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The Evolution of Decision Support Systems: From Early Expert Systems to AI-Driven Paradigms and Advanced Multi-Criteria Decision-Making

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ABSTRACT

Decision Support Systems were born in the 70s. This paper proposes an history of DSSs, tracking their evolution through their definitions and architectures. Four periods are identified in the history: the early days; the era of expert systems; the intermediary period, for which several techniques are used: Optimization and Multi-criteria decision Making; the most recent period related to Big Data and Machine Learning. Group Decision Support Systems are also detailed as well as an example of such platform. Particular attention is paid to multi-criteria decision-making methods, two of which are described in detail: Combined Compromise Solution method and Minimum of Rank method.

1. Introduction

The concept of decision making in organizations has been widely studied and numerous definitions have been proposed. In order to define this concept more precisely, we can quote the following authors. According to [1] making a decision means identifying and solving the problems that any organization will inevitably face. We can also cite [2], for whom decision making is synonymous with choosing among several existing alternatives, each with different consequences. The choice is made according to very precise criteria. [3] considers that a decision is a process that leads an actor to answer a given question. For [4], decision-making is a process of information transformation. It leads an actor or a group of actors within the organization to deal with an issue, resulting in an action. Thus, decision making can be simplified as the choice of an option from a set of alternatives or a ranking of the alternatives by an actor or a group of actors in response to a problem faced by an organization, guided by several very precise criteria.

This paper proposes firstly to define decision making as a process, then the beginning of these systems, then a review of decision support systems, their definitions, and their architectures. DSSs

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evolves to a second period Expert Systems oriented. These systems have initially been developed for single users. Technologies evolving, the decision-making process evolved to group collaborations. The concept Group Decision Support Systems and their evolution are introduced. A section is then devoted to the integration of optimization methods within DSSs. A decision is usually based on several criteria. The multicriteria approach is then important to be presented. The DSS based on Big Data and Machine Learning are presented. Finally, the two last sections present namely the current topics as well as the applications in different domains.

2. Decisional processes

Decision Making is a complex activity for which several authors have suggested defining and modeling it as a process; therefore, it is defined as decision-making process, which generally consists of several stages. For [5], considers it as cognitive process and consists of the following stages:

• Intelligence: it involves gathering information about the problem at hand, its constraints and its environment;

• Design: this is a stage of designing, developing and analyzing solutions to deal with the problem;

• Choice: this is where the choice of solution is made, considering the developed and adopted criteria in the previous stage;

• Review: this is where the previous stages are re-examined, i.e. the decision maker continues to seek information while designing a solution to the problem in a continuous loop.

Furthermore, [5] describes this process as neither linear nor sequential; the 'review' stage is always present in the mind of the decision maker, who refines the criteria guiding the decision as he or she continues to search for information and construct possible solutions. Starting with Simon's model [5], [6] has shown that from a cognitive point of view, there is a feedback loop strengthening at the final stage, i.e., the review step, back to the choice and intelligence stages. This process has also evolved at an organizational level. There is an evolution from a single decision-maker context to an environment including multiple decisionmakers, who may work in a synchronous or asynchronous mode, and located separately or together. It is therefore necessary to adapt the support systems to these particular modes of decision making more cooperative. This process is described in Figure 1.

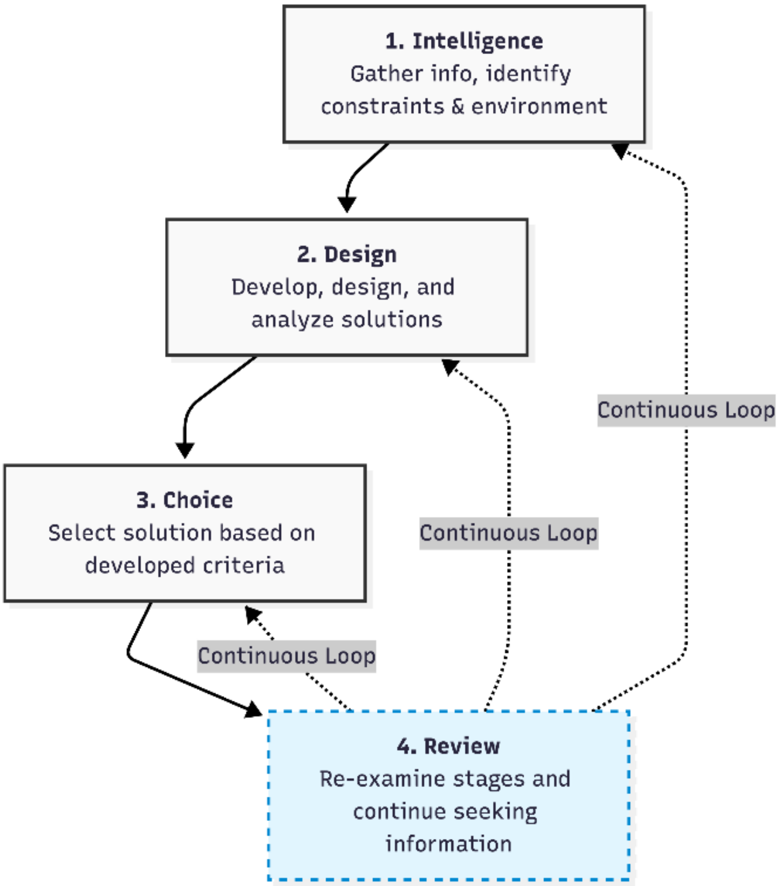

Fig. 1. Decision Making process

3. Decision Support Systems Beginning (1970-1980)

Decision support systems emerged in the 1960s with model-oriented systems, marking the beginnings of this field in operation research. Their development accelerated in the 1970s in response to criticism of traditional operation research, incorporating subjective and organizational aspects to better support decision-making processes [7].

The field of decision support has grown considerably since the 1970s, partly thanks to significant contributions in the operation research field published in journals such as the Euro Journal on Operational Research [8] but also published as PhD [7]. First published in 1977, this journal has established itself as a leading platform for disseminating research in operational research and management science, particularly regarding decision support systems [9]. The evolution of these systems has been characterized by a shift towards more sophisticated models incorporating artificial intelligence and machine learning. This trajectory reflects the growing integration of advanced analytical capabilities to address the complexity of contemporary decision-making problems [10]. Theoretical, methodological, behavioral, and organizational aspects improving the understanding and appropriate use of operations research in the various phases of the decision-making process, are studied.

This exploration will highlight the impact of artificial intelligence and machine learning on traditional decision support methodologies [11]. More specifically, the field of multi-criteria decision support, which emerged from the 19th-century work of Edgeworth and Pareto, has evolved considerably since the 1960s, focusing on solving real-world problems through various methods that parameterize the decision-maker's preferences [12]; [8]. The choice of a specific method is intrinsically linked to the decision-making problem evolving and its context of application [12]. The integration of operation research into organizational decision-making processes has led to a new conception of scientific intervention, seeking to transcend objective data to encompass the subjective aspects inherent in decision-making. Thus, decision-making modelling has become a central focus for a large scientific community, fostering the emergence of numerous theoretical models [13].

4. Decision Support Systems Definitions

Decision Support Systems were introduced in literature in the 70s. Several definitions have been proposed over the decades.

The concept of Decision Support Systems (DSS) emerged in the early 1970s. One of the very first authors to introduce and promote this concept was [14] who introduced the notion of Management Decision Systems. His book was based on research using computers, analytical models and terminals with visualization and interactive techniques. This approach is based on the analysis of key decisions and provides decision makers with an aid to their decision-making process. This aid is needed in complex and poorly structured situations and can be used by decision makers alongside their own intuitive judgment of the problem and its solution.

One of the most cited definitions is that of [15].
DSS involves the use of computers to:

- Assist decision makers in their decision-making process in semi-structured tasks;
- Support rather than replace the judgment of decision makers;
- Improve the quality rather than the efficiency of decision making.

Many other definitions have been published that refer to this definition, with certain adjustments. [15] firstly explain that this assistance is provided by machines and then specify the context in which it can be provided. Finally, in two other points, a very important distinction is made between efficiency and effectiveness. The adjective "efficient", corresponding to the term "efficiency", implies a response to a given task that is as good as possible in terms of several performance criteria, whereas the adjective "effective", corresponding to the term "effectiveness", that implies identifying what needs to be done and ensuring that the chosen criteria are relevant. The term "effective" requires adaptation and learning with the risk of redundancy and false starts, whereas "efficient" implies refocusing the objective and minimizing the time, cost and/or impact required to deliver an activity.

The concept of a decision support system is based on a balance between human judgment and computer processing of information. [15] present DSSs as systems dedicated to semi-structured tasks. The criteria for developing such systems are very different from those for structured situations. The key words are 'learning', 'interactivity', 'support' and 'evolution' rather than 'replacement', 'solution', 'procedure' and 'automation'.

[16] attempted to find common ground among numerous definitions.
It is important to note that all definitions suggest that the system must assist the decision maker in solving unprogrammed, poorly structured (or semi-structured) problems.

A definition review shows that there is a broad consensus that the system must have interactive capabilities to ask questions of the user. This interactivity allows solving the problem using inputs coming from the decision maker and not an automatic mode.

5. Decision Support Systems Architectures

[17] gave a very similar definition to [15]. DSSs can be characterized as computerized, interactive systems that assist decision makers by using data and models to solve poorly structured problems. Their definition is based on the words "data" and "models", which define the first architecture of DSSs proposed by the same authors.

This architecture consists of

• A human-computer interface;

• A database management system (DBMS) containing the database, all needed data to solve the problem;

• A model-based management system (MBMS) containing the model base, it stores all the models of the problem to be solved, the most appropriate model can be used depending on the user or the state of the problem resolution.

DSSs quickly took center stage in the Operational Research community, establishing these systems as a reference in operational research and management science [9]. [8] demonstrates that one pillar of DSSs designing is multi-criteria decision analysis methods. This reflects the interest in methodological and theoretical approaches to decision support.

The second period of DSSs is related to Expert Systems.

6. Expert Systems era (1990-2000)

The evolution of DSSs is marked by a second period during which the introduction of AI into these systems is noteworthy. The architecture itself has evolved to rise to other types of decision support systems, called Intelligent Decision Support Systems (IDSS) or Knowledge Based Decision Support Systems (KBDSS).

DSSs include a database and associated DBMS, users of these systems are faced with large amounts of data. Indeed, in the 1990s, getting the right piece of data to the right decision maker at the right time became a very important issue for organizations that store masses of information. The DBMS part of DSSs evolved into Big Data management to enable users with little knowledge of database command languages to find the right data at the right time.

The architecture itself of DSSs evolves introducing a Knowledge Base and an Inference Engine. According to [18], the components of a IDSS can usually be divided into five distinct parts:

• A database management system (DBMS) and associated database: which stores, organizes, sorts and retrieves the data relevant to a particular decision context;

• A model base management system (MBMS) and associated model base: which has a similar role than the database management system, except that it organizes, sorts and stores the organization quantitative models;

• The inference engine and knowledge base: which performs the tasks of recognizing problems and generating final or intermediate solutions, as well as functions related to the management of the problem-solving process;

• A user interface: which is a key element for overall system;

• A user: who is an integral part of the problem-solving process.

This architecture shows the emergence of a technological part derived from Artificial Intelligence, which integrates knowledge modeling into the problem to be solved. Its advantage lies in the emphasis placed on decision making reasoning.

The decade from 1990 to 2000 was a period of transition for expert systems in decision support systems, marked by growing maturity but also by the first signs of decline in the face of emerging new technologies. After peaking in the 1980s, expert systems, initially based on logical rules and knowledge bases, were criticized for their rigidity, the complexity of knowledge acquisition, and their inability to handle the uncertainty inherent in real-world operation research problems. Numerous articles are published exploring practical applications of expert systems in optimization and planning, often in combination with traditional operational research methods [9].

From the early 1990s onwards, expert systems evolved towards hybrid architectures incorporating broader artificial intelligence, such as fuzzy logic and early neural networks, to overcome their limitations [10]. For example, work published in EJOR highlighted their use in areas such as supply chain management and multi-criteria decision-making, where they facilitated the incorporation of human expertise into analytical models [11].

However, the late 1990s were characterized by a relative “AI winter” for pure expert systems, due to high development costs and the rise of approaches based on big data and emerging machine learning. Nevertheless, this period laid the groundwork for the future integration of AI into DSS [8].
This same period saw the arrival of group decision support systems.

7. Group Decision Support Systems (1990-2000)

Group Decision Support Systems (GDSS) are designed to support a group of people involved in a decision-making process.

There is abundant literature on these systems in the US, and several definitions are accepted by the community.

According to [17], a GDSS is "a mix of equipment, software, people", processes that enable a group of people to work together.

For [19] a GDSS is "a mix of computers, communications, and decision technologies working together to support problem identification, formulation and generation of solutions during work sessions".

Several authors have shown that the use of GDSS has some advantages. In general, it improves the efficiency of the group from a tangible point of view, but also from an intangible point of view. From a tangible point of view, the duration of the decision-making process is generally reduced. The

number of good ideas is generally increased by the possibility of using the system in an anonymous way. This way of working allows participants to dare to express themselves. On the intangible side, it is more difficult to quantify. It generally improves problem definition, group cohesion and commitment.

In the 1990s, GDSSs were assigned as decision rooms. In one corner of the room, the facilitator was able to show to all participants the information that could be shared. Participants could then see the shared information on a public screen. Each participant communicates in an electronic way only and has their own private screen. They can share or not the information that they judge mandatory for the group.

After some years of development, GDSSs became web oriented. Each participant can work remotely, seeing their private information and the shared information.

The use of these systems implies at least having a shared understanding of the problem to solve. In order to facilitate the convergence within the group in its decision-making process, it is therefore preferable to base decision on criteria that are shared and accepted by all stakeholders.

[20] propose a methodology called MAMCA for group decision making based on a multicriteria approach. This methodology is based on the Promethee Multi-Criteria Decision-Making (MCDM) methodology [21]. MAMCA is also implemented in software. Decision makers have the possibility to define individual preferences and private criteria. Each decision maker will reason with their own criteria. The multi-criteria aggregation is done thanks to Promethee and the final aggregation for the group is calculated thanks to a weighted sum. The main advantage of this method is the sensitivity analysis functionality able to visualize on a plan the position of each decision maker. However, the decision-makers don't have a common understanding of the problem, each of them defining their own criteria.

[22] propose a web platform called GRoUp System (GRUS) to support a group of decision makers. This platform is considered as a toolbox and is based on a multi-criteria approach. It can be used to organize collaborative sessions (meetings) in synchronous and asynchronous modes.

As GRUS is a web application, users can achieve sessions in distributed (all participants are not in the same place) and non-distributed situations (all participants are in the same room). Participants can be involved in several sessions with the same or different roles.

It integrates the classic functionalities of multi-user applications: login/logout, user management (list of users, removing a user, changing a user's password...). The GRUS system proposes several collaboration tools:

• Electronic brainstorming: stakeholders chat in an electronic mode;
• Idea Clustering: similar ideas are grouped in categories;
• Vote;
• Multi-criteria evaluation: several MCDM methods can be used;
• Consensus discussion allowing participants to reach a common decision;
• Automatic reporting: the system automatically reports all electronic exchanges, vote and alternatives evaluation.

All these different functionalities can be combined with designing different processes, as for example MCDM or Vote process. All these collaborative tools can be used for different collaborative activities.

As an example, the voting tool can be used in a voting process to achieve a Reduce pattern (by electing the ten best candidates and thus reducing the number of elements to be considered) or can be used for an Evaluation pattern (by ranking all candidates). For the multi-criteria process, decision makers have the possibility to define the dependency between two criteria. The bi-capacity Shapley index is used to calculate dependency. Choquet's integral gives the possibility to calculate the index of interaction among the criteria and the global importance of each criterion, called the Shapley value [23].

The GRUS platform has been used and tested in several contexts. It has been tested with different students from three different countries: Brazil, France and Canada [24]; [25]. The main objective of these experiments was to define whether cultural effects could be observed with such a system.

Three hypotheses were proposed, namely:

• there is a need to use private and shared criteria in a collaborative decision-making process;
• the number of private and shared criteria should be equal;
• the use of GDSS remains difficult without a human moderator.

As the main result of this study, we assume that the first two hypotheses of the three are verified, but the third is not or partially verified independently of countries.

The system has also been used in a European RISE project called RUCAPS [26]. This project aims to improve and implement knowledge-based ICT solutions in high-risk and uncertain conditions for agricultural production systems.

The GRUS platform has been tested in several situations. The main objective was to measure the usability of such a platform. Analyzing the full list of usability identified problems, the most important problems are related to the lack of awareness of the participants about the ongoing multi-step process, that is an inherently difficult problem to address from a Graphical User Interface perspective, but very relevant as one of the main features of this type of decision-making sessions [27].

Facilitation has an important impact on group performance and productivity. [28] define facilitation as: "activities carried out before, during and after a collective decision-making meeting to help the group achieve its goals as defined during the decision-making process". [29] specify that facilitation is: "defined as a process by which a person external to the group, not involved in the decision, officially recognized and accepted by the group, is used to support a group engaged in a decision-making process".

There are several types of facilitation:

• Technical: Helping stakeholders to use technology;

• Process: Facilitating the stakeholders and their interactions in accomplishing tasks to achieve emerging goals and guiding participants;

• Content: Dealing directly with the problem to be solved.

Some tools have been developed to support facilitation. Two types of facilitation support can be distinguished: content-oriented and process-oriented.

Content-oriented tools are developed by [30], which is a dynamic text guide in a multicriteria GDSS. [29] has developed a cooperative knowledge-based system to support facilitation process. [31] has implemented an automatic idea clustering tool.

Process-oriented tools have been implemented by [32], which is an agent-based system; [32] define indicators for group activity analysis.

The current trend for supporting facilitation is to put the facilitator in the box. It implies developing AI tools based on Knowledge modeling to automatically guide the facilitation process. This research is not yet finalized.

Since DSS are based on operation research, optimization is widely used to assist decision-makers.

8. Optimisation Methods integration (2000-2010)

From 2000 to 2010, the integration of optimization methods into decision support systems marked a phase of maturity, where operation research consolidated its central role in complex decision-making. DSSs evolved to incorporate advanced optimization techniques, such as mixed integer linear programming, metaheuristics, and stochastic optimization, to manage the uncertainty and dynamics of real-world problems [10]. This period saw the emergence of hybrid DSS combining mathematical optimization and decision modeling, allowing for better structuring of problems involving multiple criteria and massive data.

This integration is remarkable, particularly in the fields of OR applied to management and economics. For example, multi-criteria methods, inherited from the 1960s, were refined with robust optimization approaches to parameterize decision-makers’ preferences in uncertain contexts [12]; [8].

This evolution reflects EJOR's contribution to the bibliometrics of the discipline, where publications from this decade highlight a growth in the practical applications of optimized DSSs [9].

This integration paved the way for contemporary DSSs by strengthening the analytical capabilities of models, transcending purely objective approaches to include subjective and behavioral aspects. Thus, a smooth transition has been fostered into the era of artificial intelligence, where optimization remains a fundamental foundation [11].

9. MCDM integration (2000-2010)

The choice of a specific MCDM method (e.g., parametric optimization or ordinal approaches) depends intrinsically on the context of the decision-making problem and its organizational constraints [12]; [13]. In the evolution of DSS, MCDM has transitioned from classical models to advanced integrations with artificial intelligence and machine learning, thereby enhancing the analytical capabilities of DSS to address the complexity of contemporary decisions [11].

For example, contemporary DSSs use MCDM to structure uncertain decision-making processes by combining objective and subjective data, as illustrated by their integration into managerial decision-making ecosystems [7]. This symbiosis not only makes it possible to anticipate crises but also to optimize scientific interventions beyond purely rational approaches [7].

Plethora of MCDM models are developed to solve problems with different and non-commensurable (different units) criteria. There are situations when the evaluation of feasible alternatives must handle the compromise of established standards values, and the development of a compromise MCDM model is necessary.

[33] propose A COmbined COmpromise SOlution (CoCoSo) method for multicriteria decision problems. The purpose of this methodology is to discuss the advantages of a combinatorial approach. The combined compromise decision algorithm, with the help of some aggregation strategies, considers a distance measure derived from the grey relation coefficient and aims to increase the flexibility of the results. Thus, the weight of the alternatives in the decision process is introduced with three equations. In the final stage, an aggregated multiplication rule is used to release the ranking of the alternatives and to complete the decision process.

CoCoSo could be seen as a compendium of trade-off solutions with five steps:

- Initial performance matrix definition;
- Normalisation of criteria values based on the compromise;
- Normalisation equation [34];
- Sum of weighted comparability sequence and performance weight of comparability sequences;
- Relative weights of alternatives.

The final ranking of alternatives is provided as an output of the method.

CoCoSo is applied to several domains such as: Supply chain, battery electric vehicle evaluation, business analytics, industry 4.0 and circular economy, human resources.

For decision-makers, the problem remains choosing which MCDM methodology to use. Several methods can be used, each of them giving different ranking or choice.

Each MCDM method proposes its own ranking of alternatives to decision makers. These rankings are usually different. Decision makers felt the need to aggregate the rankings obtained by different methods, which is done in the "Minimum of Ranks" (MIRA) method [35].

Based on several applications of multi-criteria methods, several alternative rankings are obtained. The correlation coefficient is the specific measure that quantifies the strength of the linear relationship between two variables in a correlation analysis. The correlation coefficient r is a unitless value between -1 and 1. The closer r is to zero, the weaker the linear relationship. Positive values of r indicate a positive correlation when the values of both variables tend to increase together. Negative values of r indicate a negative correlation, when the values of one variable tend to increase and the values of the other variable tend to decrease. The values 1 and -1 represent "perfect" correlations, positive and negative respectively. The Spearman's and Kendall's coefficient tests are used in MIRA to measure the strength of the relationship between the obtained rankings.

The "Minimum of Ranks" (MIRA) method makes it possible to rearrange the alternatives according to their obtained ranks from at least two multicriteria decision methods. Before applying MIRA, it is essential to check the ranks similarity of the used multi-criteria decision methods. If the rank correlation is justified, the MIRA method can be applied. To validate the result obtained by MIRA, it is always necessary to check its correlation with the selected multi-criteria decision-making methods. If the correlation is justified, the MIRA result is acceptable. Two cases can be obtained: MIRA additive (M+) or MIRA subtractive (MIRA-). MIRA additive is used if the Kendall's rank correlation is positive, otherwise MIRA subtractive is used.

This approach makes possible the use of several MCDM methods, to obtain the best compromise final ranking of alternatives.

10. Current DSS: Big data, AI and Machine Learning (2010-2026)

Contemporary decision support systems incorporate advanced technologies such as big data, artificial intelligence, and machine learning, marking a significant evolution from traditional approaches [11]. Big Data enables the processing of massive volumes of heterogeneous and dynamic data, facilitating real-time analysis for more robust decisions in the face of increased uncertainty in modern business environments [10]. AI, meanwhile, enriches DSS by integrating simulated cognitive capabilities, such as hybrid expert systems and deep learning algorithms, which surpass traditional heuristics in solving complex optimization problems [11]. Machine learning excels at predicting and adapting to decision preferences via models trained on historical data, making DSS more adaptive and effective in contexts such as operation research [11]. These technologies, often combined in web-based decision-making ecosystems, are redefining decision support paradigms by promoting ethics, transparency, and the integration of behavioural criteria [11].

11. Recurrent topics

Publications on Decision support systems reveal recurring themes rooted in operational research, such as multi-criteria decision support, which emerged from the pioneering work of Edgeworth and Pareto in the 19th century and has developed since the 1960s to solve real-world problems in economics, finance, and commerce by parameterizing the decision-maker's preferences [12]; [8]. The choice of methods remains dependent on the single- or multi-criteria decision-making context [12].

12. Application in different domains

Decision support systems have been applied in a variety of operational research fields, particularly in economics, finance, and business, where they aim to solve real-world multi-criteria problems [12]. They have a central role in these sectors [9]. [36] conduct a systematic review to investigate how Human Centered Artificial Intelligence is applied within DSSs in multiple application domains.

These systems are also well studied in the management domain. Furthermore, the integration of artificial intelligence into DSSs reinforces their use in complex operational contexts, covering areas such as planning and organizational decision-making [10]. [37] integrate artificial intelligence to enhance decision-making flexibility by scaling analytics to new levels of knowledge, allowing organizations to discover complex response patterns for management purposes.

The educational domain is largely and recently studied. [38] developed and implemented an AI module within English Language Arts classes. The main objective was to promote AI literacy in secondary education that has become increasingly important. [39] investigate how English language teachers maintain and express their professional expertise while integrating Generative Artificial Intelligence (GenAI) into their pedagogical practice.

Other domains, like agri-food sector, are also recently studied. [40] propose the use of big data analytics (BDA) practices to support agri-food entities in adopting best practices in supply chain decisions for resilience improvement by using a fuzzy hybrid multiple-criteria decision analysis approach.

13. Conclusion

There is a remarkable evolution in decision support systems since the 1970s, marked by a shift from model-oriented approaches to those incorporating artificial intelligence and machine learning [11]. Progresses, covering the theoretical, methodological, behavioural, and organizational aspects of operational research are noticed by [9]. Multi-criteria decision support systems, stemming from the pioneering work of Edgeworth and Pareto, have matured to address complex problems by parameterizing decision-makers' preferences [12]; [8], while the integration of AI has transcended objective data to include subjective dimensions [7]. This trajectory highlights the continuous adaptation of DSS to contemporary challenges, such as big data and increased uncertainty.

As perspective, emerging trends are pointed to opportunities for hybrid DSSs combining optimization, AI, and ethics to better anticipate crises and promote sustainable decision-making [10]; [11]. Future research should explore the behavioural impact of these systems in dynamic organizational contexts, promoting more inclusive and resilient scientific intervention.

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