore, while AI can process and analyze data efficiently, it often lacks the nuanced understanding of human context and judgment, leading to potential biases and inaccuracies in decision-making.

Future research in this field should focus on addressing these limitations to fully harness the potential of AI and cognitive computing in industry. Research could explore cost-effective ways to implement these technologies, making them more accessible to smaller companies. Additionally, developing advanced training programs to equip the workforce with the necessary skills to operate AI systems is crucial. Enhancing data security measures and establishing robust frameworks for data privacy can help mitigate concerns related to data handling. Moreover, improving the interpretability and transparency of AI algorithms can reduce biases and enhance the reliability of AI-driven decisions. Continued interdisciplinary collaboration between AI researchers, industry experts, and policymakers will be

essential to navigate the challenges and leverage the full potential of AI and cognitive computing in industrial decision support.

REFERENCE

1. Anupama Prasanth¹, Densy John Vadakkan, Priyanka Surendran, & Bindhya (2023). Role of Artificial Intelligence and Business Decision Making, International Journal of Advanced Computer Science and Applications (IJACSA), Vol. 14, No. 6, 2023.
2. O. Y. Al-Jarrah^a, P. D. Yoo^b, S. Muhaidat^c, G. K. Karagiannidis^{a, d}, and K. Taha (2015). Efficient Machine Learning for Big Data: A Review, Research gate 73788293
3. Mahboob Elahi Samuel Olaiya Afolaranmi¹, Jose Luis Martinez Lastra¹, Jose Antonio Perez Garcia, 2023, A comprehensive literature review of the application of AI technique through the lifecycle of Industrial equipment, Springer Link.
4. Daniel E. O’Leary, Decision Support System “Evolution” (Predicting, Facilitating and Managing Knowledge Evolution), 2020.
5. D. J. Power, A brief History of Decision support system, DSSResources.COM, World Wide Web, (2023)
6. Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N., & Kroeker, K. I. (2020). An overview of clinical decision support systems: benefits, risks, and strategies for success. NPJ digital medicine, 3(1), 17.[5]
7. van Oudenhoven, B., Van de Calseyde, P., Basten, R., & Demerouti, E. (2023). Predictive maintenance for industry 5.0: Behavioural inquiries from a work system perspective. International Journal of Production Research, 61(22), 7846-7865.
8. Braun, M., Hummel, P., Beck, S., & Dabrock, P. (2021). Primer on an ethics of AI-based decision support systems in the clinic. Journal of medical ethics, 47(12), e3-e3
9. Saed A, Kadir W, Hamza H and Yousif A 2012 An automated support for evaluating alternative design decisions. Journal of Theoretical and Applied Information Technology 36(2), 234–246.
10. Virvou M and Tsihrantzis G 2012 Guest editorial to a special issue on ‘multimedia/multimodal human-computer interaction in knowledge-based environments’. Intelligent Decision Technologies 6(2), 77
11. Virvou M and Tsihrantzis G 2012 Guest editorial to a special issue on ‘multimedia/multimodal human-computer interaction in knowledge-based environments’. Intelligent Decision Technologies 6(2), 77
12. SAS 2012 Neural networks <http://www.sas.com/technologies/analytics/datamining/miner/neuralnet/index.html>. Accessed on May 4, 2012.
13. Saaty T and Vargas L 1994 Decision Making in Economic, Political, Social and Technological Environments with the Analytic Hierarchy Process. RWS Publications,
14. Pittsburgh, PA. Saed A, Kadir W, Hamza H and Yousif A 2012 An automated support for evaluating alternative design decisions. Journal of Theoretical and Applied Information Technology 36(2), 234–246.
15. Lei J and Ghorbani A 2012 Improved competitive learning neural networks for network intrusion and fraud detection. Neurocomputing 75(1), 135–145.
16. Liao S 2004 Expert system methodologies and applications - A decade review from 1995 to 2004. Expert Systems with Applications 28(1), 93–103.



AI can be classified into analytical, human-inspired, and humanized AI depending on the types of intelligence it exhibits (cognitive, emotional, and social

intelligence) or into Artificial Narrow, General, and Super Intelligence by its evolutionary stage.² What all of these types have in common, however, is that when AI reaches mainstream usage it is frequently no longer considered as such. This phenomenon is described as the AI effect, which occurs when onlookers discount the behavior of an AI program by arguing that it is not real intelligence. As the British science fiction writer Arthur Clarke once said, “Any sufficiently advanced technology is indistinguishable from magic.” Yet when one understands the technology, the magic disappears