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S.I.: ARTIFICIAL INTELLIGENCE IN OPERATIONS MANAGEMENT

Artificial intelligence for decision support systems in the field of operations research: review and future scope of research

Shivam Gupta[1] · Sachin Modgil[2] · Samadrita Bhattacharyya[3] · Indranil Bose[4]

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Abstract
Operations research (OR) has been at the core of decision making since World War II, and today, business interactions on different platforms have changed business dynamics, introducing a high degree of uncertainty. To have a sustainable vision of their business, firms need to have a suitable decision-making process at each stage, including minute details. Our study reviews and investigates the existing research in the field of decision support systems (DSSs) and how artificial intelligence (AI) capabilities have been integrated into OR. The findings of our review show how AI has contributed to decision making in the operations research field. This review presents synergies, differences, and overlaps in AI, DSSs, and OR. Furthermore, a clarification of the literature based on the approaches adopted to develop the DSS is presented along with the underlying theories. The classification has been primarily divided into two categories, i.e. theory building and application-based approaches, along with taxonomies based on the AI, DSS, and OR areas. In this review, past studies were calibrated according to prognostic capability, exploitation of large data sets, number of factors considered, development of learning capability, and validation in the decision-making framework. This paper presents gaps and future research opportunities concerning prediction and learning, decision making and optimization in view of intelligent decision making in today's era of uncertainty. The theoretical and managerial implications are set forth in the discussion section justifying the research questions.

Keywords Operations research · Decision support systems · Artificial intelligence · Systematic literature review

1 Introduction

The constantly growing need for quick and precise decision-making has made it necessary to embrace new information systems and techniques. Advances in information systems have rapidly affected traditional decision making (Yang et al. 2019; Taleizadeh et al. 2018; Shcherbina and Shembeleva 2014; Shim et al. 2002). Today, systems have become more complex due to their exposure to the cloud, other internet platforms, and extensive data gen-

✉ Shivam Gupta
shivam.gupta@neoma-bs.fr

Extended author information available on the last page of the article eration tools (Botta et al. 2016; Hashem et al. 2015). Therefore, a decision support system (DSS) needs to be robust (Power and Sharda 2007). DSSs assist management in a range of activities, from planning to executing operations throughout the value chain. Over time, the orientation of the DSS has evolved from a computer-based decision-making systems to a system that is able to acquire, acclimatize, and organize itself in an ambiguous and dynamic environment (Keith and Ahner 2019). As indicated by Geoffrion and Krishnan (2001), the third industrial revolution was about digitization, and many firms ranging from logistics and financial services to electronic markets have integrated OR into their business operations to respond aggressively (Crainic et al. 2009). OR is primarily and traditionally carried out for day-to-day business decisions and helps firms set up their DSSs. However, due to digitization, firms have started generating an enormous amount of data at an even greater speed, which needs to be harnessed for better decision making (Bhimani and Willcocks 2014). Therefore, the recently coined "fourth industrial revolution" with technologies such as AI and IoT is entering the physical, digital, and biological realm in order to advance the decision-making processes and thinking styles of businesses (Hamet and Tremblay 2017). AI's power to create near-to-real, true business scenarios and decisions makes it most appropriate in its application by organizations as a game disrupter (Wright and Schultz 2018). The scope of AI under the fourth industrial revolution will help transform the production, operations, logistics, and even governance of public systems. Therefore, combined use with AI needs to be embedded in OR for real-time and optimal decision making. In the earlier literature, most studies viewed these fields as separate entities, or either as the combination of AI and DSS or DSS and OR (Duan et al. 2019; Perraju 2013; Conejo et al. 2010; Dutta and Basu 1984). The combination of AI and OR was also not researched in detail. This gap in the literature inspired us to undertake a systematic review.

Artificial intelligence (AI) is a DSS ability that provides autonomy and flexibility in a dynamic environment (Kobbacy and Vadera 2011a, b). Therefore, AI is used for supercomputers in cognitive thinking, learning from behavior, recalling, attaining knowledge, drawing inferences and construing codes in a context (Min 2010; Russell and Norvig 1995). AI utilizes neural network models for the decision-making process (Svozil et al. 1997). In the early 2000s, with the increase in computing supremacy and developments in machine learning and big data, a new direction was provided for AI research (Wamba et al. 2017; Turing 2009). The latest achievements of systems like IBM's Watson and DeepMind's AlphaGo have established confidence among users and researchers to investigate the growing role of AI in DSSs (Lui and Lamb 2018; Kaplan and Haenlein 2018). DSSs have applications in the manufacturing and service industry along with public systems (de Sousa Jabbour et al. 2018; Kasap et al. 2018). To develop a DSS, approaches such as fuzzy logic, genetic algorithms, agent-based systems, data mining, and neural networks can be used (Kobbacy and Vadera 2011a, b; Min 2010). Agent-based systems can be helpful in demand planning and forecasting, customer relationship management, order fulfillment, and negotiating with suppliers and other value stream partners (Monteserin and Amandi 2011; Efendigil et al. 2009). Genetic algorithms can be helpful in designing the network (Kim and Han 2000). In addition, expert systems can be useful for inventory planning, make-or-buy decisions, and supplier selection-related activities (Moslemi and Zandieh 2011; Cebeci 2009; Humphreys et al. 2002).

Most firms require support in decision making for their operations, including product and process design, scheduling of machines and equipment for optimal utilization, quality, maintenance, fault identification, and a number of constraints in other supply chain activities (Mar-Ortiz et al. 2019; Laguna-Salvadó et al. 2019; Scott et al. 2015; Lin et al. 2012; Cowling 2003). A DSS is a computer vision and program that helps to determine, judge, and decide the course of action for conducting business. DSSs have the ability to analyze vast amounts of data and help with key decision-making activities (Aboytes-Ojeda et al. 2019). DSSs are capable of capturing, storing and retrieving data with a feedback control mechanism (Singh et al. 2018; Roy et al. 2015). The DSS design is dependent on the network strategies adopted and the mechanisms used in business activities (Kırlar et al. 2018). DSSs are capable of problem solving and decision making in business situations in a context of demand uncertainty (Keith and Ahner 2019). DSSs have applications ranging from humanitarian operations to real-life business dilemmas (Laguna-Salvadó et al. 2019; Scholz et al. 2017; Aringhieri et al. 2016). The case-based reasoning of AI systems helps in decision support (Montani 2008). Karacapilidis and Pappis (1997) offer a framework for using AI and OR tools in group DSSs. AI-integrated DSSs can be found in different business domains (Fan et al. 2018; Phillips-Wren 2012). Fethi and Pasiouras (2010) assessed the performance and efficiency of a banking system with the application of OR and AI techniques. In modern traffic management, AI is combined with OR to solve engineering problems (Brown and White 2012; Wang 2005; Bielli and Reverberi 1996). Businesses today need AI in phases ranging from design to marketing of products and services. For example, AI made it possible to design driverless cars with the ability to learn and identify patterns (Chan 2017). AI therefore has the ability to quantify uncertainty and anticipate user data needs. It also possesses significant predictive power and reasoning for planning and object manipulation (Tang et al. 2018; Gayathri and Uma 2018). For instance, Saranya et al. (2018) used AI to identify optimal tools and cutting parameters to significantly improve milling and turning operations. Furthermore, in the retail environment, customer navigation can be modelled with the help of distributed AI (Paolanti et al. 2018).

Building upon Duan et al. (2019), the tremendous increase in the complexity and flow of data in recent years has resulted in the need for a decision-making platform that is optimal, logical, and quick (Jeon, and Kim 2016). Therefore, in this uncertain environment where broad and partial information is available in different forms (images, text, and numbers), there is a need for technologies that not only predict missing data, but that also have the ability to constantly learn from the environment and from various scenarios in order to recommend decisions (Baryannis et al. 2019; Hamet and Tremblay 2017; Yan et al. 2017). Today, professionals and other individuals make their day-to-day decisions based on their experience, personal judgment, or traditional analyses that may be less accurate and take longer (Iansiti and Lakhani 2020). Specifically, in professions such as healthcare where clinicians have to decide on a treatment, a smart system that can utilize constraints, the available data on the patient and his or her lifestyle, and data about different disease characteristics would clearly be advantageous when deciding on the best treatment (Yu et al. 2018). This requires a combined study of AI, DSSs, and OR as well as how different synergies, differences, and overlaps help firms run business operations more effectively.

The role of AI becomes critical in decision making in the area of OR (Altay and Green 2006). OR utilizes advance investigation to make decisions based on business, computer science, and mathematics (Nedělková et al. 2018; Cheng and Janiak 2000; Simon 1979). The core goal of OR is optimization, and this can be achieved through AI by automating the decision-making process (Askarzadeh and Rezazadeh 2013; Akay and Karaboga 2012). Therefore, the central objective of this study is to conduct a comprehensive review of the role of AI in DSSs in the field of OR.

Traditional DSSs could only enable decision making through data modeling and numerical calculations. With AI in place, the decision-making process combines qualitative as well as quantitative analyses. AI helps the system simulate near-to-human intelligence. Studies have been conducted with various applications of AI in DSSs. For example, Chou and Benjamin (1992) developed a framework of AI-DSS to design a naval ship, and later, Beşikçi et al. (2016) developed a similar AI-DSS system for energy-efficient activities on the ship. Sahebjamnia et al. (2017) and Guillaume et al. (2014) developed a DSS for humanitarian supply chains. Other studies have promoted the adoption of AI in clinical decisions in healthcare (Suzuki and Chen 2018; Shortliffe and Sepúlveda 2018). DSS-based AI, GIS, and remote sensing have been applied for effective public decision making (Kouziokas and Perakis 2017). These studies utilized different capabilities of AI that were suitable in their scope, but questions still remain regarding the kind of AI capabilities that have been used to date to support decision making in different scenarios. Furthermore, the literature emphasizes the diagnostic approach of decision making (Bera et al. 2019; Suzuki and Chen 2018), which does not consider uncertainty in the environment. Therefore, in an uncertain era for many businesses such as today, it is more appropriate to use the prognostic decision-making capabilities of AI. When designing a DSS, many OR applications have been used. For example, Azadivar et al. (2009) developed a DSS for fishery management, where they applied simulation and optimization techniques to determine the annual fishing effort per area and with respect to time. In another study, Bakhrankova (2010) developed an energy optimizer for a chemical plant through multi-stage continuous manufacturing. However, the way in which AI has influenced these types of simulations or OR optimization techniques in DSSs is not specified in the literature. To sum up, we found that the gaps in the existing research concern "what type of AI capabilities are utilized for decision making", "how does the choice of AI capabilities change with the degree of uncertainty" and "what is the influence of AI capabilities using OR techniques in DSSs". Building on these research gaps, our study attempted to answer the following research questions:

RQ1: To what extent has research in the field of DSS exploited AI capabilities?
RQ2: How are AI capabilities such as prognostic decision making used to address complex problems in uncertain environments?
RQ3: How have AI capabilities contributed to DSSs in the field of OR?

In order to answer these questions, a critical assessment of the appropriate literature was conducted by addressing the following key points from each study reviewed:

1. Is any prognostic capability provided with reference to future scenarios that may affect the DSS?
2. Is there any exploitation of large data sets in the decision making process?
3. How many factors are considered when developing the DSS?
4. Is any learning capability developed to address decision making in OR?

To answer these research questions and establish the key points, we followed a systematic process delineated in Fig. 2. The three research questions are addressed in Sect. 6.3. We classified and analyzed each of the 69 considered studies and categorized them based on different parameters. This led us to extract challenges and issues from the current literature on AI, DSSs, and OR and establish the scope for future research.

We arranged the rest of this article as follows: the background of the study with reference to AI and DSSs, DSSs and OR, and AI and OR is presented in Sect. 2. Section 3 discusses the review methodology adopted for the study. Section 4 presents the findings of the literature survey. Section 5 presents the conceptual framework and propositions. Discussion on research questions along with implications for theory and practice are presented in Sect. 6. Finally, in Sect. 7, we conclude the review and establish the scope for future research. "Appendix A" shows the year-wise number of publications with regards to the journal title. "Appendix B" showcases the classification of literature. "Appendix C" lists the top 10 institutions with regards to the number of journal papers. The details of the five categories for the approaches adopted can be seen in "Appendix D". Appendix E shows the 69 journal papers used for review in this study.

2 Background of the study

This section is dedicated to analyzing the background information significant to this review. It starts with the relationship between AI and DSSs based on the available studies and research directions. Next, it discusses the relationship between DSSs and OR and AI and OR.

2.1 AI and DSSs

In the real-world setting, individuals, groups, firms, and society encounter a multitude of complications that require decisions and further action (Lipshitz et al. 2001; Eisenhardt 1989a, b). To act in a logical manner, these groups have to collect relevant data, assess the data, and apply recommendations (Boyd and Crawford 2012: Elstein and Schwarz 2002). The difficulty level grows at each step as the complexity of the problem rises. Therefore, to address these challenges, intelligent and knowledge-based systems must be designed to assist in decision making (Arnott and Pervan 2005; Nemati et al. 2002).

With the growth in structured data and processing competencies, the accuracy of AI systems for business has risen sharply (Mazhar et al. 2013). Regulated data requires security safeguards and privacy as a prerequisite for agreements between stakeholders in business scenarios (Taylor 2019). This regulated data is created with the help of sensors placed on computer-controlled machines and equipment for everyday use (Lee et al. 2015). This considerable amount of data is used to generate models in a fraction of the usual time (Wamba et al. 2018; D'Urso et al. 2017; Chen et al. 2012). These models help firms make the best decisions and maximize their profits (Rygielski et al. 2002; Gunasekaran et al. 2001). AI can help manufacturing and service firms design their activities effectively (Chien et al. 2020; Gunasekaran and Kobu 2002; Agnihothri, et al. 2002; Vandermerwe and Rada 1988). First, AI can be viewed as "the science of designing and building computer-based artifacts that are able to perform human tasks" (Simon 1969, 1981). The second definition of AI is related to its cognitive nature, i.e. "the science of mimicking human beings" (Dubois et al. 1996). AI has recently extended its applications in the area of automatic speech, humanoid robots, natural language processing, data mining, and driverless vehicles (LeCun et al. 2015; Jordan and Mitchell 2015). AI has diagnostic links through expert systems, fuzzy logic, rough set theory, and also case-based reasoning (Fan et al. 2018; Ahn et al. 2000). Therefore, AI-incorporated DSSs are being used increasingly to assist decision makers in the fields of healthcare, finance, marketing, and cybersecurity (Phillips-Wren 2012). AI offers an extremely low error rate in decision making compared to humans and other systems. AI facilitates speed, precision, and accuracy in decision making (Jarrahi 2018). AI can even work in hostile environments which would otherwise be harmful to humans (Sousa and Wilks 2018). AI tools that assist DSSs are referred to as knowledge-based systems, expert systems, joint cognitive systems, and intelligent decision systems (Lemaignan et al. 2017; Pullan et al. 2013; Phillips-Wren and Ichalkaranje 2008). When combined with DSSs, AI tools such as artificial neural networks, case-based reasoning, machine learning, cognitive computing, probabilistic reasoning, genetic algorithms, fuzzy theory, and multi-agents can help in fast decision making to evaluate and select the best alternatives (Phillips-Wren et al. 2009; Kim et al. 2004). Intelligent decision-support systems are capable of addressing complex decision making by harnessing extensive data and complex data sets (Przybyła-Kasperek and Wakulicz-Deja 2016; Xidonas et al. 2011; Lee et al. 2006; Jaramillo et al. 2005).

2.2 DSSs and OR

A DSS can be viewed as a three-stage support composed of formulation, solution, and investigation (Zigurs and Buckland 1998; Desanctis and Gallupe 1987). First, the model is generated to be acceptable to a solver. Second, the algorithm is developed, and in the last stage, a set of solutions are analyzed using "what-if" conditions (Shim et al. 2002; Ghodsypour and O'Brien 1998). OR is the combination of two words: Operational and Research. Operational can be regarded as "in working order or ready for use" and research can be viewed as "the systematic investigation of resources and foundations in order to institute the proofs and extent of new findings" (Hammer 2004; Wixom and Watson 2001; Priem and Butler 2001). Therefore, OR can be defined as "the application of systematic and mathematical systems to study and investigate the problems that support us with data to take the correct decision" (Will and Fransoo 2002; De Boer et al. 2001). OR history can be traced back to its application by the United States military in the Second World War (Chase and Apte 2007; Fortun and Schweber 1993). Since then, it has spread from large firms to many public sector entities due to its logical success (Kleindorfer et al. 2005). Today, OR is applied in a number of sectors ranging from transportation and shipping to production, education, telecommunications, and healthcare (Xu et al. 2020; Mehlawat et al. 2019; de Sousa Jabbour et al. 2018; Fan et al. 2018; Kasap et al. 2018). Now, it is almost impossible to run a firm without using OR to optimize activities and resources (Brynjolfsson and Mcafee 2017; Carton et al. 2016; Doerner et al. 2004). OR can be seen in the day-to-day decision-making process regarding the forecasting and scheduling of airlines, factories, and the operating rooms of hospitals (Aparicio-Ruiz et al. 2019; de Oliveira and Toscano 2018; Aringhieri et al. 2016). OR helps the executives of a firm decide on capacity planning and facility planning, from manufacturing to service firms (Boyer et al. 2002). Planning and development are possible with the help of OR when deciding how much capacity and competence will be required in the coming financial year for a particular company business (Laguna-Salvadó et al. 2019; Alfandari et al. 2011; Vlachos et al. 2007; Crainic 2000). OR helps finance firms provide the best offers to customers according to their requirements (Fethi and Pasiouras 2010). Sales promotions add to the value and even life-time value of customers and can be conducted with the help of OR applications (Stone et al. 2017; Nagar 2009). OR supports professionals in identifying problems based on analysis, logic, and qualitative factors (Fan et al. 2018; Meredith 1998). OR acts as an effective system by promoting cost-effective means of transportation, the replacement of old machinery, job sequencing, and production scheduling (Hervert-Escobar and López-Pérez 2018; Steenken et al. 2004; Yam et al. 2001). In this way, OR models and techniques help improve decision making and reduce the risk of making the wrong decisions (Uriarte et al. 2017). OR's efficient and effective planning models help coordinate between different divisions of a company for efficient supply chain functioning (Peinado et al. 2018; Mitchell and Kovach 2016). Decision makers can make decisions with the help of data that lead to profit maximization and loss minimization in a business scenario (Wamba et al. 2018, 2017). Decision making in business operations involves multiple actors and functions (Singh et al. 2018; Dixon et al. 2014). This brings different views and constraints to the decision-making process. Operations research is most suited to tackling complex scenarios with multiple constraints and criteria (Kumar et al. 2017; Saaty 2013). This has led to the development of model-driven decision-support systems (Kloör et al. 2018; Power and Sharda 2007; Yang et al. 2007; Shim et al. 2002). Ball and Datta (1997) addressed the situation where a DSS utilizes multiple operations research models to identify database features. In the last two decades, these models have become powerful enough to handle large amounts of data with modern decision making technologies (Wamba et al. 2019b; Choi et al. 2018; Brynjolfsson and McElheran 2016).

2.3 AI and OR

The techniques and tools of AI in the fields of reasoning and prediction can help improve human reliance on OR (Kourou et al. 2015; Min and Lee 2005). AI techniques include a rich pool of information demonstration mechanisms for dealing with various real-world problems (Sivarajah et al. 2017; Hassabis et al. 2017). These examples include the representation of constrained programming, logical reasoning, functional and declarative programming languages compared to rule-based formalism, prolog and lisp and Bayesian models (Ryman-Tubb et al. 2018; Jaffar and Maher 1994). However, these rich representations lead to inflexible problems, and are therefore less suited to real-world problems. Nevertheless, OR focuses more on tractable representations including linear programming constructions (Samsatli and Samsatli 2018; Liu and Van Ryzin 2008). OR has the ability to identify and provide optimal solutions in a well-defined problem space. Therefore, the challenge lies in providing illustrations that have sufficient expressive power for real-world scenarios and can promise fast and precise solutions (Gomes 2000). AI and OR integration is therefore recommended (Dixon and Ginsberg 2000). AI and OR can be applied to different areas of operations, i.e. (1) scheduling, (2) quality, maintenance, and fault identification, (3) process forecasting and control, and (4) process and job design (Guner et al. 2016; Kobbacy et al. 2007). These fields can be supported with the help of AI techniques ranging from case-based reasoning, fuzzy logic, knowledge-based systems, genetic algorithms, and hybrid techniques (Omisore et al. 2017; Hadavandi et al. 2011).

We have classified the synergies, differences, and overlaps among AI, DSSs and OR in terms of complexity, localization, environmental uncertainty, optimization, and adopted approaches in Table 1. The overlaps clearly indicate the close relationships between these fields. We therefore took this into account when pursuing our systematic literature review.

2.4 Taxonomies around AI, DSSs, and OR

We classified the AI, DSS, and OR taxonomies based on the literature. Starting with OR, the structure-based approach includes physical and symbolic models. Symbolic models can be either verbal or mathematical, whereas physical models can be iconic or have an analog-based approach. Furthermore, OR models can be classified by purpose as descriptive, predictive, or normative. OR models can be static or dynamic in nature. To define the degree of certainty, probabilistic or non-probabilistic models can be used. An OR problem can be further broken down based on the solution that is being sought, and whether it can be achieved through an analytical or simulation approach (Özdamar et al. 2004). OR is intricately linked to AI through expert systems. Machine learning is one of the most utilized components of AI and can be helpful in employing supervised, unsupervised, and deep learning in a network problem. AI is used in natural language processing to understand the various dialects of human language, text generation, and data classification. Another feature of AI is vision, which recognizes images positioned at certain locations. AI has the ability to convert text to speech and vice versa (Topol 2019; Ramos et al. 2008; Burgard et al. 1999). AI helps improve planning and the use of robotics in sectors ranging from manufacturing to healthcare. AI leads us towards decision making through DSSs. These DSSs can be classified into three categories, i.e.: data-driven, knowledge-driven, and model-driven. Data-driven DSSs include systems that are either database-oriented, information-oriented, or compound-oriented. In

Table 1 Synergies, differences and overlaps among AI, DSS and OR

Characteristics	Synergies	Differences	Overlaps
Complexity	Optimization through different techniques	Automation Pattern identification OR models work on rigid models with limited expressive power	Algorithm based
Localization	Convergent solution User and context driven	Use of artificial neural network Knowledge of local conditions	Logical search Decision tree NP-hard combinational optimization
Uncertainty	Measureable action	OR aims to hunt for perfect decision, whereas AI can consider the human factor also like past experience of events	Techniques Constraint based Error estimates Stochastic programming
Search and Optimization	Simulation and expert system Flexibility and adaptability	Computer vision Machine learning	Creation, execution and integration of spread knowledge Integration with stimulus agents
Methods/Approaches	Discrete event simulation Deep learning Mix integer linear programing Linear programming	Virtual agents Speech recognition Text analytics Cyber defense Image recognition Content creation	Evolutionary optimization Game theory Mathematical programming

knowledge-based systems, models that are rule or suggestion-oriented are more prevalent. In model-driven systems the majority come from representational, excel-based, solver-based, and optimization models (Hasan et al. 2017; Holsapple et al. 2008; Power 2004; Alter 1980). Figure 1 highlights the taxonomies around AI, DSSs, and OR. It should also be noted that most applications were in the areas of assessment, prediction, and selection.

3 Research methods

In this section we review the existing literature that has focused on the application and impact of AI on DSSs in the field of OR. Our literature review for this study is predominantly based on automated searches. It is appropriate to conduct a systematic review to decode the evidence in an area of interest (Snyder 2019; Tranfield et al. 2003). Therefore, we adopted a three-phase process to answer the research questions as also emphasized by Palmatier et al. (2018) and Davis et al. (2014). In addition, our review was inspired by the guiding principle indicated by Wamba (2020), Gupta et al. (2020), Baryannis et al. (2019), Dubey et al. (2017), Gupta et al. (2017), and Wang et al. (2016). The review process involved three phases, i.e.:

1. Planning for the review
2. Conducting the review
3. Reporting the review

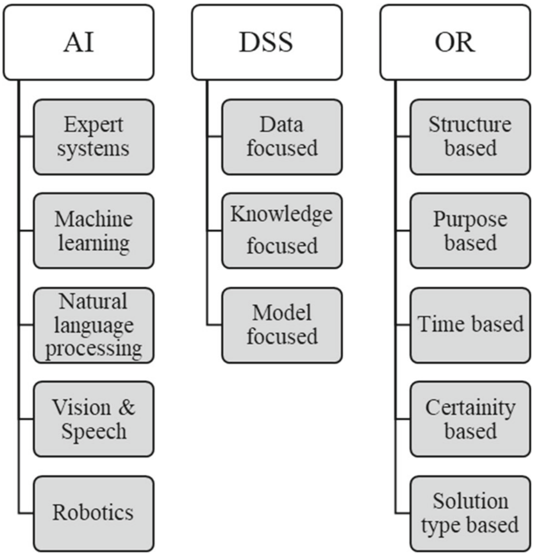


Fig. 1 Taxonomies of AI, DSS and OR

The process adopted is similar to the input process and output model of operations management. These three phases are presented in detail in the following sub-sections. Section 3.1 presents and discusses how the literature review was conducted (planning for review phase). Section 3.2 offers a summary of our literature review.

3.1 Literature review process

3.1.1 Planning for review

It is essential in secondary studies such as literature reviews to establish objectives and a protocol. The establishment of a protocol helps minimize bias when conducting the review. After establishing clear objectives and research questions, we sketched out a plan and process to utilize the advanced search options of scientific databases. After this first step, it was necessary to set the right keywords. Keywords need to be chosen carefully for the list of journal papers in search engines. To identify the keywords in this review, we adopted a structured process of independent searches, first through Scopus on AI, DSSs, and OR, respectively. In the first round, the keywords with the most frequency and that were closely related to the fields were filtered to decide on a set for AI, DSSs, and OR. This resulted in around 35 keywords in all. In the second stage, we consulted three academics and one professional from these areas of study. They suggested not including single words like "artificial", "operations", "multi-objective", etc., so we removed eight keywords and added three keywords on their suggestion, which were closely related. This approach ensured objectivity when selecting appropriate keywords. To derive a common output, we utilized the "and" operator in Scopus. We also set boundary conditions and quality measures in terms of years of publication, language, and article identification through the DOI (digital object identifier). We planned to use "and" and "or" operators to get an exact cross-section of AI-DSS-OR. We also planned to limit the search to "article, article in press, review paper; business management, accounting, and decision sciences field". To ensure the quality of the papers, we also planned to limit them to journal papers only. We searched on Scopus to get similar keyword combinations in the AI-DSS-OR domain. We planned a three-stage search. This protocol setting helped us identify documents ready for review.

3.1.2 Conducting the review

In this phase, we focused on relevant research and identified the primary studies. We used the Scopus database (https://www.scopus.com) to search the literature relevant to our study. Scopus is a large database for peer-reviewed journals, conference records, and proceedings. It has been used for systematic literature reviews in previous studies as well. Scopus displays a wide range of journal papers from different disciplines such as health sciences, life sciences, social sciences, and physical sciences along with cross-disciplinary research. At present, not only are DSSs applied in manufacturing and distribution systems, but also in healthcare, sales, enterprise resource planning, and business intelligence (Ayesta et al. 2016; Chen et al. 2016; Yang et al. 2014; Chen et al. 2012), indicating the multi-disciplinary nature of their application. Therefore, journal papers from various disciplines were of relevance to us, further justifying our choice of Scopus as a search platform. Also, it covers more academic and research journals compared to WorldCat, Web of Science, Semantic Scholar, or DBLP. Our study involves three interdependent concepts, two from the information systems discipline (AI and DSS) and one from the operations management discipline (OR). Table 2 shows search keywords used for each of these three concepts. These concepts were searched independently by using the "or" operator on Scopus for every keyword presented in Table 2. In the next step, these three concepts were combined using the "and" operator in Scopus. The number of journal papers and documents on Scopus are updated on a regular basis. The data for this study were taken from the year 2008 up to the Scopus database search date (October 21, 2018). This group of journal papers is therefore a good representation of the data displayed on October 21, 2018. The search process carried out in this study is presented in Fig. 2.

First, we conducted a search for AI-related keywords (see Table 2). This resulted in 1,468,606 hits. The second-stage search was conducted for DSS-related keywords and resulted in 1,426,166 documents. The third stage of the search was conducted for OR-related keywords, and yielded 704,798 hits. In the fourth stage of the search, we considered the intersection of AI, DSSs, and OR, and this resulted in 1,512 hits. In the fifth stage, we excluded journal papers from 2018 to 2019, as they do not present the entire year of 2018 and 2019 in terms of related research. This resulted in the exclusion of 1395 journal papers. In the sixth stage, the search was limited to journal papers, journal papers in press, and review papers in the business management, accounting, and decision sciences domains. We only considered journal papers that were in English, and this resulted in 70 relevant journal papers. We did not consider conference proceedings, as journals are more preferred outlets for publications compared to conference proceedings (Derntl 2014; Hermenegildo 2012). In the seventh stage, we went through the papers that were considered for the review and checked the papers for the digital object identifier (DOI). This resulted in 69 relevant journal papers.

Figure 3 indicates the range of studies. In "Appendix A", the list of journals in which the 69 papers were published is given. It is clear from "Appendix A" that most journals are related to DSSs and OR and their applications. The Annals of Operations Research (ANOR), the European Journal of Operational Research (EJOR), and Decision Support Systems-like journals are dedicated to OR and related practices in decision making. Figure 4 shows the number of papers at the intersection of AI, DSSs, and OR published in each year (from 2008 to 2017). It can be seen from Fig. 5 that the number of papers in the 10-year period

Table 2 Keywords used for systematic literature review (Search performed on 21 Oct 2018 on www.scopus.com). *Source:* Compiled by Author(s)

Artificial intelligence		Decision support systems		Operations research	
	"Artificial intelligence"	"decision support system*"		"operations research"	
or	"Neural network*"	"Decision support techniques"	or	"Process optimization"	or
or	"Machine learning"	"Decision support tools"	or	"Multi-objective optimization"	or
or	"Learning algorithms"	"Outcome assessment"	or	"Multi-objective optimization"	or
or	"Data mining"	"Risk management"	or	"Parameter estimation"	or
or	"Feature extraction"	"Risk assessment"	or	"Constrained optimization"	or
or	"Pattern recognition"	"Cohort analysis"	or	"Scheduling"	or
or	"Cognitive computing"			"Inventory control"	or
or	"Natural language processing"			"Production control"	or
or	"SWARM intelligence"			"Resource allocation"	or
or	"Support vector machine"				
or	"Multi agent systems"				
or	"Evolutionary algorithms"				

(2008–2017) has more or less remained the same. "Appendix B" displays the classification used for this review.

3.1.3 Reporting of literature review

This section summarizes the literature review based on the following parameters: (1) year of publication, (2) publication source, (3) institution involved in the research, (4) methodological approach, and (5) underlying theory/theories. The literature review summary is structured as per the work of Rajaeian et al. (2017) and Baryannis et al. (2019). In the review conducted by Baryannis et al. (2019), the authors focused on applications of AI in supply chain risk management and suggest the mapping of literature in terms of mathematical, big data, and machine learning capabilities. We followed their lead when classifying the studies in this paper. The review conducted by Rajaeian et al. (2017) is a review of assessment-driven support for IT outsourcing and suggests the use of the grounded theories approach. In total, we listed 69 journal papers from 31 journals that concerned AI, DSSs and OR in decision making.

Year of publication It is evident from Fig. 4 that there is an increasing trend after 2010–2011 concerning research related to AI in DSSs using OR and related approaches. This trend indicates growth from 5 studies in 2010 and 2011 to an average 7 to 8 studies from 2012 to 2017.

Publication sources Figure 4 shows the top 5 journals ranked based on their contribution to the selected studies for this review. As expected, the maximum contribution came from journals dedicated to DSSs and OR (Decision Support Systems and Operations Research).

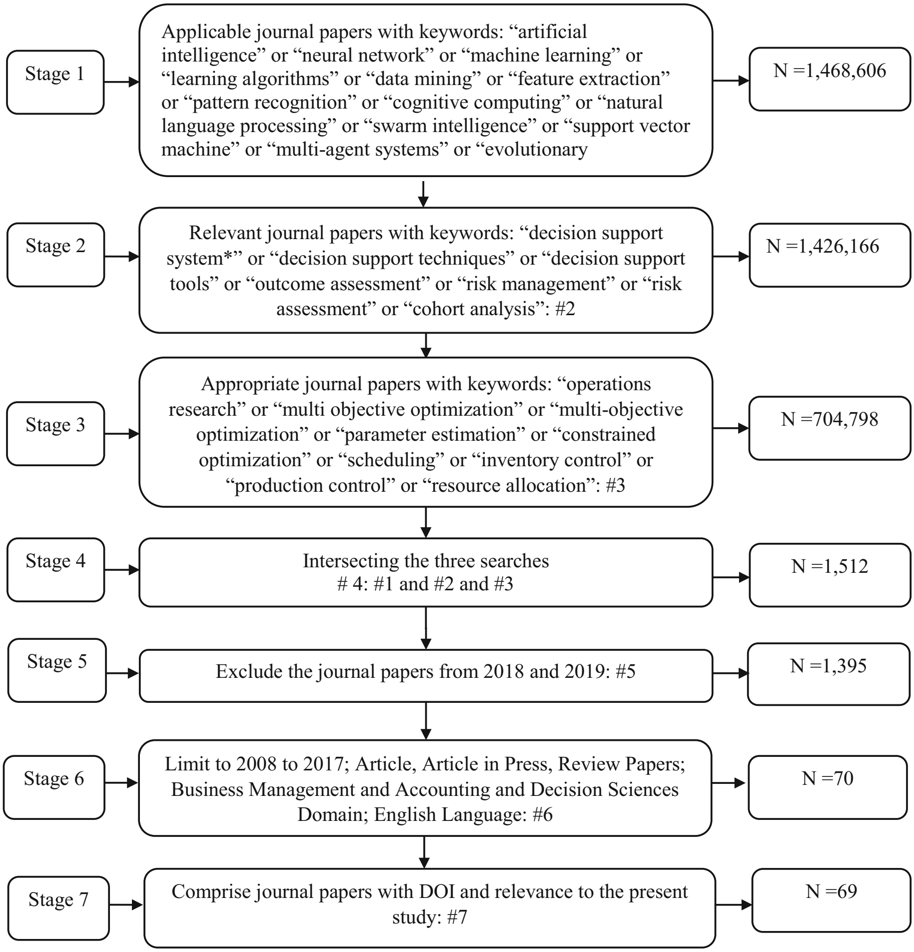


Fig. 2 Stages of data collection (Scopus Database, October 21, 2018). *Source:* Author(s) compilation

Furthermore, the list includes journals such as the Journal of the Operations Research Society, the Computers and Operations Research Journal, the Annals of Operations Research and the Journal of Advanced Manufacturing Systems and Information Sciences.

Institutions involved in research It should be noted (“Appendix C”) that the UK and Belgium are the leading players in AI-DSS-OR-related research. Countries like China, Hong Kong, and Australia are also doing their best to pursue research in these areas. Universities such as Brunel University London, City University of Hong Kong and KU Leuven in Belgium are taking the lead in this research field.

Methodological approach The studies were classified based on their methodological approach. The majority of studies contributed to model development through experiments

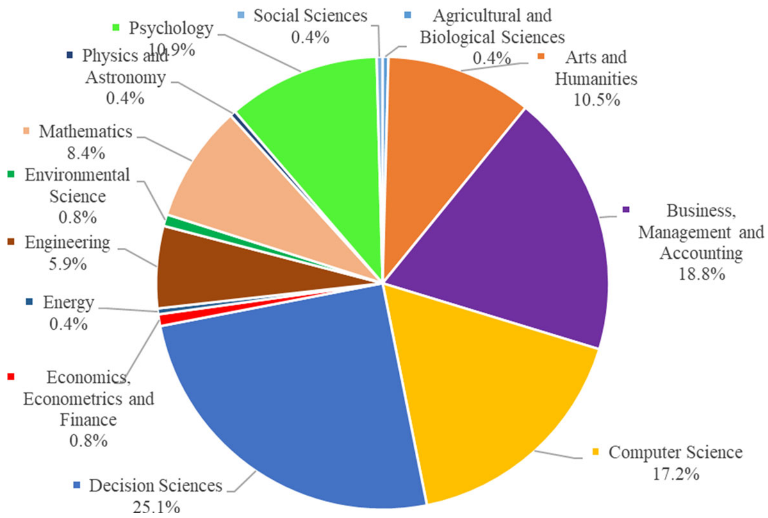


Fig. 3 Break-up of journal papers based on the subject domain. *Source:* Author(s) compilation

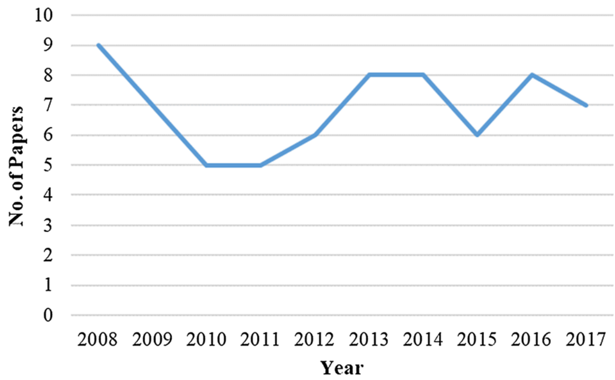


Fig. 4 Display of number of journal papers per year. *Source:* Author(s) compilation

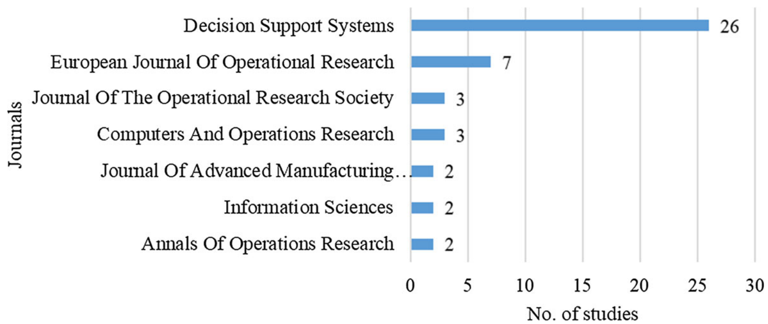


Fig. 5 Journals with the top contribution in the piloted survey. *Source:* Author(s) compilation

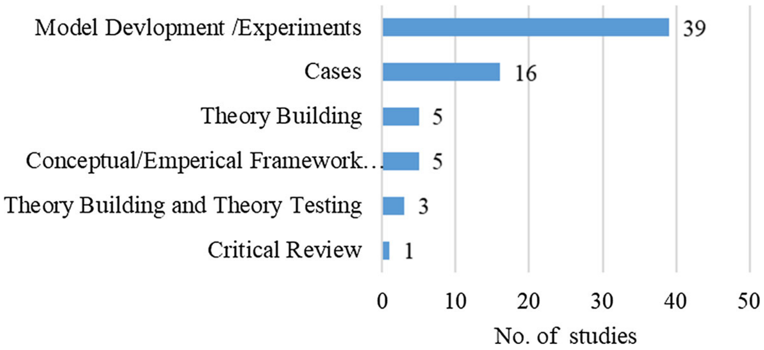


Fig. 6 Taxonomy of the studies according to the approach adopted. *Source:* Author(s) compilation

followed by the conduct of case studies. The classification presented in Fig. 6 also shows the very limited critical reviews that have been conducted in the field of AI-DSSs and OR.

3.2 Underlying theories

Resource-based allocation is one of the critical tasks in many firms' operations, and the resource-based view (RBV) enables the DSS to map the workforce at the various workstations based on the principles of OR (Montes et al. 2019; Ayesta et al. 2016; Barney 2001). Effective and efficient utilization of diverse resources in operational activities helps firms develop their capabilities. Firms adopt the dynamic capability view (DCV) by applying appropriate decision-making approaches and tools (Binder and Edwards 2010; Teece et al. 1997). This enables firms to develop under-prediction and over-prediction errors in forecasting that can be addressed with the help of the cost-sensitive global model tree suggested by Czajkowski et al. (2015). By adopting appropriate OR simulation and optimization approaches, firms develop a knowledge base using the knowledge based view (KBV) that helps them gain a competitive advantage (Giboney et al. 2015). In their transactions, firms conduct multiple transactions with different stakeholders, and suppliers are among of the most critical ones. Firms can achieve an economic advantage by minimizing the cost of exchanges with their different stakeholders. Therefore, DSSs and OR systems can help firms reduce the cost of controlling, coordination, monitoring, and managing the various transactions in their operations (Williamson 1979). Artificial neural network models can also be developed based on transaction cost economics to address risk supervision routines, commitment to risk management, stakeholder cooperation, and coordination history (Yan et al. 2017). Apart from this, in an uncertain environment, there is no correct way to make decisions in business, so contingency theory applies in decision making based on the internal and external aspects of the organization (Tarter and Hoy 1998). AI can assist in this type of decision making by analyzing both internal and external factors in an uncertain environment. When firms are unable to compete in the global landscape with their own resources and capabilities, they opt for relational networks to mobilize and strengthen external resources by adopting relational view theory (Dyer and Singh 1998). Due to the numerous factors present in today's decision making, complexity theory must be applied to analyze every aspect of problems and tasks in business operations (Glouberman and Zimmerman 2002) due to the presence of the agent-principle relationship of agency theory (Eisenhardt 1989a, b). In a decision-making network, queuing, game, control, and systems theories play a critical role in different scenarios (Chan et al. 2012; Larson 1987; Checkland 1981; Adams 1963; Von Neumann et al. 1944). Table 4 presents the underlying theories with key references and features. In addition, the literature reports the application of a range of adopted approaches, including network-based, agent-based, genetic algorithm-based, hybrid, and fuzzy-based approaches as shown in Table 3.

The classification presented in Table 3 shows that most journal papers used hybrid or mathematical approaches (33.33%) with AI, DSSs, and OR, followed by genetic algorithms (30.43%). On the other hand, fuzzy-based approaches were found in only around 5% of the journal papers. It is also important to understand why these approaches were selected. Around 66% of the journal papers used different approaches for prediction, followed by classification (17%). In network-based approaches, operations and finance are found to be the major areas of application. Agent-based approaches were found to be predominantly operational in terms of applications. Finance and operations-related applications were also found predominantly in the genetic algorithm-based studies. In the hybrid or mathematical category, finance-related applications were found more frequently, along with one or two studies in the fields of healthcare, knowledge management, project management, sales and marketing, human resources management, and information systems. Finally, fuzzy-based studies found applications in the finance stream along with healthcare and knowledge management, but with fewer journal papers.

4 Key functions of AI-DSSs in OR

Modern DSSs can be proactive-learning, fast, reliable, and predictive systems. Few decision science researchers have explored them. Therefore, the number of opportunities in this field of research is huge in terms of integration of AI-DSSs and OR. Some of these opportunities are described in this section.

4.1 Learning capability and prediction

Data mining and machine learning techniques are deployed to automate decisions in firms. In dynamic business environments, machine learning, multi-agent systems, evolutionary algorithms and artificial neural networks can be exploited. Particle swarm optimization can optimize the network design problem of a complex system like transportation (Babazadeh et al. 2011). Research is required with regard to the following points: (1) How can trust be developed among decision makers using AI-facilitated decisions? (2) How can decisions be made with less machine processing power in business? (3) What about the integration of convolutional neural networks with AI for improved DSSs? and (4) What about the inclusion of social and ethical aspects in AI-supported decision making? The limited use of hybrid techniques offers an excellent opportunity for AI-based progress (Kobbacy and Vadera 2011a, b). Furthermore, Lau et al. (2013) stressed the exploration of the relationship between minimum description length and the bullwhip effect to reduce and optimize the cost of running a supply chain (Chien et al. 2020; Baryannis et al. 2019). There is enough data to conduct a study in modeling of categorical and binary issues in negotiation counter-offer predictions (Carbonneau et al. 2011). Apart from this, multilingual knowledge management can solve the cross-lingual problem of inter-operability with the help of advanced AI techniques (Yang et al. 2008).

Table 3 Details of the methodological approaches used with their different applications

Approach	References	Area	Application
Network based	Simeunović et al. (2017)	Operations	Workforce scheduling and planning
	Xu et al. (2016)	Finance	Estimation of financial market risk
	Lieckens et al. (2015)	Operations	Contract design and logistics network design
	Marinakos et al. (2014)	Finance	Cash flow management
	Lau et al. (2013)	Operations	Demand management
	Yolcu et al. (2013)	General	Forecasting
	Dey et al. (2011)	Operations	Transportation Network
	Jin and Zhang (2011)	Project Management	Risk allocation in public–private partnership projects
	Carbonneau et al. (2011)	Operations	Electronic negotiation system
	Wassertheurer et al. (2008)	Healthcare	Development of device for measuring systemic cardiovascular parameters
	Yang et al. (2008)	Knowledge management	Management of multilingual knowledge on the basis of backward and forward evaluation algorithm
	Yu et al. (2008)	Finance	Optimal portfolio selection
Agent-based	Ballouki et al. (2017)	Operations	Optimal selection of supply chain configuration in terms of product re-design and supply alternatives.
	Ayesta et al. (2016)	Human Resources	Sharing of resources among firms facing financial crunch
	Hu and Sheng (2015)	Operations	Analysis and valuation of catastrophe spread in a multifaceted resource network
	Neshat and Amin-Naseri (2015)	Operations	Sustainable power generation expansion
	Dahal et al. (2013)	Operations	Traffic control system

Table 3 continued

Approach	References	Area	Application
	Lee et al. (2012)	Operations	Quantification of expert knowledge to access the impact on final product
	Ketter et al. (2009)	Operations	Identification of dominant market conditions and estimate the fluctuations over a planning horizon
	Lin et al. (2008)	Operations	Distributed coordination mechanism for order fulfillment.
	Mes et al. (2008)	Operations	Choosing a robust schedule for logistics using degree of dynamism and objectives of the firm
Genetic algorithm-based	Román et al. (2017)	Finance	Optimization for maximizing the expected value and minimizing the risk of insurance loss in a firm
	Brasileiro et al. (2017)	Finance	Investment decision
	Hayashi et al. (2016)	Finance	Credit risk assessment
	Ferreira et al. (2016)	Sales and Marketing	Pricing and demand in retail
	Moghaddam and Nof (2015)	Operations	Generalized best matching problem with independent preferences
	Czajkowski et al. (2015)	Finance	Minimization of mis-prediction cost in the case of loan change
	Lenin et al. (2014)	Operations	Layout planning
	Udías et al. (2014)	Environment	Waste water reclamation program
	Alvim et al. (2013)	Finance	Stock market operations without human intervention
	Hu et al. (2013)	Knowledge Management	Knowledge based modelling
	Kisilevich et al. (2013)	Information Systems	Hotel booking system
	Stevanovic et al. (2013)	Operations	Optimization of traffic signal timings to ensure safety and minimize the risk of possible crashes

Table 3 continued

Approach	References	Area	Application
	Liu et al. (2012)	Operations	Business process simulation
	Can and Heavey (2012)	Operations	Comparative analysis of genetic programming and artificial neural network for discrete –event simulation meta-modelling
	Bhattacharya et al. (2011)	Finance	Analytical review through decision support system for identification of financial fraud and degree of involvement in fraud
	Baesens et al. (2009)	Finance and Marketing	Challenges and trends in data mining and operation research
	Chi et al. (2009)	Operations	Manufacturing System
	Cao and Parry (2009)	Finance	Genetic algorithm usage to forecast earnings per share through neural networks
	Khalafallah and El-Rayes (2008)	Operations	Reducing the security risk in expansion projects at airports
	Willis and Jones (2008)	General	Optimality of alternative solutions
	Lancaster and Cheng (2008)	Operations	Enhancing the effectiveness of solving the engineering design and operational problems
Hybrid or mathematical	Lwin et al. (2017)	Finance	Market risk assessment
	Reutterer et al. (2017)	Sales and Marketing	Segmentation of marketing campaigns
	Chen et al. (2016)	Healthcare	Personal health index
	D'Haen et al. 2016	Sales and Marketing	Automated lead qualification
	Silbermayr and Minner (2016)	Operations	Dual sourcing
	Zou et al. (2016)	Project Management	Gap in knowledge and experience
	Romanowski et al. (2015)	Operations	Resource allocation in emergency
	Otoiu et al. (2014)	Human Resources	Human well-being quantification

Table 3 continued

Approach	References	Area	Application
	Wang et al. (2014)	Project Management	Allocation of security grants to airport improvement program
	Chen and Wang (2014)	Finance	Designing the portfolio and developing strategies for effective stock trading with different risk capabilities
	Zeng et al. (2013)	Information Systems	Process mining for work flow integration
	Van Der Zee et al. (2012)	Operations	Simulation based serious gaming
	Aranha et al. (2012)	Finance	Selection and evaluating commercial resources while focusing on maximum return and minimum risk involved.
	Zhang (2012)	Finance	The selection of dynamic adverse models
	Kuo and Lin 2010	Operations	Reduction of setup time for surface mount technology.
	Martens et al. (2010)	Finance	Credit scoring
	Yang et al. (2010)	Healthcare	Length of hospital stay
	Zhang et al. (2010)	Finance	Credit decision making
	Armstrong et al. (2010)	Finance	Solving the hidden action and adverse selection through generalized principal-gent models
	Eryarsoy et al. (2009)	Knowledge Management	Arrangement of Domain knowledge
	Hu and Ansell (2009)	Finance	Comparison of credit scoring techniques
	Takeda and Kanamori (2009)	General	Conditional value-at-risk measurement
	Combes and Rivat (2008)	Sales and Marketing	Modeling International Sales
Fuzzy based	Nazemi et al. (2017)	Finance	Modeling the loss in corporate bonds
	Zhang et al. (2014)	Finance	Credit risk evaluation
	Yang et al. (2014)	Healthcare	Risk assessment of coronary heart-disease
	Greco et al. (2011)	Knowledge Management	Financial risk

4.2 Decision making

Semantic reasoning coupled with large data sets using multi-agent systems is common in DSSs. DSS accuracy depends on its architecture and how it interacts with the principles of the system. Furthermore, DSS output depends on the input based on the technological and economic terms it acquires. There is the possibility of integrating DSS with the cloud for event-based business decisions (Skulimowski 2011). DSSs can offer different scenarios, trends, and rankings within a particular time period. Integrated DSSs can address structured, semi-structured and unstructured decisions (Hosack et al. 2012). Ballouki et al. (2017) mentioned the scope for future research on supply chain configuration considering the dynamic and stochastic demand for products. In the supply chain, humanitarian logistics is one of the complex issues to be handled when disasters occur (Akter and Wamba 2019). Optimization and network development is still challenging when establishing a rescue program, as well as the determination of the scale based on the spread of the disaster (Hu and Sheng 2015). In logistics, on-road transportation is a difficult area due to traffic congestion. Dahal et al. (2013) investigated this problem and developed a system in Saudi Arabia. This study has not tested the inter-relationship between traffic control actions at various locations or considered the topology of the network. In any business, decisions are taken by integrating the opinions of multiple experts, which are usually unstructured. This problem can be addressed by integrating agent-based models in particle swarm intelligence. Furthermore, multi-agent-based knowledge integration mechanisms can be assimilated to agent-based models for better decision making (Lee et al. 2012).

4.3 Optimization

The number of problems for businesses seeking to make adequate decisions is increasing every day and requires the help of mathematical models to remedy this confusion and complexity. Firms today face challenges such as designing appropriate products for the market, production management and control, scheduling in plants, traffic control on the road, and transportation planning to deliver products quickly and efficiently. Advanced optimization techniques can address each of these issues. Methodologies including network optimization, system dynamics, simulation, and multi-criteria decision making, to name a few (Sforza and Sterle 2017).

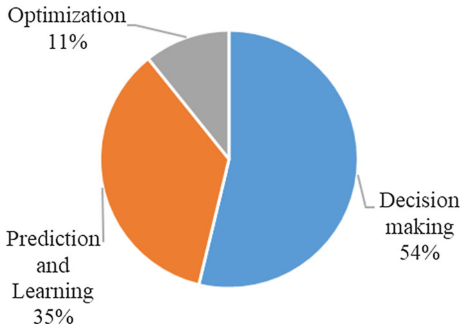
Optimization needs to be combined with data science for better results in the decision-making process. The literature is lacking in studies of OR where modeling can lead to policy making, local development, and knowledge creation. Therefore, there is an opportunity for OR to bring about social change and engage the community at large. A study conducted by Román et al. (2017), recommends the synchronized optimization of business reinsurance programs for risk diversification. This may require a study on interdependence of business losses and multiple re-insurance programs (Avanzi et al. 2016). The authors suggest including the cost of multiple attributes in a test model that can be applied to diverse real-world forecasting complications. Artificial neural networks and genetic programming are helpful in developing complex systems of surrogate models and can be considered by future researchers. Adaptive sampling methods can be incorporated to improve sampling in genetic programming (Can and Heavey 2012).

All three areas mentioned here offer exciting and challenging opportunities and propositions for handling real-world problems through the integration of AI-DSS and OR. Until now, few researchers conducted reviews in a similar context. For instance, Bose and Mahapatra (2001) conducted the review on data mining techniques for businesses through machine learning, where they categorized applications into functional and problem categories and presented different techniques. In another similar study, Phillips-Wren (2012) investigated the role of AI in DSSs. The literature also offers sector, function and disease-specific decision system reviews (Baryannis et al. 2019; Ngai et al. 2014; Lisboa and Taktak 2006). In all of these reviews, first and foremost the OR link with AI and DSSs was not considered. Second, the query executed in the database was not clear enough to obtain journal papers for the mentioned titles. Moreover, this study is adequate and unique due to its greater focus on the application of AI in DSSs and OR in a number of business operations. According to a survey, around 24% of businesses are planning or implementing AI in their DSSs and improving their OR capabilities (Tenfold 2019). The world today is entering the digital era, and there is a need for smart and quick DSSs that combine OR and AI. AI enables cognitive computing for decision making under multiple constraints in terms of resources and the operating environment. Not only does AI enhance efficiency and effectiveness, but it also improves innovation capabilities to tackle modern world business challenges. Therefore, the review presented here is relevant and discusses the issues, challenges, and future scope of research in the field of AI in DSSs for OR. The literature indicates the underlying theories and approaches adopted. We present them in Sects. 4.3.1 and 4.3.2.

4.3.1 Theories adopted

Collaboration is critical for a robust DSS design. Collaboration allows the elements of decentralized support systems to share their responsibilities, information, and resources to obtain mutual benefits. However, the degree of collaboration will depend on the level of information sharing to cover the network. Therefore, collaborative control systems have a significant impact on production and service activities through design-thinking elements (Moghaddam and Nof 2015). For firms in business, the allocation of resources and their effective use are strategic situations. Decision making using support systems can help designate resources obtained from the surrounding environment as well as the firm's internal resources (Ayesta et al. 2016; Hu and Sheng 2015). Many transactions occur during an organization's decision-making activities, and cost is one of the critical aspects. Transaction costs include information, the design of a contract with suppliers, and negotiation. DSSs process the information that is necessary to coordinate between machines and employees to perform tasks and benefit from economies of scale (Silbermayr and Minner 2016; Czajkowski et al. 2015; Jin and Zhang 2011). The information retrieval capability of DSSs utilizing AI and OR concepts can help obtain practically the exact information required for decision making (Otoiu et al. 2014). As stated previously, the literature indicates the greatest application of AI-DSS-OR in the prediction category, and this highlights how firms have enhanced their capabilities. Statistical learning theory enables the predictive function for large data-driven systems (Akter et al. 2016; Wamba et al. 2015). The design of AI for DSSs using statistical and functional analysis is derived from statistical learning theory (Zhang et al. 2014). To enhance the decision-making capabilities of the organization, it is necessary to consider the technological, organizational, and environmental (TOE) framework. The technological framework helps firms decide on the technologies, their design and their usage based on whether they are internal or external to the firm. Factors such as degree of formalization, firm size, and degree of association among employees define the context of the organization and hence the utilization of AI-DSS and OR elements. The size and structure of the market and competitors will define the degree of adoption of AI-DSS-OR in the decision-making system (Dey et al. 2011).

Fig. 7 Key functions of AI-DSS in OR



4.3.2 Approaches adopted

We found five categories for the approaches adopted, i.e. network-based, agent-based, genetic algorithm-based, hybrid or mathematical, and fuzzy-based. Each approach is further divided up by area of application, purpose and the type of application for which the approach is utilized. In the network-based approach ("Appendix D", Table 7), it was found that market risk, cash flow management, and optimal portfolio selection are the major areas of application in terms of finance (Xu et al. 2016; Marinakos et al. 2014; Yu et al. 2008). In terms of operations, applications in the transportation network, scheduling of workforce, and negotiation systems were found (Simeunović et al. 2017; Lieckens et al. 2015; Dey et al. 2011; Carbonneau et al. 2011). Agent-based systems ("Appendix D", Table 8), help in predicting and creating the presence of complex phenomena. In our study, the agent-based approach finds its application in terms of supply chain configuration, distributed coordination, and humanitarian operations in disaster relief (Ballouki et al. 2017; Hu and Sheng 2015; Lin et al. 2008). In the genetic algorithm-based approach ("Appendix D", Table 9), operational applications are found in layout planning, manufacturing system design, and business process simulation (Lenin et al. 2014; Liu et al. 2012; Chi et al. 2009). On the other hand, applications such as stock market simulation, financial fraud detection, credit risk assessment, and investment decisions are found in the finance domain (Brasileiro et al. 2017; Hayashi et al. 2016; Alvim et al. 2013; Bhattacharya et al. 2011). The mixed or mathematical approach ("Appendix D", Table 10) was seen to be more inclined towards financial aspects in terms of portfolio design, risk assessment, and credit scoring (Lwin et al. 2017; Chen and Wang 2014; Aranha et al. 2012; Martens et al. 2010; Zhang et al. 2010; Takeda and Kanamori 2009). To this end, fuzzy-based systems ("Appendix D", Table 11) found financial applications in terms of modeling loss in corporate bonds and credit risk assessment (Nazemi et al. 2017; Zhang et al. 2014). In addition, the studies indicate that for operations-related problems, agent-based systems were preferred, whereas for finance-related aspects, genetic algorithm-based approaches were more preferred. Figure 7 presents the studies in the areas of AI, DSSs, and OR.

5 Conceptual framework and propositions

The reviewed studies indicate that most of these approaches have developed a prognostic capability beginning with the network-based approach and followed in order by the agent-based, genetic algorithm-based and hybrid and mathematically-based approaches. Fuzzy

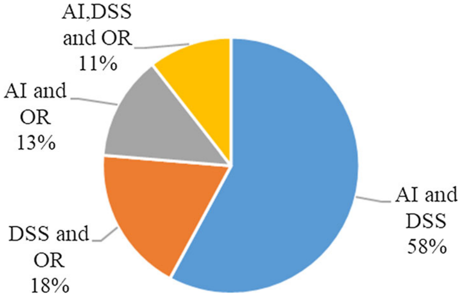


Fig. 8 AI-DSS and OR

logic-based studies lack this prognostic capability. This is the first point that needs to be highlighted. It was then observed that fuzzy logic and genetic algorithm-based studies are lacking compared to the others when it comes to harnessing large data sets that can be utilized through AI and OR for DSSs. This is the second key point. Decision-making frameworks contain a number of constraints when it comes to real-world business problems. Our findings indicate that network-based approaches consider a maximum of 27 factors when using AI for DSSs in OR, and this is the third point that must be emphasized. Learning capability is very important for modern algorithms, and yet it is hardly seen in the literature, which is the fourth important point. These observations clearly indicate the need for AI and the role it can play in advancing DSSs by working on the core principles of OR.

5.1 Key lessons learned

In this review, we learned three key lessons that can be classified in the fields of AI, DSSs and OR into content, process, and mix of both categories. First, a majority of the studies applied mathematical models based on different approaches ranging from artificial neural networks to swarm particle optimization and their integration. In terms of process, most of the studies lay out a set of assumptions and boundary conditions to conduct their numerical experiment and simulation-based validation. Very few studies were found to have conducted or developed a model and then further validated it through a business case or empirical study. We learned about the fields of research in AI, DSSs and OR, and where and why certain concepts are used in particular settings. We also learned how OR, which originated during World War II, can advance AI techniques through its classical approach to decision making. AI can also help address the behavioral issues of decision makers and the people involved in implementing AI systems.

5.2 Propositions and framework

5.2.1 Context, trust, ethics, and social advantages

OR can facilitate social science by utilizing its findings in practice, and in turn, social science can help in determining and reflecting on their discussions. As the use of OR and AI increase in decision making, defining responsibility becomes more complex and problematic (Khalafallah and El-Rayes 2008). For example, if mistakes are made that hamper business performance, who should bear the risk? This can probably be addressed through transparency by setting the boundary and limits for AI systems. In the design and context of AI and OR applications, it needs to be clear that AI-driven systems need to expressly state why, how, and when the decision was made to retain transparency (Zhang et al. 2018). OR-driven AI systems should be independent and inclusive of multi-lingual aspects to avoid any discrimination and promote social equity and diversity (Agerri and Rigau 2019). The ethical values and principles of AI need to be defined first before thinking of applying them to business. Therefore, we propose:

Proposition 1 *The design of AI architectures and OR algorithms can improve trust, ethical concerns and social aspects among different stakeholders during decision making.*

Proposition 2 *Advanced versions of AI and OR-originated systems and processes can make the job easier for decision makers, even in an uncertain environment, rather than replacing them.*

Proposition 3 *Intelligent decision-support systems that use AI and OR capabilities can overcome complex problems by also promoting the spread of knowledge in multicultural and multi-format environments.*

5.2.2 Range of applications in terms of ecology and complexity

OR applications coupled with AI are known for solving social and practical problems in almost every sphere. In terms of practical problems, there are not only the individual problems of profit maximization or cost reduction, but there are also other constraints that may be required to some extent. These constraints may require an intelligent DSS to help establish the scale of a disaster and recommend suitable approaches that can provide relief to the affected population (Fan et al. 2019). For a straightforward OR-oriented system, it may be difficult to deal with inference from the speech, images, videos, sentiments, and geographical uncertainty of the area where the disaster occurred (Poria et al. 2016). The integration of AI with OR principles helps design the qualitative and quantitative content in the pre-, per- and post-disaster environment. Therefore, we propose:

Proposition 4 *Advanced decision-making ecosystems can utilize not only single targets, but also multiple-objective problems involving qualitative and quantitative content.*

Proposition 5 *AI and OR can help define the scale of a disaster and recommend the best suitable approach towards relief activities.*

5.2.3 Risk diversity and sustainable performance

Firms are increasingly operating in a VUCA (Vulnerable, Uncertain, Complex, and Ambiguous) environment. This poses a challenge in terms of multiple risks and disruptions to their businesses (Ivanov et al. 2019). With the advent of technology, firms today are competing very closely in highly customer-driven and saturated markets (Matzler et al. 2015). Each organization is working and seeking continuously to reduce its risk in an uncertain environment, so that it can bear the minimum loss in case of an unforeseen event (Chung et al. 2013). In this scenario, it becomes extremely difficult for a firm to survive sustainably in the long run. Sustainable performance requires a balance between various pillars including environmental, social, economic, legal, and political aspects. Therefore, we propose.

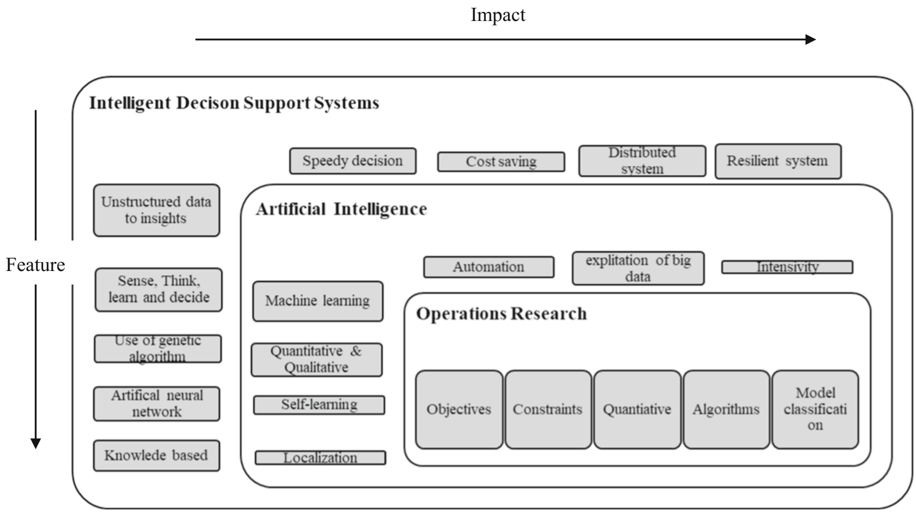


Fig. 9 Systems framework for AI, DSS and OR

Proposition 6 *With the help of the OR fundamentals ingrained in AI systems, firms can be in a better position to decide on an appropriate response when balancing the economic, environmental, and social aspects of sustainable performance.*

Proposition 7 *Firms can better decide on the proportion of risk diversity with regard to different stakeholders based on their constraints and capabilities formulated through OR and presented by AI.*

5.2.4 Capabilities, resources, and costs

OR applications make a system robust, but may lack security and safety. AI-coupled OR systems can help develop and train employees to reducing bias and improve transparency in decision making. In addition, capabilities such as innovation, shared values, agility, and speed in supply chain operations can be attained significantly with AI systems (Warner and Wäger 2019). These capabilities help employees (resources) and machines to be more interactive and involved in firms' decisions (Duan et al. 2019). Apart from making sure that productivity is on track, AI-driven DSSs can help facilitate strategic investments by bypassing multiple agents in payment systems and ultimately reducing the cost of operations (Miranda and Kim 2006).

Proposition 8 *The combination of AI, DSSs, and OR can help firms to better design, develop, and allocate their transactions (transaction cost economics), resources (resource based view), and capabilities (dynamic capability view) along the supply chain.*

After developing our propositions based on the findings, we developed a system framework presented in Fig. 9 in terms of features and the impact of AI and OR on intelligent DSSs. The intelligent DSS works using the elements of OR and AI and helps businesses make speedy and optimal decisions that are driven by distributed and resilient systems to achieve a competitive advantage for the organization.

6 Discussion

Based on the findings presented in the previous section, the research questions posed at the beginning of this review have been answered. Below, we present the implications for theory and practice offered from our literature survey.

6.1 Implications for theory

The role AI (Duan et al. 2019) and OR in decision making (Li et al. 2007; Power and Sharda 2007) is well understood. However, the interaction between AI, DSSs, and OR is rare in the business environment. Three key features of our review contribute to operations research literature. First, in the era of big data and digitization, decision making needs to be automated and the focus needs to be on human–machine symbiosis. In this combination and interaction between humans and machines, ethical and social trends need to be taken into consideration. Second, we would like to emphasize that it is important to view prediction and learning ability as dynamic capabilities and resources to help deal with business uncertainty. We also show that AI can impact the short-term and long-term goals of an organization with each decision related to a collective target. Earlier studies focused on experimental model development (Brasileiro et al. 2017; D'Haen et al. 2016; Cao and Parry 2009), yet those theories can be adopted while integrating the relationship between AI, DSSs, and OR. Dynamic capabilities, statistical learning and the TOE framework can be better employed in designing intelligent DSSs, hence our contribution to the literature. Third, we developed a systems framework that can lead to an intelligent decision-support system via the integration of AI and OR. Many of the limitations of OR are addressed by AI to create synergies and a robust system. Our study promotes an integrative view of AI and DSSs that is supported by earlier studies (Challen et al. 2019; Kasie et al. 2017; Seng-cho et al. 1997; Van Hee and Lapinski 1988). However, these studies do not present the critical component of OR that we have considered in this review. Our framework promotes the use of advanced technologies to address concerns related to security, speed, and accuracy (Khalafallah and El-Rayes 2008).

6.2 Implications for practice

The findings of the conducted survey indicate that DSS researchers are more inclined to examine and develop AI-facilitated DSSs using scientific programming rather than exploring the potential fusion of AI-DSSs and OR. This may be due to less exposure to big data, OR-based reasoning, and machine learning in the DSS research domain. Moreover, researchers are less familiar with techniques such as support vector machines, swarm intelligence, and stochastic programming.

This imbalance impacts business decision makers who are unaware of the potential of AI-DSS-OR-based intelligent systems in the fields of uncertainty and risk management on a day-to-day basis. The traditional DSS can be improved through AI while utilizing OR principles. This will help executives tackle large data sets and multiple constraints in the decision-making setting. DSSs developed in this manner can help with more accurate decision making along with high-performing learning and predicting capabilities. Professionals dealing with decisions regarding uncertainty should therefore recognize these techniques and technologies and join hands with researchers to improve the decision-making process. This does not imply that AI can make decisions on its own, but AI can be viewed as a tool to assist decision makers and help them make the best decisions. The extension of human decision making to AI was discussed by Jarrahi (2018). AI can make use of large amounts of data to facilitate decision making that is more suitable for today's businesses, as these businesses generate huge amounts of data through their business processes (Akter and Wamba 2019). Therefore, managers and other stakeholders should focus on ensuring data security and accuracy. Managers may also help researchers with available data to identify and develop suitable frameworks for their decision-making processes. AI uses data, learning algorithms, and patterns to execute decisions for businesses and can be fine-tuned according to the business context.

6.3 Addressing the research questions

RQ1: To what extent has research in the field of DSS exploited AI capabilities?

Figure 8 indicates the dearth of studies in the AI-DSS-OR domain. Only 11% of the total studies fall under the intersection or AI, DSSs, and OR. AI and DSSs make up a larger portion than the other categories in the surveyed journal papers.

Most of the studies reviewed focused on designing and developing models based on multi-agent systems, genetic algorithms, and neural networks dealing with risk, safety, and accuracy of decisions. There has been less focus on analyzing the practicability of the proposed models. Many journal papers have not validated their proposed frameworks for decision making, and many considered fewer constraints than there are in real world problems. For instance, in trading scenarios, hundreds of constraints exist, but the studies included a limited number. Factors such as brokerage fees, transaction charges, and taxes levied on investors are not considered in these studies (Lwin et al. 2017). The studies have developed a credit scoring and evaluation system to differentiate between defaulters and non-defaulters with models of explanatory powers. However, the algorithm extension to leverage the endless targets and develop the deterioration rules to model the exposure in loss incurred at the default parameters is not incorporated (Martens et al. 2010). In emergency and complex situations such as disasters and catastrophes, AI capabilities remain unexploited (Wamba et al. 2019a; Romanowski et al. 2015). Additionally, AI capabilities have yet be realized on a larger scale in public systems and governance. So far, business decision making has been emphasized through potential AI applications, but studies that discuss its societal needs in decision making scenarios are lacking.

The existing models struggle with decision-making ability when minimal data is available. The reviews conducted have presented the application of genetic algorithms in healthcare and the pharmacy sector to make decisions concerning diagnoses, recommendations, and distribution (Marinakos et al. 2014; Yang et al. 2014). However, the role of psychology and behavior during disease is not addressed in the literature. Baesens et al. (2009) made a point of requiring studies on fraud detection and credit scoring. Still, there is a need for DSS to predict firm failures more precisely with the help of AI and thus answer the first research question. Recent advances and technologies such as big data, the industrial internet of things, and blockchain technologies have yet to be exploited for better DSSs through AI and OR principles. To the best of our knowledge, very few studies have considered an integrated approach to AI and OR by creating and developing DSSs with recent advancements. AI has the potential to strengthen DSSs with regard to real-world problems in many fields, ranging from improving public systems to economic activities and events.

RQ2: How are AI capabilities such as prognostic decision making used to address complex problems in uncertain environments?

Disease-specific and general-purpose DSS frameworks simulate payment options and healthcare policies and advise patients like a real doctor (Yang et al. 2014; Bennett and Hauser 2013). In other systems, prognostic uncertainty can be reduced via monitoring data on a continuous basis through artificially intelligent systems (Dubey et al. 2019; Zeng et al. 2017; Thompson et al. 2013). AI uses probabilistic theory, truth maintenance, and fuzzy logic to aid decision making when there is uncertainty. When information is lacking, AI utilizes network agents to model sequential decision making in the uncertain environment (Mata et al. 2018). AI helps in uncertain environments such as military operations to devise the next move. AI systems look for new approaches to train with the data and make decisions that are closest to reality. AI systems are capable of avoiding noise and offer predictions in new and uncertain environments (Shenfield et al. 2018). In order to make effective decisions, AI systems in uncertain environments seek more data and learn how to navigate confusing situations. AI capabilities need to be harnessed to improve real-time DSS capabilities. Therefore, this answers the second research question.

RQ3: How have AI capabilities contributed to DSSs in the field of OR ?

Complementarity between AI and humans has been highlighted by Jarrahi (2018) and can extend the decision-making capacity of the system. DSSs utilize the data stored in the knowledge warehouse and can make certain decisions with the help of OR models (Nemati et al. 2002). In a system like banking where a lot of data is available, we can use OR and AI techniques to assess the performance of a firm. AI can help tackle routing decisions, which is an OR problem (Nowakowski et al. 2018). AI can help optimize the different combinations of elements to develop a product (Zhang et al. 2018). OR problems like network designing, scheduling, inventory, and queuing are benefiting from the application of AI techniques for better decision making (Grzonka et al. 2018; Zhang et al. 2018; Javaid et al. 2018). AI and OR have a range of possibilities to contribute to DSS. However, the modern capabilities of AI need to be integrated into big data analytics, swarm intelligence, and cognitive computing. This therefore answers the third research question.

7 Conclusion and future research directions

In this study, we conducted a review of AI, DSSs, and OR and the features that allow them to help businesses. We identified 69 journal papers through a structured approach that were relevant in this review. We adopted a three-step approach of planning, conducting, and reporting the review. We presented the existing research gaps in the form of learning capability, prediction, decision making and optimization. Following the three-step approach, we presented the key findings and developed propositions resulting in a conceptual framework that defines the impact and features of AI, DSSs, and OR. We answered the individual research questions to make it clearer. We also mapped the organizational theories to describe more specific research gaps highlighted in Table 4. Our review does not have many limitations. One of the limitations is that although we have undertaken an exhaustive study, it is possible that we were not able to include all the keywords for the topics that we sought to address. We categorized the journal papers considered in our study, but this is not an exhaustive classification, as there can be more categories in which these papers could be categorized. The reviewed studies have developed a number of models for decision making. Today's algorithms must be self-adapting and evolutionary in terms of optimization. Inter-operability of different kinds of data in real-time decision making is another aspect of future research where AI can be applied in combination with OR to achieve a sophisticated DSS. AI also

Table 4 Key theories and research gaps for future research

Theory	Key references	Key features of the theory	Research gaps and future research directions
Dynamic Capability Theory	Silbermayr and Minner (2016), Hu and Sheng (2015), Aranha et al. (2012), Lin et al. (2008), Wassertheure et al. (2008)	(1) Businesses need to create, modify, and extend their central capabilities to remain competitive in the market (Ambrosini and Bowman 2009) (2) Firms need to develop a set of systems including hardware, software, and performance management to build capabilities	(1) In business, events are often interdependent and influence each other. Therefore, it is critical to include the features of supply chain risk orientation to enhance the existing capabilities of DSSs (Silbermayr and Minner 2016) (2) In the service-based system, it is critical to develop operations strategies to make phase-wise decisions. Therefore, an intelligent system (AI-based) can be deployed and researched that can decide and monitor service quality, cost feasibility of the different tasks, and profitability (3) In investment portfolio optimization, the decision point is central with regard to minimizing risk and maximizing returns. Therefore, tree-based algorithms can be integrated with terrain-based algorithms to decide on the market index and could be further explored (Aranha et al. 2012)

Table 4 continued

Theory	Key references	Key features of the theory	Research gaps and future research directions
Resource Based View	D'Haen et al. (2016), Ayesta et al. (2016), Lieckens et al. (2015), Romanowski et al. (2015), Wang et al. (2014), Liu et al. (2012), Yang et al. (2010)	(1) The resources of an organization act as a primary means of achieving firm performance (2) Businesses need to deploy specific capabilities to achieve efficient utilization of resources	(1) The mechanism that affects decision making also includes the regulatory framework in most cases. However, the allocation of financial, social, and environmental resources in the integration remains unexplored in balanced decision making (Wang et al. 2014) (2) Apart from core activities, manufacturing firms outsource activities such as maintenance in the form of contracts. Usually a contract is based on cost and equipment uptime, which is influenced by overhaul and network response. Therefore, multinomial logit models can aid decision making and should be further investigated (Lieckens et al. 2015)
Relational View	Ballouki et al. (2017), Chen and Wang (2014), Lau et al. (2013), Can and Heavey (2012), Bhattacharya et al. (2011), Dey et al. (2011), Cao and Parry (2009)	(1) Firms can utilize their cooperative relationships to achieve a competitive advantage (2) Firms select their partners to cope with the global competitive environment.	(1) In a product lifecycle, firms re-design the products in their supply chain often. Multi-agent system engineering can benefit from suppliers and their technology. The negotiation protocol through AI-supported decision making can be explored to enhance system efficacy (Ballouki et al. 2017) (2) The bullwhip effect in the supply chain has a deteriorating impact on the cost of operations and executives struggle with many decision points. The direct relationship between the bullwhip effect and an artificial neural network including a minimum description length can be researched for better decision making (Lau et al. 2013)

Table 4 continued

Theory	Key references	Key features of the theory	Research gaps and future research directions
Transaction Cost Economics	Ballouki et al. (2017), Ayesta et al. (2016), Czajkowski et al. (2015), Kisilevich et al. (2013), Zeng et al. (2013), Jin and Zhang (2011), Khalafallah and El-Rayes (2008)	(1) The cost of an offering is defined as the value of the economic exchange between receiver and provider (2) The value of the exchange may rise due to constrained knowledge or distorted information (3) The value of the exchange (cost) of products, processes and activities is directly influenced by stakeholders such as suppliers and distributors (4) The exchange of value (cost) among two parties is also influenced by the hierarchy of the organizations	(1) Default events and activities give rise to costs for companies. Reducing overall costs for firms facing a financial crunch is increasingly critical. Therefore, AI-based Multi-Armed Restless Bandits models can be developed that can help reduce the cost and optimize the allocation of resources and capabilities (Ayesta et al. 2016) (2) In service industries such as hotels and travel, many intermediaries are present, and they do not have a clear idea about the actual cost of a hotel room. AI-based GIS-based decision support can be developed in the future to estimate the price of the different services offered by the hotel, which can help intermediaries exchange information with customers and enhance their business value (Kisilevich et al. 2013)
Contingency Theory	Kisilevich et al. (2013), Martens et al. (2010), Hu and Ansell (2009), Wassertheure et al. (2008)	(1) Different approaches can be adopted for decision making (2) The optimal decision depends on internal and external factors present at a particular point of time	(1) Many institutions including financial ones do an internal credit system rating/audit. Future studies can be undertaken where researchers can extend the antminer to expose continuous targets and set regression guidelines (Martens et al. 2010) (2) Credit risk evaluation is critical for most businesses. Sequential minimal optimization can be researched further, where listed and non-listed firms and their internal and external factor fit can be examined along with how it impacts the DSS (Hu and Ansell 2009)

Table 4 continued

Theory	Key references	Key features of the theory	Research gaps and future research directions
Complexity Theory	Lwin et al. (2017), Hayashi (2016), D'Haen et al. (2016), Moghaddam and Nof (2015), Dahal et al. (2013), Can and Heavey (2012), Willis and Jones (2008)	(1) The ability of a system to adapt to changes quickly (2) The mechanism of a phenomenon can be examined in terms of uncertainty (3) Decision making when scenarios are unpredictable and multi-dimensional.	(1) Portfolio optimization involves the trade-off among profit and risk. Therefore, studies need to be conducted that can consider the multiple constraints ranging from market trends, buying and selling proportion, brokerage, taxes imposed on the portfolio along with transaction costs (Lwin et al. 2017) (2) Uncertainty leads to complexity in business operations. Therefore, matching demand to supply from a multidimensional view becomes a challenge. In the future, studies can be conducted on how group versus individual decision making, or the influence of social networks and the emotions of others influence the DSS. This requires a multidisciplinary approach to investigation (Moghaddam and Nof 2015)

Table 4 continued

Theory	Key references	Key features of the theory	Research gaps and future research directions
Agency Theory	Ballouki et al. (2017), Simeunović et al. (2017), Neshat and Amin-Naseri (2015), Dahal et al. (2013), Zhang (2012), Van Der Zee et al. (2012), Lee et al. (2012), Armstrong et al. (2010), Ketter et al. (2009), Mes et al. (2008)	(1) A relationship among principals and agents exists for business reasons (2) Agents work to carry out business activities as per the expectations of the principals (3) Due to a lack of trust in the agents, the principals employ a monitoring mechanism, and that costs the agency	(1) Sustainable development of business operations requires decision making and often maintaining the trade-off between price and quantity. For adequate distribution in markets like the energy sector, studies needs to be conducted that consider the effort among supplier agents for demand, supply, and coordination with the help of game theory with OR and AI assistance (Neshat and Amin-Naseri 2015) (2) Unstructured group decision making presents the challenges of computational inefficiency and the inability to unify the knowledge of experts. Therefore, AI can be explored in future studies that can integrate the knowledge of multiple agents scattered geographically to address the problem of large group decision making (Lee et al. 2012)

Table 4 continued

Theory	Key references	Key features of the theory	Research gaps and future research directions
Queuing Theory	Ballouki et al. (2017), Lieckens et al. (2015), Dahal et al. (2013), Stevanovic et al. (2013)	(1) Evaluation of characteristics of arrival and service processes including the number of customers and servers in the system (2) Facilitate the design of a cost effective and efficient workflow system	(1) The development of after service maintenance contracts influenced by design and logistics networks to support contact. A multidisciplinary model following queuing equations can be explored in the future with the help of multinomial logit models along with price and downtime parameters (Lieckens et al. 2015) (2) The traffic system can be controlled better when the topology of the network can be considered, therefore the interrelationship among various locations and established traffic systems can be developed with local conditions and limitations (Dahal et al. 2013).

Table 4 continued

Theory	Key references	Key features of the theory	Research gaps and future research directions
Game Theory	Neshat and Amin-Naseri (2015), Van Der Zee et al. (2012)	(1) Analysis of conflict situations (2) Application of social modeling where multiple actors try to maximize their returns (3) Applied in determining different strategic decisions in business	(1) Retail games including agents in the form of suppliers, top management, retail managers, retail shops, market and competitors can utilize the softer aspects of simulation for future research on the coordination of knowledge exchange and lean management (Van Der Zee et al. 2012)
Network Theory	Lieckens et al. (2015), Moghaddam and Nof (2015), Cao and Parry (2009), Wassertheurer et al. (2008)	(1) Study of social relationships in a network (2) Mechanism and process interaction with networks to yield certain outcomes (3) The variables in the network define the consequences	(1) In most networks, players are group oriented and have a common objective, but when individual firms or actors are self-oriented, the individual may conflict with the goal of the network. Therefore, best matched preferences and interdependent preference (BMP-IP) need further research to align these individual goals to those of the network (Moghaddam and Nof 2015) (2) Actors in a network may change perceptions (positive or negative) about each other after a certain period of time. Therefore, further modifications and research in formulation and definitions of BMP-IP are required (3) Humans as actors in a network are influenced by many emotions. In social networks, these emotions are not straightforwardly quantifiable and can have a non-linear association with IP. Therefore, there is room for both quantitative and experimental research ((Moghaddam and Nof 2015)

Table 4 continued

Theory	Key references	Key features of the theory	Research gaps and future research directions
Systems Theory	Ballouki et al. (2017), Can and Heavey (2012), Baesens et al. (2009), Wassertheurer et al. (2008), Yang et al. (2008)	(1) The complex arrangement of social elements and how they are related to a whole (2) The common approach of examining the organizational patterns	(1) Genetic programming capabilities can be further researched with reference to meta-models that can help enhance the efficiency of automated material handling systems (Can and Heavey 2012) (2) Sampling approaches can be adopted in future research to improve the generalized ability of genetic programming (3) Agent-based models are appropriate for product design and simultaneous supply chain development, assuming product demand is known. More complex models such as stochastic models can be explored to undermine the uncertainty of demand and its influence on supply chain design (Ballouki et al. 2017)
Control Theory	Dahal et al. (2013), Van Der Zee et al. (2012), Liu et al. (2012), Yang et al. (2010), Chi et al. (2009), Mes et al. (2008)	(1) Represents the behavior of dynamic systems, where inputs can be manipulated to influence output by a controller (2) The decision and control models include the elements of time delay, optimal prediction, observation noise, and optimal estimation	(1) Event graphs can be utilized to simulate operational decision support. The case arrival cannot be configured in cases where simulation data is not available, so further exploration is required to develop a framework that can analyze the simulation logs and improve results (Liu et al. 2012) (2) A business modeling approach needs to be developed to integrate the time gap and loop along with current state loading and advanced visualization for cases of e-commerce and online shopping (Liu et al. 2012)

has an opportunity to be combined with geophysical and atmospheric sciences, integrate data from both disciplines, and process it using AI and OR tools to design an effective and sustainable DSS. Authors like Kuo and Lin (2010) indicated that studies using Tabu search clustering and clustering algorithms based on simulated annealing to decide the number of clusters could be conducted in the future. Not many studies have been able to integrate AI and OR (Fethi and Pasiouras 2010). There is a lack of studies incorporating the predictions of models when assimilating meta-classifiers. An expert system could be developed to consult on legal issues through OR and AI. Furthermore, the applications can be extended to music composition and media planning and reporting. Robotics can be advanced to recognize and track inventory and replenishment with the help of AI and OR. Further research needs to be conducted to map consumers in a retail setting to offer complimentary products via AI and OR. In addition, research could be carried out to design a system to identify a vehicle and guide the driver towards it in a large parking lot. OR could also be enhanced in terms of deep learning with the assistance of quantum computing and then combined with AI for effective DSSs. AI can be combined with the variables from each stakeholder in a supply chain along with their constraints in terms of capacity, demand, and profit expectations to determine the effort needed from each of them to achieve the target.

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Appendix A

See Table 5.

Table 5 Year- wise number of publications with regards to journal title. *Source:* Compiled by author(s)

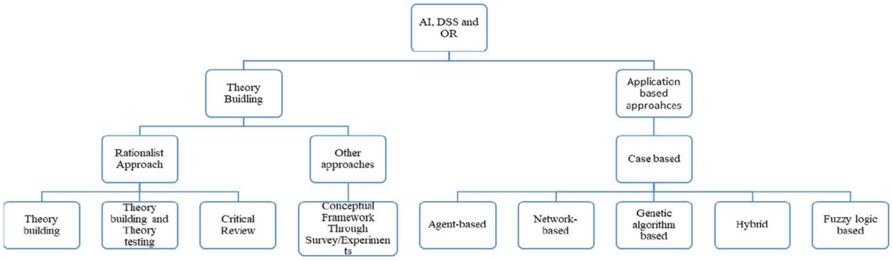
Journal Title	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total
Advances in Production Engineering and Management										1	1
Annals of Operations Research				1			1				2
Applied Stochastic Models in Business and Industry									1		1
Central European Journal of Operations Research							1				1
Computers and Operations Research	1				1			1			3
Decision Support Systems	4	4	2	2	2	7		2	2	1	26
Ecological Indicators							1				1
Engineering, Construction and Architectural Management									1		1
European Journal of Operational Research							2		1	2	7
Industrial Management and Data Systems							1				1
Information Sciences					1			1			2
International Journal of Critical Infrastructure Protection								1			1
International Journal of Production Economics	1										1
International Journal of Production Research	1										1
International Journal of Project Management				1							1
Journal of Advanced Manufacturing Systems							1			1	2
Journal of Business Economics										1	1
Journal of Cleaner Production								1			1
Journal of Computational and Graphical Statistics				1							1
Journal of Construction Engineering and Management	1										1
Journal of Forecasting		1									1
Journal of the Operational Research Society		1	1							1	3
Manufacturing and Service Operations Management									1		1
Mathematics of Operations Research					1						1
Operations Research			1								1
Operations Research Letters									1		1

Table 5 continued

Journal Title	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total
Operations Research Perspectives									1		1
Personal and Ubiquitous Computing							1				1
Simulation Modelling Practice and Theory	1										1
Technological Forecasting and Social Change					1						1
Transportation Research Part C: Emerging Technologies						1					1
Total	9	7	5	5	6	8	8	6	8	7	69

Appendix B

Classification of literature. *Source:* Author(s) Compilation.



Appendix C

See Table 6.

Table 6 Top 10 institutions with regards to the number of journal papers

Name of the Institution	Country	No. of journal papers
City University of Hong Kong	Hong Kong	3
Brunel University London	United Kingdom	3
KU Leuven	Belgium	3
Wirtschaftsuniversitat Wien	Austria	2
Ministry of Education China	China	2
Purdue University	United States	2
Hogeschool Gent	Belgium	2
National Tsing Hua University	Taiwan	2
Deakin University	Australia	2
Chinese Academy of Sciences	China	2
University of Southampton	United Kingdom	2
University of Queensland	Australia	2

Appendix D: Five categories of approaches adopted

See Tables 7, 8, 9, 10 and 11.

Table 7 Network-based approaches to DSS

Reference	# variables	Large datasets used	Support to decision making	Prediction capability	Interpretation and learning capability	Validated with a case
Xu et al. (2016)	N/A	Yes	Yes	Yes	No	No
Lieckens et al. (2015)	N/A	Yes	Yes	No	No	Yes
Marinakos et al. (2014)	12	Yes	Yes	Yes	No	Yes
Lau et al. (2013)	5	No	Yes	Yes	No	No
Yolcu et al. (2013)	N/A	No	Yes	Yes	No	Yes
Carbonneau et al. (2011)	27	No	Yes	Yes	No	No
Wassertheurer et al. (2008)	N/A	No	Yes	Yes	No	Yes
Yang et al. (2008)	N/A	No	Yes	No	No	Yes
Yu et al. (2008)	N/A	No	Yes	Yes	Yes	Yes

Table 8 Agent-based approaches to DSS

Reference	# variables	Large datasets used	Support to decision making	Prediction capability	Interpretation and learning capability	Validated with a case
Ballouki et al. 2017	3	Yes	Yes	No	No	Yes
Hu and Sheng (2015)	N/A	No	Yes	Yes	No	No
Neshat and Amin-Naseri (2015)	28	Yes	Yes	Yes	No	Yes
Dahal et al. (2013)	N/A	Yes	Yes	Yes	No	Yes
Lee et al. (2012)	24	No	Yes	Yes	No	Yes
Ketter et al. (2009)	N/A	Yes	Yes	Yes	No	Yes
Lin et al. (2008)	N/A	No	Yes	No	No	Yes
Mes et al. (2008)	N/A	No	Yes	No	No	Yes

Table 9 Genetic algorithm-based approaches to DSS

Reference	# variables	Large datasets used	Support to decision making	Prediction capability	Interpretation and learning capability	Validated with a case
Román et al. (2017)	N/A	No	Yes	Yes	No	Yes
Czajkowski et al. (2015)	N/A	No	Yes	Yes	No	No
Stevanovic et al. (2013)	9	No	Yes	No	No	No
Can and Heavey (2012)	N/A	No	Yes	No	No	No
Bhattacharya et al. (2011)	N/A	Yes	Yes	Yes	No	No
Baesens et al. (2009)	N/A	No	No	No	No	No
Cao and Parry (2009)	N/A	No	Yes	Yes	No	No
Khalafallah and El-Rayes (2008)	3	No	Yes	No	No	Yes
Lancaster and Cheng (2008)	N/A	No	Yes	Yes	No	No

Table 10 Hybrid and mathematical approaches to DSS

Reference	# variables	Large datasets used	Support to decision making	Prediction capability	Interpretation and learning capability	Validated with a case
Lwin et al. (2017)	N/A	Yes	Yes	Yes	No	No
Chen and Wang (2014)	N/A	Yes	Yes	Yes	No	No
Aranha et al. (2012)	N/A	Yes	Yes	Yes	No	No
Zhang (2012)	N/A	No	Yes	Yes	No	No
Kuo and Lin (2010)	8	No	Yes	Yes	No	Yes
Armstrong et al. (2010)	NA	No	Yes	No	No	No

Table 11 Fuzzy logic-based approaches to DSS

Reference	# variables	Large datasets used	Support to decision making	Prediction capability	Interpretation and learning capability	Validated with a case
Nazemi et al. (2017)	N/A	No	Yes	No	No	No
Zhang et al. (2014)	20	No	Yes	No	No	No
Yang et al. (2014)	8	No	Yes	Yes	No	No

Appendix E: Papers used in this study for review

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Affiliations

Shivam Gupta[1] · Sachin Modgil[2] · Samadrita Bhattacharyya[3] · Indranil Bose[4]

Sachin Modgil
s.modgil@imi-k.edu.in

Samadrita Bhattacharyya
samadrita.bh@gmail.com

Indranil Bose
bose@iimcal.ac.in

1 Department of Information Systems, Supply Chain and Decision Making, NEOMA Business School, 59 Rue Pierre Taittinger, 51100 Reims, France

2 International Management Institute, 2/4 C, Judges Ct Rd., Alipore, Kolkata, West Bengal 700027, India

3 Operations Management, Quantitative Methods and Information Systems Area, Indian Institute of Management Udaipur, Udaipur, Rajasthan 313001, India

4 Indian Institute of Management Calcutta, Diamond Harbour Road, Joka, Kolkata, West Bengal 700104, India