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Artificial Intelligence Applications in Management Information Systems: A Comprehensive Systematic Review with Business Analytics Perspective

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A B S T R A C T

The need to solve very complex problems and the desire to model and understand human behavior are the most important factors that trigger artificial intelligence studies. In addition, today, when digitalization has become a necessity with the industrial revolution, the importance of management information systems located at the interface of information, business and industry has increased even more. In this study, which was prepared by taking these two approaches into consideration, it was aimed to examine the use of artificial intelligence techniques in management information systems literature in a multidimensional and systematic manner, and in this direction, a systematic literature review method supported by semi-automatic modern technique such as text mining was proposed. As a result of the literature review, it has been observed that studies in the field of deep learning and swarm intelligence have gained importance in recent years. When evaluated in terms of application, although information system support and information management are at the forefront in the field of informatics, it is thought that there is a shift towards cybercrime and security and fault detection. Similarly, it can be said that there has been a tendency towards environmental factors in other business areas where production and supply chain studies are seen more. In sectoral evaluations, the value of the health sector has increased while manufacturing-oriented areas are ahead as a result of the digital transformation. When all these findings are evaluated together, it is thought that a detailed guide is presented to the academicians and professionals who will work in the field.

1. Introduction

In parallel with the developments in information technologies in recent years, businesses tend to use information systems intensively and effectively for control and decision support purposes. This situation reveals the importance of Management Information Systems (MIS) located at the intersection of business, informatics, and industrial applications. When this multi-disciplinary structure of MIS is evaluated, it can be said that it is an umbrella concept that includes important sub-concepts, especially in decision support. It is seen that the studies in the field of decision support have shifted to the business intelligence (BI) axis, especially in the early 2000s, due to its superior visualization ability. On the other hand, BI includes many activities, from extracting data within the enterprise to presenting it appropriately for decision support to the end-user. Business analytics, which is the crucial point of this transformation, is the name given to all numerical methods that enable converting data into information within the BI architecture [1]. In this sense, business analytics, which includes a wide range of methods from statistical methods to modern approaches, is supported by Artificial Intelligence (AI) techniques at every stage.

Artificial intelligence is an algorithmic replica of a living system (human or other living creatures) or a nature-based phenomenon (physics or biology-based) created in a computer environment to solve NP-Hard problems. In this context, artificial intelligence can be expressed as a multi-disciplinary process based on both information infrastructure and mathematics. As a result of the transformation of employment based on companies' work in the field of digitalization in recent years, AI approaches have moved to the focus of industrial applications and academic studies. AI approaches, which have a place in many academic fields, also occupy an important area in MIS literature, whose primary purpose is decision support. The multi-disciplinary nature of the MIS field and the wide-ranging use of AI approaches make it difficult to make an overall assessment of the literature in both areas. This study aimed to evaluate AI studies in MIS literature to turn such diversity into a potential opportunity for academics and professionals. As a result of the ease of access to online publications, a systematic approach is required to assess the large number of publications that can be subject to the literature review. Also, the review procedure should include the variety of the methods used in the publications, the business, and information functions and industries in which they are applied.

Literature reviews are evaluated under two categories, document-based and context-based [2]. In publication(document)-oriented studies, each publication in the field is examined one by one, and a generalization is tried to be made about the area. In context-based studies, instead of each document one by one, articles are combined under various topics and evaluated together. Thus, it is necessary to create a subject list and examine many publications depending on this list. Systematic literature reviews are often preferred in context-based studies to make integrated evaluations of many sources. The critical activity in the systematic review process is to prepare the necessary index for coding the articles. In this context, an automated method may be needed if the number of publications increases too much, especially in coding on the axis of the subject, method, and application area. Text mining approaches can meet this need, especially with term-document matrices that they offer as outputs [3].

In this study, which was prepared to question AI studies in MIS literature in detail, a systematic literature review approach supported by the text mining process was preferred. Thanks to this approach, it is thought that it can guide academicians and professionals who want to perform research in the field by evaluating them with new opportunities, potential publication areas, and trends.

The following research questions will be considered in the literature review research to determine the objectives mentioned above in the study.

RQ1: What is AI studies' status in the MIS literature over the years, and how has it transformed in recent years?

RQ2: At what level do AI studies support business analytics approaches?

RQ3: Among the MIS journals, which ones are prominent in publishing AI, and do these journals differ in business analytics publications?

RQ4: How and to what extent do AI approaches support informatics-related factors affecting businesses?

RQ5: What is the preference of AI methods in business functions that are not related to informatics?

RQ6: Which industries are at the forefront of AI use in MIS literature?

RQ7: Which concepts are prominent in AI studies in the MIS literature, and has this changed over the years?

In the next part of the study, systematic and manual literature reviews on AI will be presented. Then brief information about the concept of artificial intelligence and the techniques used will be given. After explaining the methodology of the study, the findings will be presented, and in the last part, the results will be evaluated with possible future studies and limitations.

2. Motivation and Background

Literature reviews are studies that gain increasing importance among academics and professionals with their success in presenting the general picture of a particular academic field [4]. In this sense, as in almost every academic field, such studies are frequently encountered in the field of MIS and AI.

In his literature review on AI usage in manufacturing applications, Oke (2008) manually examined around 150 articles on inference, genetic algorithms, expert systems, artificial neural networks, and information representation [5]. A similar study was conducted on the use of AI in decision support applications in diabetes management in the health sector, and 141 articles were examined and evaluated under different decision support strategies [6]. In health, AI has been preferred in many areas, from medical diagnosis to health management, especially in recent years. In two separate manual reviews in the field of health management in 2018 and 2020, AI applications on health crisis management and patient safety were presented, respectively [7, 8]

Manual reviews also appear in the MIS literature that focuses on a business or information function rather than a specific industry. Keding (2019) evaluated 58 articles containing AI methods in strategic management under subheadings such as data-driven workflows, managerial willingness, organizational determinants, managerial cognition, the value of complementary skills, human-machine collaboration, design of decision-making governance, agility and participation in strategy development, and predictive logic in business models [9]. Di Viao et al. (2020) examined sustainable growth in their study using a bibliometric approach [10]. In addition to the studies evaluating AI approaches in informatics-related fields such as intellectual property analytics [11] and user interaction [12], general comprehensive studies prepared without being limited to a specific area or function [13] are also encountered in the literature.

Until the early 2000s, publication-oriented approaches, in which relatively few publications were subjected to detailed reviews and generalized, were frequently preferred in literature reviews. However, in parallel with the developments in the science of bibliometric, especially in recent years, the number of scope-oriented systematic reviews in which a large number of articles are evaluated in an integrated manner is increasing rapidly. On the other hand, systematic literature reviews are studies in which the representation ability is increased by examining a large number of articles together using various automation and coding steps from article selection and evaluation. In such studies, when the number of attributes (the number of classes used in article evaluation) increases, valuable results can be obtained by integrating tools such as text mining into the systematic structure during the coding stage [14, 15]. As shown in Table 1, both types of approaches are preferred in literature reviews focused on AI.

Industrial evaluations are an approach that is also studied in systematic reviews. For example, a limited number of publications have been examined in studies that include AI in the field of health management [16], transportation [17], and tourism [18]. A systematic review was used in these studies not to classify (encode) articles but to select the correct papers. In another study on the private sector [19], a comprehensive systematic review was presented by evaluating the entire field, AI methods, and published journals separately. However, in this study, a limited number of articles were examined, and the representation ability could not be clearly evaluated.

Grover, Kar & Dwidevi (2020) focuses on Production management in the study where he examined 181 articles. Unlike other systematic reviews, a hybrid approach, in which text mining and sentiment analysis results made with data obtained from social media are also added to the analysis, was preferred, and digitization and AI's role in this process were questioned [20]. Jourdan, Rainer & Marshall (2008) evaluated AI approaches as a subtitle in their study, in which they focused on the field of business intelligence. Journal-based analyzes were also included in the study, in which 167 articles were examined [21]. In another study, which targets the current situation of AI approaches in the digital transformation era. It evaluates them independently; a limited number of resources (41) were examined and focused on deep learning.

Table 1: Literature review studies related to artificial intelligence

Author(s)	Review Type	Corpus		Application Area
		Duration	Sample Size	
Oke, 2008 [5]	Manuel	1993 - 2007	~150	Manufacturing Applications
Jourdan, Rainer & Marshall, 2008 [21]	Systematic	1997 - 2006	167	Business Intelligence
Contreras & Vehi, 2018 [6]	Manuel	1987 - 2017	141	Health Management
Fernandez-Luque & Imran, 2018 [7]	Manuel	2012 - 2017	26	Health Management
Aristodemou & Tietze, 2018 [11]	Manuel	2006 - 2018	57	Intellectual Property
Rzepka & Berger, 2018 [12]	Manuel	1983 - 2018	96	Technological Evaluation
Duan, Edwards & Dwivedi, 2019 [13]	Manuel	1983 - 2018	123	General
Kedra et al., 2019 [16]	Systematic	2013 - 2018	55	Health Management
de Sousa et al., 2019 [19]	Systematic	2000 - 2018	59	Public Sector
Nascimento et al., 2020 [17]	Systematic	1987 - 2017	59	Transportation
Samara, Magnisalis & Peristeras, 2020 [18]	Systematic	2001 - 2018	102	Tourism
Di Viao et al., 2020 [10]	Manuel	1990 - 2019	73	Sustainable Development
Choudhury & Asan, 2020 [8]	Manuel	2010 - 2019	53	Health Management
Grover, Kar & Dwivedi, 2020 [20]	Systematic	2010 - 2019	181	Operations Management
Borges et al., 2019 [22]	Systematic	2009 - 2020	41	General
Keding, 2019 [9]	Manuel	1983 - 2019	58	Strategic Management

In the detailed evaluation of AI, both systematically and manually, it has been observed that they have different advantages and limitations. For example, when Table 1 is examined, it is seen that the number of sources may not be sufficient in terms of representation ability. This situation is not different in studies where the whole of a particular field is evaluated [13, 22]. Besides drawing a general picture of a specific area, many sector and business-oriented studies are also attracting attention. De Souza et al. (2019) performed business function, method, and journal-based evaluations in the literature review [19]. Aristodemou & Tietze (2018) and Borges et al. (2019) used approaches in which different industries are compared in terms of the use of AI techniques [11, 22]. Di Viao et al. (2020) added Bibliometric science to their work with the R Biblioshiny package's help for more understandable and visual presentations [10]. A systematic review methodology that integrates all of these approaches that add value to literature reviews can be instrumental. Also, the use of an extended sample so that representation ability will be eliminated will add value to the study. This study, prepared on this axis, is planned to be in a systematic structure that includes these advantages.

3. Artificial Intelligence

Intelligence is an integrated combination of many abilities such as thinking, reasoning, comprehension, learning, judgment, and inference. Thanks to intelligence, people can carry out activities such as learning from experience, producing solutions to different and uncertain problems encountered, and responding to a new situation as soon as possible [23]. These activities are the core of AI approaches. Artificial intelligence is the whole of techniques that can produce solutions with similar designs to solve problems and try to imitate humans' intelligence or other living organisms in the computer environment in this process. The main benefit of these approaches for business and individual life is their success in problems that are very difficult to solve with classical methods called NP-Hard. In this context, a wide range of artificial intelligence approaches is used, from multi-purpose to non-linear solutions, from estimation to classification and clustering.

There is no widely accepted classification of artificial intelligence approaches. In this study, AI techniques are evaluated under the titles of Fuzzy Logic (FL), Artificial Neural Networks (ANN), Expert Systems (ES), and AI-supported Meta-heuristics (MH) approach.

3.1. Fuzzy Logic

Many problems encountered in real life are vague, imprecise, and ambiguous by nature. Solving such problems is often possible by flexing the crisp foundations of mathematics. In this sense, there is a need for methods that constitute intelligence's mathematical infrastructure to produce solutions in uncertain and vague situations. This method, which is called soft computing, is defined as "modeling the human brain's learning and inference abilities in uncertain and vague situations" [24]. Fuzzy logic approaches, based on the fuzzy set theory put forward by L. Zadeh in 1965, is a soft computing technique that offers the ability to deal with uncertainties in real-life problems [25].

Essentially, FL is an information preparation process based on fuzzy clusters that work in integration with other methods (with or without AI), improving the problem-solving capabilities of these. This process offers significant benefits in the problem-solving phase by stretching the binary structure of classical set theory and logic with membership functions.

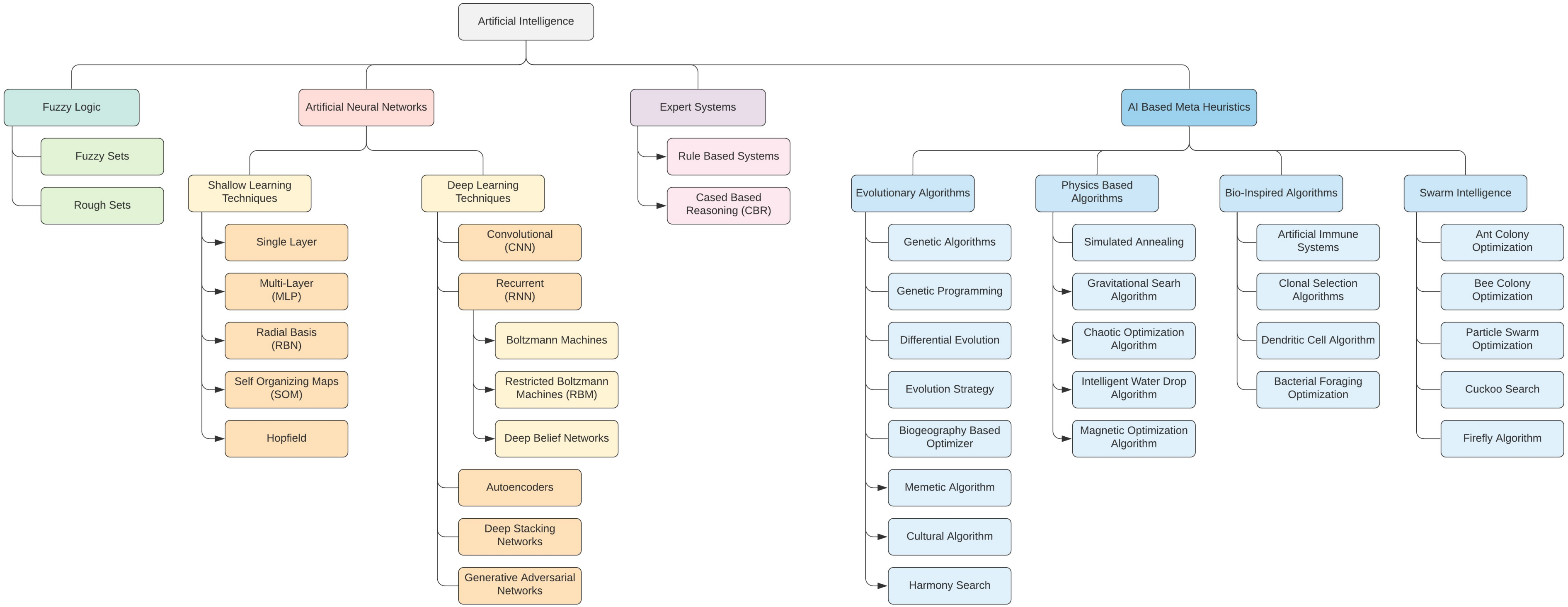

Figure 1: Artificial intelligence techniques overview

Another critical theory in the knowledge preparation process is Rough-Set Theory (RST). Based on the clustering approach proposed by Pawlak, the approximation ratios of crisp values to the possible upper and lower bounds are taken into account [26]. Although it is based on classical set theory, there are also fuzzy extensions. While FL emerges as an alternative to classical set theory, RST gives set theory the ability to deal with uncertainties. The RST approach, the primary use of rule reduction in data sets, has been preferred in many AI approaches in recent years.

3.2. Artificial Neural Networks

The human brain is in a gigantic network structure where millions of brain cells, aka neurons, are connected by synapses. This structure can produce solutions to varying difficulty problems in very different areas in a short time. The modeled version of this neural network in the computer environment is called Artificial Neural Networks (ANN). ANN, which is relatively the most used AI technique, can produce very successful results in many data analysis areas, from clustering, classification, estimation to optimization, by working with both continuous and discrete data [27].

ANN methods are evaluated under two categories as shallow and deep learning models [28]. In Shallow models, inputs and outputs are designed as artificial neurons, and there is a data flow from input to output.

Table 2: Shallow artificial neural networks models

SL Technique	Structure	Definition
Single Layer Neural Network [29]	Feed Forward	It is a binary classifier learning algorithm that predicts the output class from actual values based on a specific threshold function.
Multi-Layer Perceptron (MLP) [30]	Feed Forward	The structure in which the error propagates backward by adding the back-propagation algorithm to overcome the single-layer network's problems in XOR problems. MLP models work as a universal approximator which they can approximate any continuous function [31]
Radial Basis Neural Networks [32]	Feed Forward	Another feed-forward shallow model uses Gaussian activation function and distance-based calculations, unlike MLP
Recurrent Neural Networks [30]	Feedback	They are memory-based neural networks where each stage's outputs are used as inputs for the next stage.
Self Organizing Map (SOM) [33]	Feedback	An unsupervised approach tries to obtain a low-dimensional sample from a high-dimensional input set with its unique self-mapping technique.
Hopfield Neural Networks [34]	Feedback	In this neural network, which is based on associative memory, there is no separate output layer. It is generally preferred in classification problems.

In recent years, ANN studies have started to turn towards Deep Learning (DL). However, to better understand the concept of DL, it is necessary to understand machine learning. Machine Learning (ML) can be defined as predicting possible new situations by learning from past data. In this sense, there is a direct effect of machine learning's human factor in presenting historical data to the algorithm, unique algorithms, and, if necessary, to tune algorithmic parameters in cases where prediction success is not sufficient. If the algorithms do not achieve a suitable learning performance in DL methods, they update themselves and perfect the process without human touch. From this point of view, DL, a sub-branch of ML, can be the modern version of ML methods that have evolved in recent years [35].

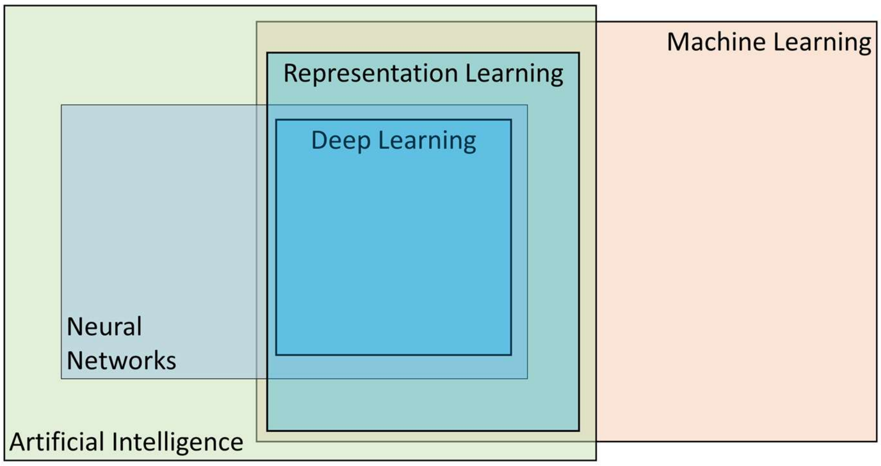

Figure 2: The place of deep learning in the artificial intelligence ecosystem

There are many ANN techniques used in the DL area. It is an extension of the Convolutional Neural Network (CNN) MLP model, which is the most popular of these techniques, including various filtering and sampling layers developed to solve the overfitting problem. Although CNN is mainly used for image and video processing and identification, it has applications in many areas, from natural language processing to time-series predictions. Other important deep learning models are given in table 3.

Table 3: Most popular deep learning techniques

DL Technique	Definition
Boltzmann Machines [36]	It is a stochastic RNN approach in which Markov chains are added to the architecture. The network, which is a special Hopfield ANN structure to which hidden layers are added, is generally preferred in classification and prediction models.
Restricted Boltzmann Machines [37]	It is a structure where hidden and visible layers are separated, and the connections between these layers are limited.
Deep Belief Networks [38]	This structure is a neural network with Restricted Boltzmann Machines architecture. In this network, all neurons, except those in the first and last layers, assume a dual role, acting as input and hidden layers.
Autoencoders [39]	It aims to learn how to convert any data to code automatically. In this structure, the high amount of attributes is reduced to a lower number of features with a specific decode-encode system and a particular representation level. Thus, good results can be created in a much shorter time with other classification and clustering approaches.
Deep Stacking Networks [40]	It is a special deep learning architecture that uses parallel learning logic to learn the large CPU clusters' parameters.
Generative Adversarial Networks [41]	High decoder performance can be achieved by converting actual data into synthetic in this neural network where two different ANN structures have competed together.

Boltzmann Machines, Restricted Boltzmann Machines, and Deep Belief Networks are essentially complex DC derivatives of the RNN structure, one of the shallow learning methods.

3.3. Expert Systems

Expert systems are computer software that makes knowledge-based inferences to solve complex problems. Since human experts encounter a case, they enter the information and solution they use to solve a knowledge base. Then, an inference engine returns this existed information to rules, and finally, decisions are generated from the rules with the help of reasoning [42].

Knowledge bases sometimes consist of cases that include the definition of a problem and its solution instead of rules. In this situation, a new decision is created by choosing the most appropriate solution from the scale of similarity measures. This process, called Case-Based Reasoning (CBR), can be evaluated as an expert system because it is based on expert knowledge [43].

3.4. Artificial Intelligence-based Meta Heuristics

Optimization is a technique that requires mathematical modeling of data, is continuous in most cases in which the most suitable alternative is selected for a specific objective. However, it may not be possible to reach the best solution in every problem area. Heuristic approaches are preferred in this type of NP-Hard problem where it is not possible to achieve the best solution, which is called the global optimum. Although heuristic approaches cannot reach the optimum result, they can get a sufficiently good result within a reasonable time frame. Most of the heuristic techniques are problem area dependent.

On the other hand, Meta Heuristics (MH) are higher-level, complex approaches that work independently of the problem area. MH approaches can use nature-based (biology, chemistry, physics) computational intelligence approaches in the solution stages. These problems are evaluated under AI-based Meta-Heuristic methods, and they are categorized under four groups as Evolutionary Computation, physics-based algorithms, bio-based algorithms, and swarm intelligence.

Evolutionary computation (EC) is the collection of methods based on natural selection and evolution theory [44]. The most known EC method is genetic algorithms. Genetic algorithms (GA) [45] are a special optimization approach based on biological evolution principles and gene crossover. In this approach, the well-defined problem is encoded by transforming it into a suitable gene sequence. The process is repeated with an iterative procedure until an acceptable solution is reached with crossing and mutation operations at each stage. Other well-known EC approaches are given in Table 4.

Table 4: Evolutionary computation techniques in meta heuristics

EC Technique	Definition
Genetic Programming [46]	It is a type of GA where individuals' representation is in the form of trees instead of genes. This approach can also be called "hill-climbing"
Differential Evolution [47]	In the model that tries to solve in an iterative way like GA, there is no need to convert the numbers to genes initially. As a result, the method differs from GA in mutation and crossover steps.
Evolution Strategy [48]	It is an EC method using real numbers. Compared to the Differential Evolution technique, there are structural differences in the sequence of real numbers and the mutation stages [49].
Bio-Geography Based Optimization [50]	The starting point is the distribution of species in time and space and the theory of evolution. Each solution called habitat is evaluated with the habitat suitability index.
Harmony Search [51]	It is an evolutionary optimization approach inspired by the improvisational abilities of musicians to achieve natural harmony.
Memetic Algorithm [52]	It is a hybrid technique that searches between predetermined local optimums rather than the entire solution space.
Cultural Algorithms [53]	It is an EC method inspired by cultural change, using an information component under the name of belief space and the population component in the GA structure.

Another type of nature-based MH algorithm is physics-based (PB) approaches inspired by physical events. Simulated Annealing (SA), the most commonly used PB algorithm, is a popular MH local search method used to address discrete and more minor scale optimization problems (Traveling Salesman Problem) [54]. Other popular PB techniques are summarized in Table 5.

Table 5: Physics-based meta heuristic algorithms

FT Technique	Definition
Gravitational Search Algorithm [55]	In the model, which is based on the laws of motion and gravity, solutions are designed as objects, and the optimum is found by calculating the global movements that occur as a result of the gravitation between them.
Chaotic Optimization Algorithm [56]	Based on the foundations of chaos theory, the algorithm can solve complex problems quickly.
Intelligent Water Drops algorithm [57]	It is the method that aims to replicate the principle of always choosing the optimum route for rivers to reach their destination in the computer environment.
Magnetic Optimization Algorithm [58]	It is an algorithm that optimizes based on magnetic repulsion and pulls between objects.

Some MH algorithms are inspired by events in biological science. The most popular of the Bio-Inspired Algorithms, Artificial Immune Systems [59], mimics the biological principles of clone production, propagation, and maturation. Some other bio-inspired algorithms are given in Table 6.

Table 6: Bio-inspired meta heuristic algorithms

SI Technique	Definition
Clonal Selection Algorithms [60]	It is an approach that focuses on adaptive immunity. It is an acquired immuno-based approach that focuses on improving the response of lymphocytes to antigens over time.
Dendritic Cell Algorithm [61]	It is an immune-inspired stochastic optimization algorithm based on the function of natural dendritic cells.
Bacterial Foraging Optimization [62]	It is the mathematical modeling of the foraging behavior (finding, using, and swallowing) of the E. coli bacillus.

The last MH method group is the Swarm Intelligence (SI) approach, which has been increasingly used in recent years. These approaches are inspired by the movements of animals that live in herds in nature. Among the more than 50 [63] SI methods, the six most frequently preferred methods are summarized in Table 7.

Table 7: Well-known Swarm intelligence techniques in meta heuristics

SI Technique	Definition
Ant Colony Optimization [64]	It is an optimization adaptation of the method "always finding the shortest path for ants to return to their nest during foraging"
Bee Colony Optimization [65]	It was inspired by the bees communicating with each other during foraging to carry out the process in the fastest and most effective way.
Particle Swarm Optimization [66]	It is the optimization modeling of bird flocks' finding rich food sources and avoiding predators.
Cuckoo Search [67]	The SI algorithm is inspired by the parasite reproductive behaviors developed by the cuckoo birds to lay their eggs in other nests.
Firefly Algorithm [68]	It is the mathematical modeling of the specific behavior of fireflies in which they tend towards the brighter ones and avoid the less bright ones.

AI provides support at different decision levels in businesses with the help of the techniques mentioned above. Analytical architecture that supports every decision level is evaluated under the umbrella concept of business intelligence [23]. These supports are assessed in 3 different categories: descriptive, predictive, and prescriptive, and each category contains more technical information and complex decisions than the previous one. On the other hand, these decisions often require AI approaches since they are in an NP-Hard structure. In this context, AI methods can significantly benefit problem areas that are getting more difficult, from descriptive to prescriptive. Information on these three problem areas is presented in Figure 3.

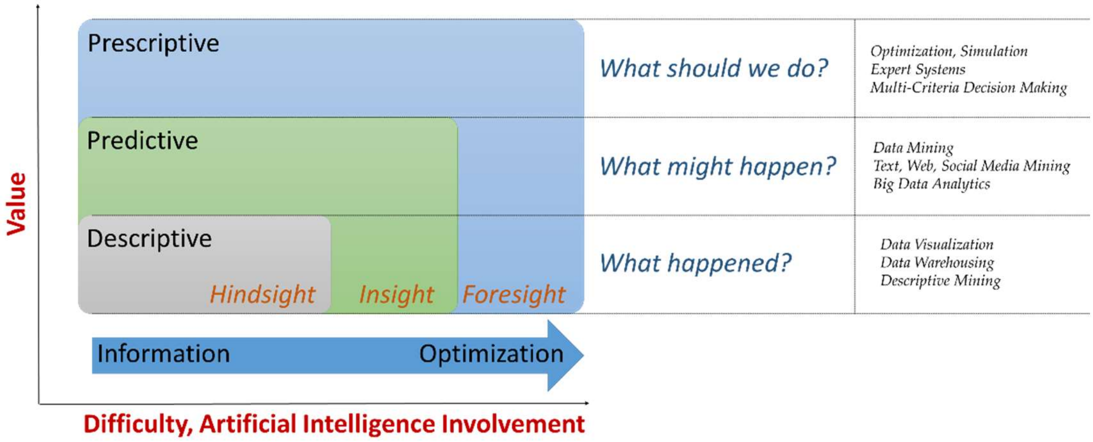

Figure 3: Business analytics levels

In this study, while evaluating the studies on AI techniques and the method-based approaches, the problem areas supported by the business intelligence architecture will also be taken into consideration.

4. Methodology

Systematic literature reviews are often preferred with their context-based generalization capability and high representation ability. Perhaps the most critical step in this review process is the creation of a corpus with appropriate documents. In this context, different review articles have their selection and evaluation processes. In this study, it was considered appropriate to use a 5-stage selection and analysis process.

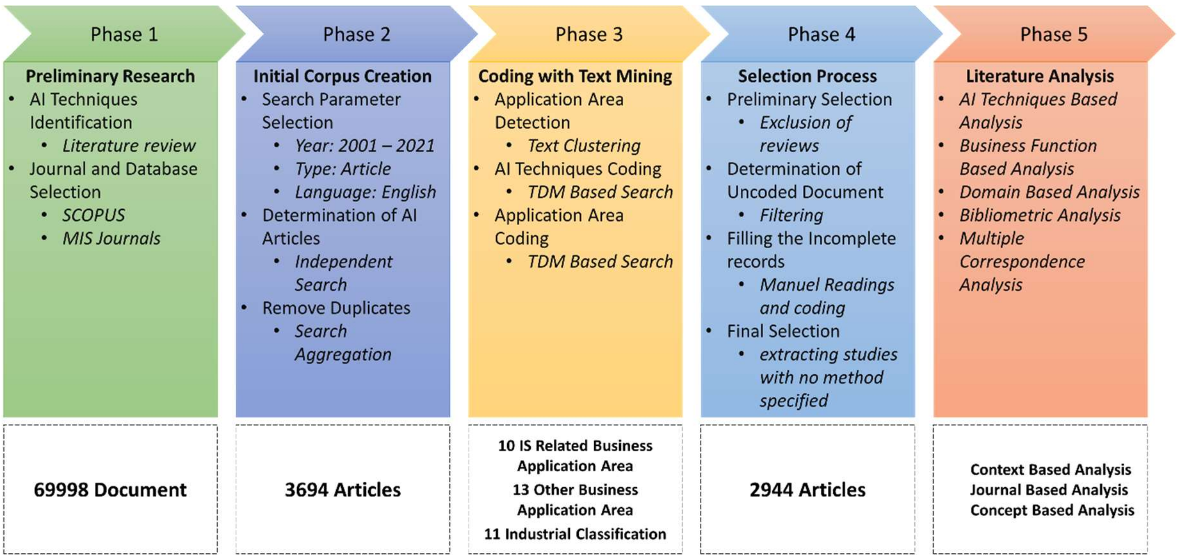

Figure 4: Systematic review methodology

As can be seen in Figure 4, the first stage is preliminary research. In this section, artificial intelligence techniques that will be subject to analysis should be determined with a detailed literature review and classified with a certain categorization. After this process, the population to be studied is selected. The critical step in the population determination process is to determine the academic database from which the contents will be drawn. The SCOPUS database is preferred for systematic reviews of the literature, mainly because of its extensive publications catalog [4,69].

In the process of creating the first corpus, separate searches for each AI technique should be performed with the year (2001-2020), publication type (article), and publication language (English) parameters. Then, the search integration process is performed to remove the duplicate records from the collection. In the third stage, it is necessary to determine the subjects in the MIS field. At this stage, the Bag-Of-Words method, one of the text mining methods, and text clustering approaches for pre-evaluation were used by the R programming language. After the topics are determined, the application area and artificial intelligence method coding are performed with advanced search codes over the Term Document Matrix, a text mining output. At the end of this stage, 3694 individual articles are transferred to the next step.

After the first three stages, the coded document should be checked, and the final corpus should be created. The first step for this is to exclude literature review studies from the review. Afterward, the documents that could not be coded in the previous step are coded manually, and during this process, irrelevant articles are removed from the collection. The final corpus consists of 2944 articles. In the last stage, the process is completed by making bibliometric and clustering analyzes together with context, journal, and concept-based evaluations. The tool used in the previous step is the R Biblioshiny package.

5. Findings

AI has increased its importance in recent years following the developments in digital transformation and industry 4.0. The MIS area, which puts the focal axis in the cross-section of industry, computer, and business, can be considered a locomotive area for these studies. In this context, the current AI studies in MIS and its orientation over the years are tried to be evaluated as context, method, journal, and concept. Research findings will be presented on the axis of research questions previously determined.

RQ1: What is AI studies' status in the MIS literature over the years, and how has it transformed in recent years?

Valuable inferences can be made to answer the research question from Table 8, where the evaluation of academic publications in the axis of AI methods is presented. When the table is examined, it is seen that the publications over the years are proportionally distributed in the fields of Fuzzy Logic, Artificial Neural Networks, and AI-supported Meta-Heuristic. However, it is seen that especially Expert Systems publications are not preferred much in the MIS literature in the last 20 years. It can be thought that the reason behind this situation is the difficulties in preparing the knowledge base, and the relatively old field has reached a maturity stage. Also, it was evaluated that fuzzy logic studies did not lose their place in the literature thanks to their information preprocessing capabilities for other methods. The ANN literature has gained momentum with DL approaches' development in the last ten years and strengthened its place. When evaluated in this context, it can be stated that the field's potential is very high, and the studies in the field of DL have not yet reached saturation in the MIS literature. Most of the Meta Heuristic approaches were introduced after the 2000s, and the existence of a method that can be hybridized very easily with other methods such as Genetic Algorithms can be considered the potential of this field is still precious.

Additional evaluations may be needed to give a more appropriate answer to the RQ1 question. Table 9 prepared for this purpose provides the number of articles and citation averages and trends over the years.

Table 8: Artificial intelligence techniques in management information systems literature

AI Technique	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Total
Fuzzy Logic	***18***	***11***	***8***	***11***	***15***	***28***	***26***	***29***	***24***	***41***	***42***	***68***	***87***	***74***	***87***	***92***	***85***	***74***	***83***	***93***	***996***
Fuzzy Sets	18	11	6	10	15	23	23	28	23	33	36	45	71	60	70	67	66	58	69	78	810
Rough Set Theory	1	0	2	1	1	5	3	3	2	9	9	27	16	16	19	29	25	18	17	15	218
Neural Networks	***16***	***11***	***8***	***22***	***18***	***30***	***15***	***21***	***27***	***20***	***34***	***46***	***39***	***27***	***33***	***58***	***64***	***92***	***169***	***291***	***1041***
Shallow Learning	13	10	8	21	18	29	15	21	25	20	33	43	36	26	29	39	41	43	72	69	611
Deep Learning	3	1	0	1	0	1	0	0	2	0	1	3	3	1	4	19	23	49	97	222	430
Expert Systems	***22***	***15***	***11***	***9***	***19***	***25***	***11***	***22***	***7***	***7***	***11***	***13***	***20***	***19***	***12***	***14***	***18***	***15***	***15***	***15***	***300***
Rules Based Systems	15	13	8	6	14	16	6	11	5	5	4	9	16	8	9	12	14	12	11	10	204
Case Based Reasoning	8	2	3	3	5	9	5	12	2	2	7	4	5	11	3	3	4	3	5	5	101
AI Based Meta Heuristics	***8***	***10***	***5***	***10***	***18***	***33***	***20***	***34***	***39***	***30***	***55***	***39***	***71***	***51***	***65***	***106***	***111***	***101***	***123***	***145***	***1074***
Evolutionary Algorithms	7	9	4	10	15	29	15	29	28	22	40	28	49	30	40	66	64	55	61	75	676
Physics Based Algorithms	0	1	1	0	5	2	3	2	5	7	4	4	12	9	7	18	20	19	23	29	171
Bio Inspired Algorithms	1	0	0	0	0	0	1	0	1	0	0	1	3	3	0	4	3	3	5	1	26
Swarm Intelligence	0	0	0	0	0	4	4	5	10	4	15	11	25	23	27	47	49	54	60	81	419
Total	**49**	**41**	**29**	**38**	**60**	**100**	**61**	**90**	**82**	**79**	**119**	**142**	**173**	**151**	**170**	**233**	**237**	**255**	**338**	**497**	**2944**

** There is more than one method in some articles,so the total number of articles containing the methods is higher than the general total.*

Considering the citation rates in Table 9, although there is no significant difference between AI methods, it is seen that the Expert Systems area lags a little. Depending on the number of publications, this situation can be considered to be expected. On the other hand, it is seen that rough set theory approaches have come to the fore in recent years. The most crucial factor behind this situation is that these approaches can significantly benefit size and feature reduction studies. Another important observation is that SI publications are at the forefront of citation with the effect of new methods introduced in recent years.

Table 9: Citation average and article number trends of AI techniques

	Article		Citation	
Artificial Intelligence Technique	**Number**	**Trend**	**Average**	**Trend**
Fuzzy Logic	***996***	***5,07***	***3,700***	***0,19***
Fuzzy Sets	810	3,89	3,414	0,16
Rough Set Theory	218	1,33	4,969	0,22
Neural Networks	***1041***	***7,84***	***3,452***	***0,18***
Shallow Learning	611	2,52	3,327	0,08
Deep Learning	430	5,32	3,629	0,40
Expert Systems	***300***	***-0,05***	***2,964***	***0,15***
Rules Based Systems	255	0,12	3,180	0,22
Case Based Reasoning	101	-0,04	2,699	0,01
AI Based Meta Heuristics	***1074***	***6,74***	***3,248***	***0,21***
Evolutionary Algorithms	676	3,40	3,006	0,20
Physics Based Algorithms	171	1,30	3,441	0,36
Bio Inspired Algorithms	26	0,18	3,054	0,00
Swarm Intelligence	419	3,74	4,988	0,50

Trend values give the increasing trend of the number of publications and average citations in the field. From this point of view, the most prominent subject in terms of both the number of publications and citations is deep learning. So, it can be predicted that there is still a severe potential for academicians considering publishing in the field. Another critical issue is that, although it is not clear in the slope of the number of publications, it stands out as SI when the citation slope is taken into account. These approaches provide significant benefits to optimization in many areas with their problem-independent perspectives, and they are particularly successful in improving the performance of deep learning algorithms.

RQ2: At what level do AI studies support business analytics approaches?

AI, by its nature, gives outstanding results in problem areas called NP-Hard. In this sense, as the problem area gets more complicated, more AI support is needed. When table 10, which presents the evaluations on the axis of business analytics models, is examined, it is expected that most publications are in the field of prescriptive analytics. There are a significant number of publications in the field of predictive analytics, where deep learning approaches are often preferred. It is also seen that the citation average of this area is ahead of the other fields. On the other hand, it is thought that the preference of MH techniques in the predictive field and being valued by taking too many citations may stem from the need for resource optimization, especially in big data analytics and deep learning studies. On the other hand, the descriptive area is an area where AI techniques are not preferred much with its less complex problem structure. Descriptive data mining approaches cover most of the preferred publications in this field.

Table 10: Evaluation of artificial intelligence techniques from the business intelligence perspective

	Descriptive		Predictive		Prescriptive		Total	
AI Technique	**Total Article**	**Average Citations**	**Total Article**	**Average Citations**	**Total Article**	**Average Citations**	**Total Article**	**Average Citations**
Fuzzy Logic	176	3,432	417	3,743	532	3,825	996	3,7
Neural Networks	155	3,409	870	3,766	373	3,687	1041	3,452
Expert Systems	52	2,494	183	3,745	351	3,073	300	2,964
AI Based MetaHeuristics	155	2,978	422	4,255	1070	3,252	1074	3,248
Total	472	3,288	1569	3,812	1840	3,414	2944	3,431

RQ3: Among the MIS journals, which ones are prominent in publishing AI, and do these journals differ in business analytics publications?

According to 2020 data, 128 journals are indexed in the SCOPUS database in the MIS area. In 85 of these journals, at least 1 AI publication has been published in the last 20 years. Table 11 shows the 20 MIS journals with the highest number of publications in the field. When the table is examined, most of the publications made have occurred in the "Knowledge-Based Systems" journal. This journal uses AI methods in 16.1% of its publications in the last 20 years. In recent years, other noteworthy journals in terms of this ratio are the "Big Data and Cognitive Computing" and "International Journal of CIS and Industrial Management Applications" journals, which are relatively new journals indexed in SCOPUS. When the field is evaluated in general, it is seen that the rate of publication of AI articles in the first 20 journals is around 6%.

Considering the order of MIS journals in the SCOPUS database, it is seen that the first five journals have a place among the first 20 journals in terms of their number of the publication. The exception here is the "MIS Quarterly: Management Information Systems" journal, which prefers relatively theoretical publications. According to the SCOPUS 2020 MIS journal ranking, 8 of the first 20 journals are Q1, five are Q2, three are Q3, and four are Q4.

The most prominent journal in terms of average citation is the "Information and Management" journal. In the journal, where relatively few AI articles are published proportionally, each publication has a very high citation value of 15.01 on average. Decision Support Systems, a journal with a relatively low AI publication rate, also has a high citation rate.

When examined in terms of the level of business analytics, the journals' different preferences are once again revealed. For example, while an increase from descriptive to prescriptive is expected (or at least close) in the field in general, it is seen that some journals make different choices. For example, "International Journal of Logistics Systems and Management" journal accepts prescriptive publications in the vast majority," Knowledge-Based Systems "and" Decision Support Systems "journals, which receive the most publications in the field of predictive analytics.

If the journal-based evaluation results are generalized, it can be evaluated that although AI has an essential place in the MIS literature, such publications are primarily preferred in technical journals (engineering origin). The "Artificial Intelligence" sub-field under computer science in SCOPUS subject taxonomy generally hosts AI publications. The "Knowledge-Based Systems" magazine, which publishes the most in this field, is a periodical that is ranked among computer sciences in various sub-fields, in a way to verify this situation.

Table 11: Journal base evaluation of artificial intelligence techniques from the business intelligence perspective

	SCOPUS			AI Total			Descriptive		Predictive		Descriptive	
Journal Name	**Quartile**	**Rank**	**Article**	**AI Article**	**Rate**	**Citation**	**Article**	**Citation**	**Article**	**Citation**	**Article**	**Citation**
Knowledge-Based Systems	Q1	3	8478	1363	0,161	3,51	228	4,22	837	3,07	785	4,17
Decision Support Systems	Q1	7	6795	264	0,039	8,94	40	6,53	180	9	172	10,05
Int. Journal of Business Intelligence and Data Mining	Q3	72	749	90	0,120	0,44	30	0,7	58	0,33	64	0,34
Int. Journal of Logistics Systems and Management	Q2	45	2186	89	0,041	0,69	8	0,32	12	0,74	80	0,73
Industrial Management and Data Systems	Q1	9	4013	83	0,021	2,93	16	2,41	34	2	50	3,65
OPSEARCH	Q2	49	926	79	0,085	0,5	7	0,58	7	0,22	71	0,52
Construction Management and Economics	Q1	19	4335	72	0,017	6,82	5	1,64	28	6,9	55	6,99
Int. Journal of Information and Management Sciences	Q4	84	1564	67	0,043	1,21	10	0,39	21	1,31	33	1,28
Int. Journal of Business Information Systems	Q2	44	2014	52	0,026	0,36	18	0,34	32	0,27	39	0,32
Journal of Decision Systems	Q3	55	529	41	0,078	0,47	7	0,37	17	0,36	29	0,46
Int. Journal of Data Mining, Modelling and Management	Q2	42	1335	41	0,031	0,35	11	0,21	32	0,38	30	0,34
Int. Journal of CIS and Industrial Management Applications	Q3	62	209	36	0,172	0,06	6	0,06	22	0,05	22	0,05
Int. Journal of Mobile Network Design and Innovation	Q4	87	543	35	0,064	0,34	10	0,41	14	0,46	24	0,23
Int. Journal of Information Management	Q1	1	3084	35	0,011	2,84	4	1,74	24	1,91	13	5,05
Big Data and Cognitive Computing	Q4	102	97	32	0,330	0,24	5	0,1	24	0,26	8	0,21
Int. Journal of Supply Chain Management	Q1	2	1260	31	0,025	0,1	4	0,16	14	0,11	17	0,05
Int. Journal of Grid and Utility Computing	Q2	40	687	28	0,041	0,35	5	0,22	8	0,08	21	0,39
Information and Management	Q1	4	3421	27	0,008	15,01	1	9,2	13	23,32	16	21
Int. Journal of Systems Science: Operations and Logistics	Q4	88	534	25	0,047	0,53	2	0,12	2	2,09	21	0,39
Int. Journal of Services Operations and Informatics	Q1	22	252	25	0,099	0,47	1	0,11	9	0,65	20	0,57

RQ4: How and to what extent do AI approaches support informatics-related factors affecting businesses?

In recent years, it is seen that AI techniques are frequently preferred in some subjects in informatics. Table 12 presents these informatics-related issues together with the number of publications and citations and their trend status. To give a clear and detailed answer to the research question, it would be appropriate to evaluate the fields in the table in detail.

Information Systems Support: The most basic information systems task is control and decision support [70]. AI plays an essential role in decision support. Information systems that support people's decisions in different areas are among the subjects studied a lot over the years. In this study, it was determined that AI techniques benefit five different decision support system structures.

- Decision Support Systems [71,72,73,74]
- Enterprise Resources Planning [75,76,77]
- Customer Relationship Management [78,79,80]
- Geographical Information Systems [81,82]
- Management Information Systems [83]

In addition to a large number of publications in information system support, it is seen that the trend is also very high. Although it does not reach high values in terms of the number of citations and trends, it can be considered a potential field for publication.

Table 12: Current situation and trends of information-related issues in MIS literature

	Article		**Citation**	
Information Related Issues	**Number**	**Trend**	**Average**	**Trend**
Information Systems Support	305	0,63	3,135	0,18
Knowledge Management	242	0,56	3,498	0,15
Software Development	130	0,5	2,904	0,26
Information Technologies	107	1,29	3,106	-0,01
Recommender Systems	99	0,75	4,254	0,46
e-Business	87	0,32	3,352	0,28
Security and Privacy	73	0,7	2,81	0,25
Cyber Crime	66	0,45	3,882	0,19
Fault Detection	54	0,32	5,2	0,53
Innovation and R&D	41	0,32	2,124	0,07

Knowledge Management: Information management is an informatics function that covers the extraction [84,85,86], integration [87,88,89,90], sharing [91,92] and distribution [93,94,95,96] of the information produced within the enterprise. From this point of view, the increase in the density of the produced information and its differences in form and area requires different perspectives, and in this sense, the role of AI techniques is important. It has a high number and trend in this field, similar to the publications related to information system support.

Software Development: Software development is essentially a system analysis and design activity and requires the execution of serial tasks related to project management. This series of activities includes requirement analysis, process modeling, logic modeling, interface design. Software engineering studies that evaluate each activity in the software development process in detail are applications that AI methods provide significant support [97,98,99,100,101,102]. Human-computer interaction and specifically interface design is another field of study [103,104,105,106,107]. Software evaluation is important as perhaps the most important link in this series of activities that touches the end and the customer [108], and evaluations in this area generally focused on usability [109,110]. Although the average citation rate of the publications in this field over the years is low, it is seen that it has a rising trend.

Information Technologies: Many factors such as the need for digitalization, industry 4.0 adaptation, globalization, survival in the market, and high costs require businesses to move towards new and more efficient technologies. On the other hand, AI emerges as a critical support point in developing and managing these technologies. Important information technology examples are given below.

- Cloud Computing [111,112,113]
- Internet of Things [114,115]
- Radio-Frequency Identification (RFID) [116,117]
- Virtual Reality [118,119]
- Augmented reality [120]
- 3-D printing [121]

Analysis of publications on information technologies turned out to be a fascinating result. Although these publications are the fastest growing (the highest trend), they have remained remarkably stable in receiving citations and do not show any inclination.

Recommender Systems: Information systems that anticipate a user's views about a product and make suggestions to him are called an adviser or recommendation system. These systems naturally need AI techniques as they have to predict human nature and behavior. There are a considerable number of suggestion system publications in the literature in recent years [13,122,123]. Also, when table 11 is examined, there is an increasing trend in both the number of publications and citations.

e-Business: Conducting activities such as purchasing/selling goods, customer service, communicating with employees, customers, and business partners using the internet infrastructure is called e-business. These activities can communicate with other systems without people with infrastructures such as electronic data exchange. This need for automation may require the support of AI methods [124,125]. As a sub-component of e-business systems, e-commerce is a direct contact point with the customer, so they use AI techniques in many areas such as customer understanding, profiling, and segmentation [126,127].

Security and Privacy: As the use of information systems increases, the number and methods of accessibility channels have also diversified. Besides, when businesses prefer cloud technology in terms of cost advantage, the value of security and privacy issues will increase significantly. AI studies did not remain insensitive to this situation and showed themselves in publications in the field of cybersecurity [128,129,130] and information privacy [131,132]. The increasing number of studies in this field in recent years can be seen with a trend value of 0.70. However, the number of article citations is slightly lower than in other areas.

Cyber Crime: The increasing importance of security and privacy issues has led to an increase in the number of publications, especially on fraud detection [133,134], intrusion detection [135,136,137], Deception Detection [138,139,140], forensics [141,142] and Cyberbullying [143] in recent years. While the publications in this area are highly cited, they still have a rising publication trend.

Fault Detection: With the developments in information and communication technologies and the increase in the use of automation applications, the processes of detecting, isolating, and, if necessary, correcting an error (or fault) that may occur on the system are gaining increasing importance. On the other hand, AI techniques provide significant benefits in both detection and isolation, thanks to their analytical capabilities. This process manifests itself with different names in the MIS literature, such as error analysis [144,145], failure analysis [146,147], and fault detection [148,149]. It can be predicted that this area, which is highly cited and is ahead of other methods in the citation trend, will become an essential field of study in the years to come.

Innovation and R&D: Learning human behavior in the best possible way has always been the focus of AI studies. This need for learning has brought studies to the birth of deep learning approaches. All AI techniques, DL, in particular, appear as an essential research tool that performs very valuable activities in terms of research and development and innovation studies [150]. This is why, in recent years, innovation [151,152] and R&D [153] have started to find a place for themselves in AI studies.

RQ5: What is the preference of AI methods in business functions that are not related to informatics?

AI adds value to almost every enterprise activity, thanks to the analytical support it provides at the decision-making point. As shown in Table 13, studies on all core business functions, especially production planning and control, logistics, sales and marketing, finance, and human resources, are found in AI literature. Also, support activities such as performance management, management and organization, risk management, environmental management, and occupational health and safety can be counted among the business functions where AI methods can be applied.

Table 13: Current situation and trends of several business-related areas in MIS literature

	Article		Citation	
Business Functions	**Number**	**Trend**	**Average**	**Trend**
Product Management and Control	481	2,37	1,929	0,05
Supply Chains and Logistics	284	1,78	1,954	0,15
Sales / Marketing	221	0,62	2,873	0,08
Finance / Accounting	169	0,7	3,713	0,17
Performance Evaluation	162	0,77	2,477	0,17
Environmental Issues	138	1,13	3,853	0,27
Management and Organization	110	0,3	2,282	0,05
Risk Management	102	0,49	3,568	0,07
Project Management	68	0,09	1,843	0,04
Human Capital Management	42	0,12	2,411	0,09
Disaster and Crisis Management	37	0,26	3,094	0,25
Occupational Health and Safety	36	0,21	2,97	0,33
Investment Analysis	16	0,12	3,981	0,25

When Table 12 is examined, most articles were published in the field of production planning and control. It can be said that this is not surprising since AI is the focus of the industry 4.0 concept announced in 2011 and digitalization studies in other countries. As a natural consequence of the support of fuzzy logic to multi-criteria problems and the excess of AI-supported MH approaches, it can be thought that the number of publications has increased in the field of supply chain and logistics. When the trends in these two areas are examined, it can be said that they have not yet reached maturity and that the area maintains its potential. It is seen that AI publications on environmental issues have an increasing trend in recent years, and it can be evaluated that the citation values of this field are ahead of the others. Performance management, which is complex and multi-dimensional due to its nature and creates analytical requirements due to indicators that are not clear and cannot be measured easily, is trendy within the AI field.

RQ6: Which industries are at the forefront of AI use in MIS literature?

Industries must be grouped with taxonomy to make an assessment that will answer the research question appropriately. Therefore, the Global Industry Classification Standard (GICS), a taxonomy preferred for this purpose in the literature [154,155] and developed by Standard & Poors and Morgan Stanley Capital International in 1999, was chosen in the article.

Table 14: Artificial intelligence application in different industries

	Article		Citation	
Industry	**Number**	**Trend**	**Average**	**Trend**
Industrials	361	2,13	3,549	0,25
Health Care	286	1,92	3,456	0,22
Consumer Discretionary	274	1,47	2,863	0,16
Information Technology	201	1,32	2,082	0,07
Financials	98	0,51	4,776	0,29
Communication Services	86	0,56	2,22	0,09
Consumer Staples	61	0,37	1,855	0,10
Materials	58	0,35	2,765	0,21
Energy	44	0,34	3,59	0,32
Utilities	39	0,29	3,799	0,40
Real Estate	10	0,05	1,956	0,11

According to the numbers given in Table 14, the most preferred sector is "Industrials", which covers activity areas such as machinery manufacturing, transportation, and construction. Perhaps the most remarkable result in the table is that the health sector is the second category with the highest number of publications and the highest trend. This is a result of the increasing use of AI techniques in the fields of medical diagnosis [156,157], anthropometry [158,159], bioinformatics [160,161], electronic record management [162], and clinical DSS [163,164] in recent years. Other noteworthy values are seen in the Consumer Discretionary sector group. It is thought that the sector, which includes the sub-fields of Auto Components and Automobile Manufacturers, Household Durables, Consumer Services (restaurants, cafe, education Services), and retailing, has been involved in many publications primarily in the axis of customer relations. The Information Technology sector is the last area to be the subject of a large number of publications. Utilities, Energy, and Finance sectors are at the forefront in citation-based evaluations, respectively. The common point of these three areas is that they are the subject of AI-supported MH studies. As emphasized in previous analyses, the increasing trend in these areas is reflected in sectoral studies.

RQ7: Which concepts are prominent in AI studies in the MIS literature, and has this changed over the years?

To answer the last research question of the study, Multiple correspondence analysis, which is a type of principal component analysis applied on categorical data, was preferred in addition to bibliometric analysis. The analysis calculates the association of the Euclidian distance in a two-dimensional plane. As can be seen from Figure 5, concepts have been collected in 6 different groups.

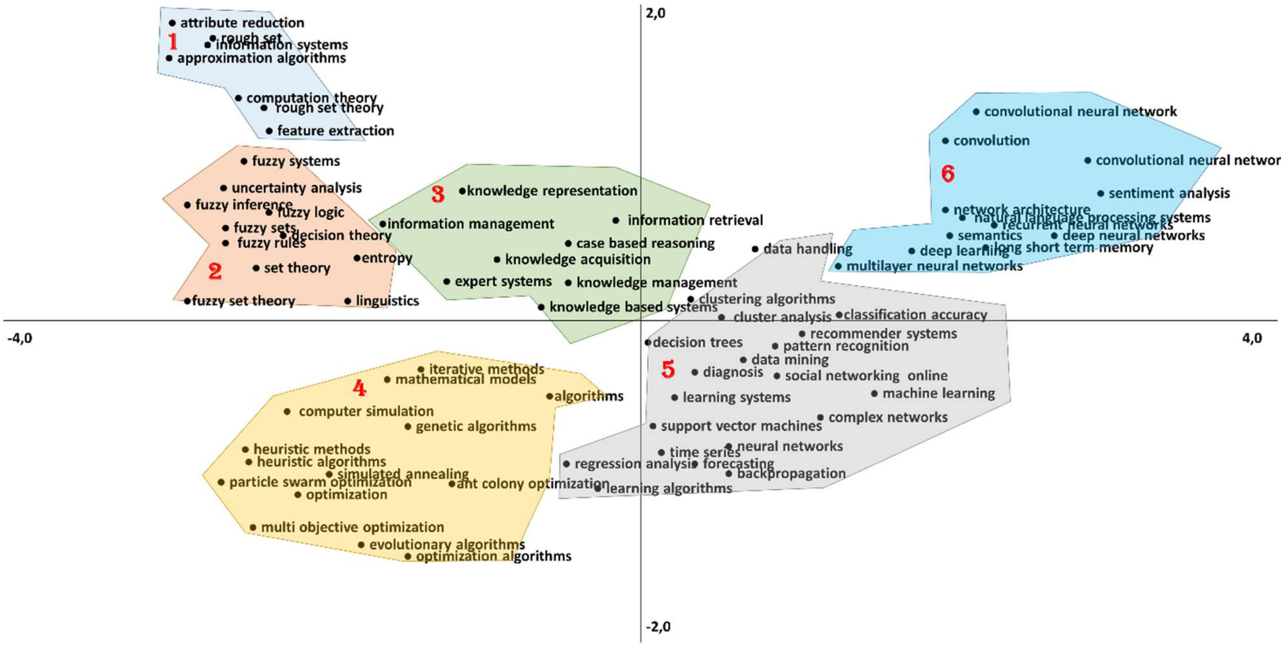

Figure 5: Concept clustering representation

When the figure is examined, cluster number 1 includes feature extraction and reduction and rough sets, which is the most preferred approach in this field. Cluster number 2 is directly related to fuzzy clusters. Also, these two clusters, which are very close to each other in terms of distance, can be considered information processing and preparation clusters. Cluster number 3 evaluated the expert system and knowledge management issues together. Number 4 generally includes metaheuristic approaches. Besides, mathematical modeling, iterative methods, and computer simulation concepts are also seen here, all of which point to prescriptive analytical techniques. While the cluster shown with the number 5 includes prediction and classification approaches related to predictive analytics. The analysis method used assigned the concepts related to deep learning to a different cluster. This situation also supports the previous comment that "machine learning has evolved towards deep learning".

Evaluating the trends of concepts in the literature can gain different perspectives while answering the research question. For this purpose, the logarithmic states of the frequencies in the Term Document Matrix obtained by the text mining bag-of-words method are given in Figure 6 below. The frequencies in the figure are taken logarithmically to increase the readability of the graphic.

When the figure is examined, it shows that especially the studies of artificial neural networks came to the fore in 2014, and after 2018, they directly shifted towards deep learning. It has been observed that the studies in the field of MH have increased significantly in the MIS literature since 2016. Apart from these, it is seen that fuzzy logic and rough clustering studies were very prominent between 2013 and 2016 but did not stand out much except these dates. On the other hand, it can be observed that the trend of the expert system works was observed only at the beginning of the 2000s, and then the trend decreased. All these conceptual inferences support our previous article-based evaluations.

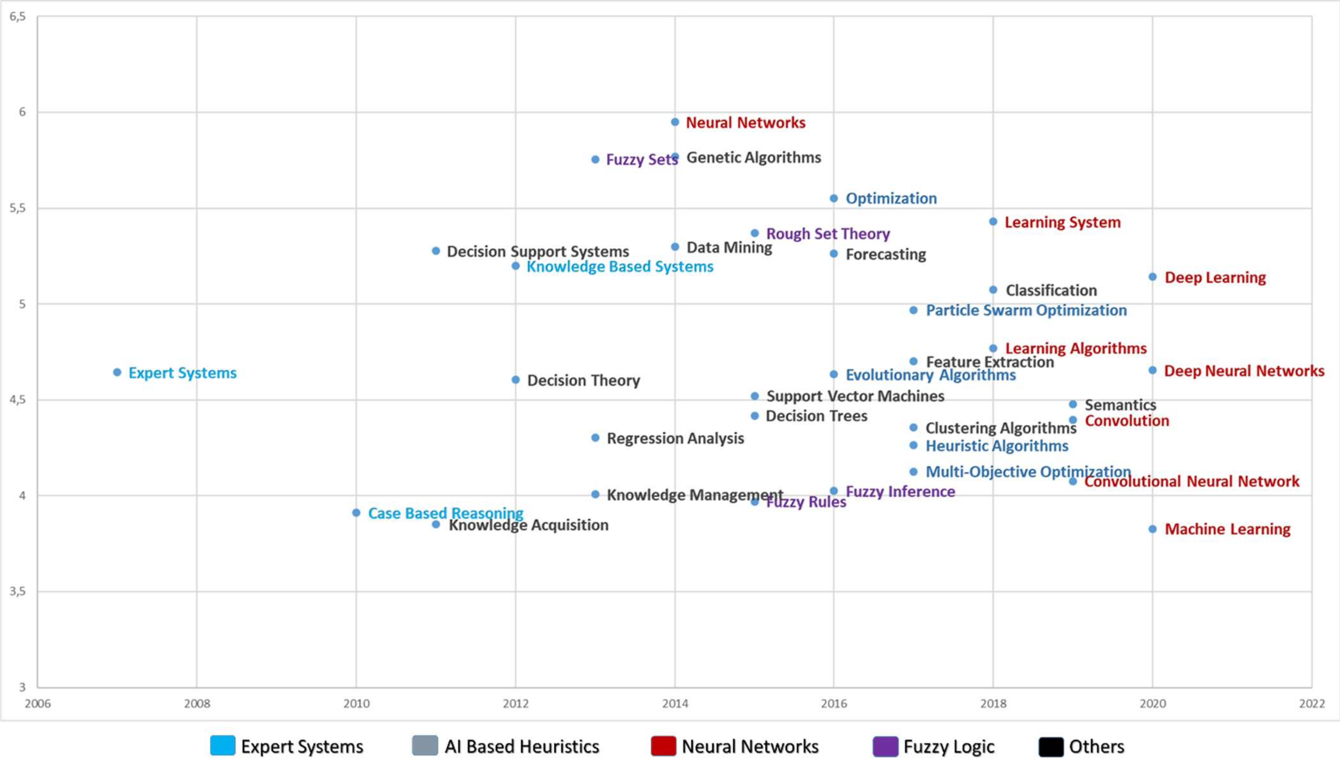

Figure 6: The trend of artificial intelligence-related concepts over the years

The literature findings have shown that the MIS literature has not yet reached maturity in AI methods in many areas. The analyses can also offer different perspectives and the general picture, giving the trend of the field.

5. Conclusion

Digital transformation, very complex (Often NP-Hard) problems, and companies' desire to model and understand human behavior are essential factors that trigger artificial intelligence studies. Especially with the fourth industrial revolution, the importance of management information systems, which are located at the interface of information, business, and industry, has increased even more today, when digitalization has become a necessity. This study, which was prepared by considering these two concepts, aimed to examine the use of AI techniques in MIS literature in a multi-dimensional and systematic manner. In this direction, a systematic literature review method supported by the semi-automatic text mining method was proposed in the study.

As a result of the analysis, it has been concluded that the studies conducted in the field of FL, ANN, and MH are proportionally distributed in the literature. Still, this distribution has shown a shift towards ANN and MH due to deep learning and swarm intelligence methods in recent years. Also, it has been seen that these areas are at the introduction or growth level in the MIS literature, and it has been evaluated that they have a high publication potential. It is predicted that fuzzy logic will continue to support other methods and rough clustering approaches as an information processing tool in the following years. In this respect, it is recommended that academicians include these techniques in the learning cycle. On the other hand, due to the difficulties in building a knowledge base in recent years, it has been revealed that expert system approaches are less preferred, and there is no trend towards this field.

AI methods have been evaluated in two categories in the MIS literature regarding the functions they are applied to or support. When applications in functions related to informatics are examined, it is observed that there are a significant number of articles especially in the field of information system support and information management. However, it has been determined that the number of articles on the use of AI techniques, especially in the field of information technologies, has increased over the years due to the digital transformation and the need to develop new technologies accordingly. However, it is seen that the recommender systems, which come to the fore with the deep learning approaches being the focus of machine learning processes, are highly valued in the literature. The last and most meaningful conclusion is that the areas of cybercrime and security and error detection are the rising fields of recent years.

When AI support to other business functions is evaluated, production planning and control activity are at the forefront of the industrial transformation through digitalization. Although the studies in this field of activity continue to increase, it has been determined that it does not see enough value as a citation. Behind the strikingly high number of publications in the field of supply chain and logistics is the need for multi-criteria and optimization problems due to the nature of the field. As a result of this need, MH and AI-based multi-criteria/objective decision-making approaches are the most popular methods in the problem area like, supplier selection, performance evaluation and, efficiency analysis. Another noteworthy result of the study is that publications on environmental issues have increased with an increasing trend. Although there are not many in the literature, it is seen that the publications on disaster and crisis management and occupational health and safety are highly valued.

In the last stage, industrial uses of AI techniques were evaluated. In this context, "industrials" is expected to appear at the top of the analyzes. As emphasized before, our age is the age of digital transformation and industrial revolution, and in this respect, manufacturing-oriented studies are expected to increase. Perhaps the most valuable output in the analysis is the use of artificial intelligence in health management in recent years.

In this study, the current situation and orientation of AI studies in MIS literature are presented in detail by performing context, journal, and concept-based analysis using AI method preferences, areas of application, sector preferences perspectives. In this sense, the results presented are intended to guide academicians and professionals who want to work in the field. However, the following suggestions can be offered to the academicians who will do systematic work in the future.

- By adding coding with natural language processing to the text mining method used, a systematic review can be presented to examine many more articles.
- The proposed method can be used in other academic fields.
- The efficiency of the process can be increased by adding intelligent filters into a systematic approach.
- The sample can be expanded with other academic databases.

It is certain that the study, which is predicted to significantly contribute to the field, has some limitations. Below are the restrictions on the systematic literature review methodology.

- Only SCOPUS has been chosen as the academic publication database.
- During the coding process of the articles, the elimination and editing were done only by the author.
- The artificial intelligence taxonomy discussed in the article was aggregated by the author from different papers.

Abbreviations

AI	: Artificial Intelligence
ANN	: Artificial Neural Networks
BI	: Business Intelligence
CBR	: Case-Based Reasoning
CNN	: Convolutional Neural Networks
DL	: Deep Learning
EH	: Evolutionary Computation
ES	: Expert Systems
FL	: Fuzzy Logic
GA	: Genetic Algorithms
GICS	: Global Industry Classification Standard
MH	: AI-supported Meta-heuristics
MIS	: Management Information Systems
ML	: Machine Learning
MLP	: Multi-Layer Perceptron
PB	: Physics-based
R&D	: Research & Development
RNN	: Recurrent Neural Networks
RST	: Rough Set Theory
SA	: Simulated Annealing
SI	: Swarm Intelligence
SOM	: Self-Organizing Map

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