The Evolution of the Organizational Decision Making Process: A Predictive Analysis of the Impact of Artificial Intelligence

Completed Research Paper

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Abstract

Although artificial intelligence (AI) is expected to significantly alter strategic decision making (DM) on an organizational level, only a few scientific articles examine the evolution of AI within the organizational DM (ODM) process. Most contributions lack empirical insights to allow predictions of the development of DM under the influence of AI or show outdated perspectives on the capabilities of AI in ODM. This work addresses this gap by conducting a multi-vocal literature review (MLR) and a quantitative analysis of patents on AI-based decision support systems (DSS). Overall, the findings advance current research on AI in ODM by providing an overview of existing theoretical contributions and predicting a trend toward an increasing augmentation of human intelligence by AI throughout the ODM process. This enables managers to take strategic action and adapt organizational structures and managerial tasks based on our prediction of the future evolution of AI within the ODM process.

Keywords: Artificial Intelligence, Decision Making Process, Organizational Decision Making, Patent Analysis, Multi-Vocal Literature Review

Introduction

The last two decades have been marked by significant improvements in artificial intelligence (AI), driven by a significant increase in computing power and the increased data storage and processing capabilities of machines (Baabdullah, 2024; Choudhary et al., 2023; Von Krogh, 2018). In addition to the impact AI will have on the personal and professional lives of individuals, the technology is expected to significantly change organizational decision making (DM) (Giachino et al., 2024; Haenlein and Kaplan, 2019; Vincent, 2021; Von Krogh, 2018). “The question is less whether AI will play a role (…) but more which role it will play and more importantly how AI systems and humans can (peacefully) coexist next to each other. Which decisions should be taken by AI, which ones by humans, and which ones in collaboration will be an issue all companies need to deal with in today’s world” (Haenlein and Kaplan, 2019, p. 9). Technological developments in recent years have enabled AI to move from merely performing repetitive tasks to taking on analytical roles within organizations, increasingly assisting or replacing humans in managerial tasks (Haenlein and Kaplan, 2019;

Vincent, 2021). Indeed, several studies suggest that AI-driven DM has a positive impact on organizational performance, especially when combined with increased data processing capabilities of machines to harness knowledge from data (Ahdadou et al., 2023; Brynjolfsson and McAfee, 2012; Giachino et al., 2024; Hemmer et al., 2024). Decision performance can potentially increase by a factor of two to six when humans and AI collaborate in DM, as AI assists humans in making better-informed decisions by providing tailored reports and guidance (Hemmer et al., 2024).

However, barriers to AI adoption remain. According to previous studies, employees prefer human judgement to algorithmic judgement, mainly due to distrust in AI and lack of knowledge about the technology (Araujo et al., 2020; Booyse and Scheepers, 2024, Bader and Kaiser 2019). As a result, decision makers continue to rely on experience and intuition and do not fully leverage the potential of AI in DM, even though data-driven DM can improve the operational performance of organizations (Brynjolfsson and McAfee, 2012). Correspondingly, the consequences of replacing humans with AI cannot be ignored (Metcalf et al., 2019; Phillips-Wren, 2013; Trunk et al., 2020). However, current AI technologies still have significant shortcomings in terms of transparency, which reduces the quality of the outcomes of the DM process (Bolander, 2019; Metcalf et al., 2019). This could have a negative impact on the perceived legitimacy of an organization's actions, threatening its credibility and economic success (Martin and Waldman, 2023).

Predicting the future evolution of the DM process under the influence of AI allows managers to successfully guide organizations on their journey of adopting AI decision support to reap the benefits of its data processing capabilities and overcome the associated challenges and risks (Armstrong and Sotala, 2015; Bolander, 2019; Gruetzemacher et al., 2021). However, the dynamic development of the AI landscape and the increasing capabilities of autonomous DM make it difficult to anticipate future threats and opportunities based on technological advances (Armstrong and Sotala, 2015; Haenlein and Kaplan, 2019). Overall, there is a need for qualitative and quantitative studies on the de facto progress of AI in DM and its future impact on the organizational DM (ODM) process, as most existing contributions either rely solely on qualitative methods, which limits the predictability through less data points (Baabdullah, 2024) or are outdated by now (Trunk et al., 2020). Therefore, scholars call for further scientific contributions and empirical studies on AI in DM to measure its impact on the ODM process (Gruetzemacher et al., 2021; Haenlein and Kaplan, 2019). To address this gap, we pose the following research question:

How does the decision making process change over time under the influence of AI, and what are the implications of this development for the future of organizational decision making?

Given the rapidly evolving and uncertain nature of the AI landscape, technology predictions risk becoming quickly outdated due to unforeseen developments (Armstrong and Sotala, 2015). To address this challenge, we complement our research with an exploratory component. Our twofold approach starts with a multi-vocal literature review (MLR), following the guidelines of Garousi et al. (2019), to derive qualitative insights for the development of ODM. In parallel, we conduct a quantitative analysis of patents related to AI-driven decision support systems (DSS) to track recent advances and project future developments in AI-assisted decision making. In doing so, we combine qualitative insights into how the ODM is changing and at the same time quantitatively show the current state of the evolution of AI in the DM process.

In summary, this study makes the following contributions. First, it synthesizes the existing literature on AI in ODM, integrating perspectives from different scientific domains. Second, it provides a comprehensive overview of the technological evolution of AI in decision making based on 14 years of patent data. Third, it draws on these findings to predict which steps of the decision making process are most likely to be augmented by AI, providing both theoretical contributions and practical guidance for designing human-AI collaboration in organizational contexts.

Theoretical Background

Organizational Decision Making

Organizations initiate DM to address a problem or exploit an opportunity in an operational or strategic context to achieve individual or organizational goals (Mintzberg et al., 1976; Frederickson, 1984). Therefore, in the context of this paper, we focus on strategic DM in organizational and managerial contexts, which is carried out through a standardized organizational process. We define strategic organizational decisions as highly complex, multivariate group DM under uncertainty (Harrison, 1996; Rousseau, 2018). Strategic decisions have a significant impact on the long-term development of an organization and are therefore made by teams or groups of managers at the top management level (Harrison, 1996). In contrast to individual DM settings, ODM can be influenced or constrained by politics, affect several stakeholders at once and make decision makers accountable for their own as well as other's decisions (Rousseau 2018).

The strategic organizational decision making process is concerned with novel, complex scenarios due to the limited knowledge of an organization about the decision context, the DM path, and the design of a possible solution (Mintzberg et al., 1976). The process flow as proposed for this work is deduced from several studies that examined DM processes in real organizational settings (Mintzberg et al., 1976; Naylor, 1980; Nutt, 1984; Trunk et al., 2020). It is imperative to define this process, as it will provide the structure for the subsequent patent analysis. Figure 1 provides a synoptic representation of the process.

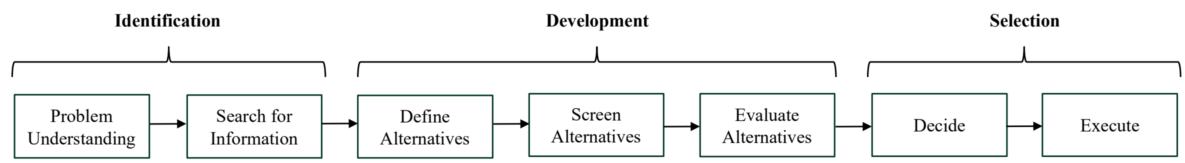

Figure 1. The Organizational Decision Making Process Model (derived from Mintzberg et al., 1976; Naylor, 1980; Nutt, 1984; Trunk et al., 2020)

In all process models, three underlying phases of (1) *Identification*, (2) *Development,* and (3) *Selection* can be found in alignment with groundwork research in decision science (Mintzberg et al., 1976). The process begins with the **Identification** phase encompassing the first step of *Problem Understanding,* i.e. the recognition and close examination of the decision problem or the decision opportunity, and the second step *Search for Information* (Naylor, 1980; Nutt, 1984; Trunk et al., 2020). By formulating organizational needs and challenges, problem understanding is further enhanced, and decision objectives can be set based on the specific problem (Mintzberg et al., 1976; Nutt, 1984). The accuracy and thoroughness carried out within this process step ultimately shape the quality of subsequent steps and the final decision solution (Trunk et al., 2020). In *Search for Information*, knowledge that is related to the decision problem is collected (Naylor, 1980). It can be differentiated into explicit or implicit knowledge, with the latter also being referred to as tacit knowledge (Rousseau, 2018; Metcalf, 2019). Whilst explicit knowledge includes facts, numbers, and routines and can thus be communicated, stored, and processed, tacit knowledge is based on unique human experience and intuition, which makes it difficult to be expressed in language or numbers (Metcalf, 2019). The subsequent **Development** phase encompasses the third, fourth, and fifth step of the DM process. In the third step *Define Alternatives*, possible design solutions addressing the decision problem are searched and defined based on the previously gathered knowledge and the interpretation of this information (Mintzberg et al., 1976; Nutt, 1984). Subsequently, in the fourth step *Screen Alternatives*, the possible solutions are screened to sort out the most feasible options (Naylor, 1980). In the fifth step of *Evaluate Alternatives*, these strategic options are assessed based on their individual benefits and costs to enable the responsible group to make the final decision (Nutt, 1984; Trunk et al., 2020). The final **Selection** phase includes the sixth and seventh step. After all design solutions were evaluated in the previous step, the DM unit performs the sixth step *Decide* to determine the best option (Mintzberg et al., 1976; Naylor, 1980). In the last step, authorization needs to be acquired to *Execute* the final decision by seeking approval on all required levels of the organizational hierarchy, which can either lead to the implementation of the decision or a new iteration of the DM process after a rejection (Mintzberg et al., 1976; Nutt, 1984).

Artificial Intelligence in Decision Making

A DSS is composed of three elements: First, a database containing information to solve a decision problem; second, a knowledge base providing further guidance for the search and selection of alternatives; and third, a model base representing the algorithmic approach (Phillips-Wren, 2013). DSS have been shown to generate output in the form of forecasts and recommendations, as well as explanations for their results (Phillips-Wren, 2013). Since the advent of DSS, a plethora of DM tools have been developed to address specific challenges, ranging from managerial support, investment, and logistics decisions to innovative problem-solving and idea generation (Phillips-Wren, 2013; Buchanan and O'Connell, 2006). The primary focus of these individuals is the completion of analytical and procedural tasks; however, they do not prioritize autonomous DM (Simon, 1987). The initial development of DSS, encompassing the domain of expert systems, was founded on mathematical and statistical methods. Consequently, they demonstrate strong performance in standardized decision making contexts. For instance, IBM's Deep Blue supercomputer achieved a notable victory over the world chess champion, Garry Kasparov, in a match played under strict rules (Haenlein and Kaplan, 2019). Nevertheless, in contradistinction to contemporary machine learning (ML) algorithms, they exhibit a divergent capacity to learn from disparate data inputs, such as natural language.

The application of DSS tools in various scenarios involving quantitative, standardized, and analytical DM has been well documented (Simon, 1987). However, the utilization of these tools in qualitative and intuitive decisions under uncertainty remains less prevalent. This paradigm has undergone a significant shift in the context of the technological advancements in machine learning (ML) that have transpired over the past decade. As ML-based AI methods have become increasingly prevalent in DSS, intelligent decision support systems (IDSS) have emerged as a result (Howard, 2019; Phillips-Wren, 2013). In contrast to expert systems, IDSS emulate human cognitive functions and derive meaning from data autonomously through bottom-up methods such as neural networks (Haenlein and Kaplan, 2019). They facilitate enhanced insights and powerful support in problem-solving by processing large amounts of data, often in real-time, applying advanced reasoning and learning from experience (Phillips-Wren, 2013). The mounting pertinence of IDSS with the expanding autonomy of AI in the DM process is exemplified by the scholarly interest in these systems. As Storey et al. (2024) have demonstrated, most recent publications on the subject of decision support refer to DM systems in which AI is responsible for the majority of DM activities, thus limiting the human role to oversight and monitoring functions. To date, IDSS have been applied to DM in various industries, including the medical and public sector (Howard, 2019; Butner and Ho, 2019). To differentiate between the levels of AI involvement in ODM, scientific research typically follows three categories: (1) Decision Support, (2) Decision Augmentation, and (3) Decision Automation (Ahdadou et al., 2023; Hilb, 2020; Raisch and Krakowski, 2021).

Method

The objective of this study is to explore how ODM evolves under the influence of AI. In light of the paucity of contemporary empirical research on the development of AI in decision making, a robust methodological approach was imperative to achieve both a current and forward-looking understanding. Existing predictions, including that of Trunk et al. (2020), are becoming increasingly outdated due to the rapid advancements in AI capabilities. The AI landscape is characterized by considerable dynamism and marked by significant uncertainty, rendering traditional forecasting approaches susceptible to obsolescence (Armstrong and Sotala, 2015). To address these challenges, we employed a two-stage research design. First, we carried out a qualitative MLR to synthesize insights from both academic and practitioner sources, thus enabling the understanding of how AI is expected to reshape the decision making process. This exploratory step provided a conceptual foundation for the subsequent identification of relevant technological developments. Second, to further expand upon this, we conducted a quantitative patent analysis of AI-driven DSS to ascertain the current state of technological innovation. Third, we derived data-driven predictions about the future evolution of AI in decision making. This combination of qualitative and quantitative methods provides a comprehensive overview of both the anticipated process changes and the technological trends that are shaping them.

Multi-Vocal Literature Review

An MLR integrates a structured literature review, encompassing relevant academic articles, with contemporary insights from grey literature (GL) (Garousi et al., 2019). GL is used to denote publications from practitioners and researchers that have not undergone the peer-review process. The aforementioned sources encompass academic papers, research and committee reports, government reports, blog articles, patents, conference papers, and white papers (Paez, 2017; Garousi et al., 2019; Adams et al., 2017). In the context of GL, Garousi et al. (2019) delineate between first-tier, second-tier, and third-tier GL, with the degree of outlet control and credibility decreasing from first- to third-tier GL. It has been demonstrated that GL has the capacity to contribute significantly to research insights that are not found within commercially published academic literature (Adams et al., 2017). This, in turn, can facilitate the reduction of publication bias. Consequently, GL publications of a high standard, credibility, and retrievability were incorporated into our MLR (Adams et al., 2017). The research design for peer-reviewed white literature employed within our MLR aligns with other systematic literature reviews conducted in the domains of AI and DM (Trunk et al., 2020; Borges et al., 2021; Shepherd and Rudd, 2013). As illustrated in Figure 2, the subsequent process of literature search and article exclusion is delineated in detail.

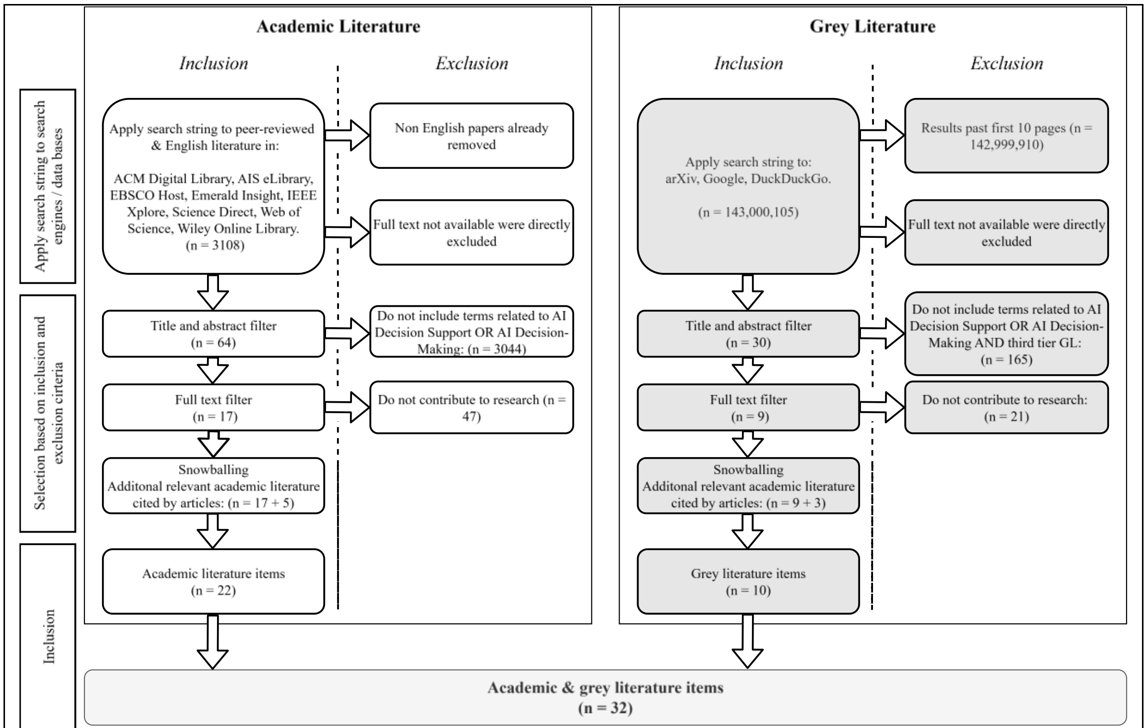

Figure 2. Research Approach for Multi-Vocal Literature Review

We used eight prominent scientific databases, in accordance with the methodology outlined by Gramlich (2023). We employed a two-part search string, comprising keywords related to artificial intelligence ("AI" OR "artificial intelligence" OR "machine learning" OR "automation" OR "algorithmic") and organizational decision making ("decision making" OR "decision-making" OR "decision making process" OR "decision-making process" OR "decision support"). It is acknowledged that each database possesses distinct search functionalities and filtration mechanisms. Considering this, the search string underwent necessary adjustments to accommodate these variations. To guarantee both relevance and quality, we applied pre-set search filters to limit results to peer-reviewed articles available in English and in full text. The initial search yielded 3,108 results. In the subsequent phase, we conducted a rigorous one rater screening process, whereby we evaluated titles and abstracts, and excluded articles based on predetermined criteria. The selection of articles was constrained to those that met the following criteria: First, they had to be available in full text in English; second, they had to be peer-reviewed journal articles or conference papers; and third, they had to contribute to the body of literature on AI in decision making (Garousi et al., 2019). We did not define a specific range for the date of publication. The present study specifically focuses on articles that explicitly mention "AI Decision Support" or "AI Decision Making". Consequently, articles that were not available as full text, did not deliver relevant insights into the use of AI in ODM, and focused on DM in contexts other than management, strategy and organizations were excluded (Garousi et al. 2019). This process yielded a total of 64 articles that were deemed to meet the specified criteria. We then initiated a comprehensive full text screening process, resulting in the exclusion of 47 papers that failed to contribute to the extant literature on AI in decision making within the context of management, strategy, or organizations. Following the analysis, a total of 17 articles were selected for inclusion in the final sample. As recommended by Garousi et al. (2019) and Adams et al. (2017), we further performed forward and backward searches to add more literature to the review. As a result, we identified another 5 papers bringing the final number of selected articles to 32 (see figure 2). Concurrently, a parallel process was initiated to identify relevant GL. Utilizing the same search string, we queried general-purpose search engines such as Google, which is frequently employed in GL research (Paez, 2017), as well as DuckDuckGo to minimize algorithmic bias introduced by personalized search results. In addition, we included the website www.arxiv.org to identify non-peer-reviewed yet influential contributions from the research community. This approach is in accordance with the approach proposed by Gramlich et al. to include first-tier GL in the MLR (2023) (see Figure 2).

The search process for the MLR was conducted between March and September 2024. Table 1 provides an overview of the final selection of literature categorized into the key findings they contribute to. It should be noted that some selected articles contribute to more than one key finding. Hence, some articles are mentioned more than once in Table 1. When conducting the LR and reviewing the literature, we did not intend to analyze the chronological evolution of the ODM process under the influence of AI, but rather how AI is expected to reshape the decision making process. Hence, we synthesized the literature by grouping the selected articles into clusters around the most relevant developments, which we refined ongoingly throughout the reviewing process. The final clusters are outlined in the results section of our paper.

Key finding	**Articles**
Key finding 1	Ahdadou et al., 2023; Hilb, 2020; Jarrahi, 2018; Ivanov, 2023; Van Quaquebeke and Gerpott, 2023; Vincent, 2021; Shrestha et al., 2019; Trunk et al., 2020; Watson, 2017
Key finding 2	Bolander, 2019; Borges et al., 2021; Jarrahi, 2018; Shrestha et al., 2019; Simon, 1987; Trunk et al., 2020; von Krogh, 2018
Key finding 3	Ivanov, 2023; Mentzas et al., 2022; Vincent, 2021; Shrestha et al., 2019; Trunk et al., 2020
Key finding 4	Araujo et al. 2020; Breidbach, 2024; Haesevoets et al. 2021; Leyer and Schneider 2021; Lüthi et al. 2023; Martin and Waldman 2023; Orwat et al. 2022; Solberg et al. 2022

Table 1. Overview of Selected Articles from Multi-Vocal Literature Review

Patent Analysis

Patent analysis has been utilized as a research method for a variety of purposes, including the analysis and prediction of future technological trends and developments (Abbas et al., 2014; Krestel et al., 2021). This is due to the fact that patent data are openly shared, thus offering a valuable opportunity to present the status quo of a technology. According to Abbas et al. (2014), a patent analysis is comprised of a series of sequential steps. The following three stages were involved in the process: first, patent extraction from databases; second, information extraction from patents; and third, analysis and interpretation of the extracted information. In the field of patent analysis, tools are available that facilitate the extraction of information from both structured and unstructured text data found in patents. These tools can be categorized into two distinct methods: text mining methods and visualization methods (Abbas et al., 2014). Natural Language Processing (NLP) is a prevalent text mining technique that can be grounded in both basic Machine Learning (ML) methodologies and sophisticated Deep Learning (DL) architectures, encompassing transformer models (Abbas et al., 2014; Krestel et al., 2021). In recent years, there has been an observed increase in the publication of patents across a range of disciplines, accompanied by a growth in the volume of technical data contained within these documents. This has presented a significant challenge to scholars and experts in analyzing these patents (Abbas et al., 2014; Krestel et al., 2021). Consequently, the utilization of AI-based techniques in the domain of patent analysis has become increasingly significant. This is primarily due to the augmented information processing capabilities of AI, its enhanced accuracy, and its capacity to facilitate more rapid analysis. In the field of IS, scholars have employed various NLP techniques to analyze patents for a novel AI model (Boyd and Andalibi, 2023). Furthermore, different types of transformer models, such as BERT and GPT-2, have been employed to perform different tasks in patent analysis (Choi et al., 2019; Lee and Hsiang, 2020). In accordance with the recommendations of scholars and the most effective practices identified through further research in the IS field (Boyd and Andalibi, 2023; Krestel et al., 2021), this work employs a text mining technique based on a GPT model to conduct a structured patent analysis, which was randomly validated by the author team.

We executed the patent analysis in three stages. First, we conducted a comprehensive search for patents relevant to IDSS in three major patent databases: DEPATISnet, Google Patents, and Espacenet. The search terms employed were “decision support” and “AI”, the rationale being that these terms would be the most suitable for covering all relevant patents and DSS from the past 14 years, thus from 2010 to 2024. Moreover, the utilization of the search term “decision support” ensured that patents lacking a primary focus on DSS were excluded from the analysis. To concentrate on IDSS, we excluded all patents published prior to 1 January 2010 and after 30 June 2024. The reason for this is that IDSS are far more advanced due to their extensive data processing and reasoning capabilities in contrast to earlier DSS. It is evident that patents published in languages other than English are not considered in this case. A total of 244 patents were identified through the utilization of DEPATISnet, of which we selected 168 for further analysis. We excluded a total of 74 patents from the study because they were not available in English. A subsequent search on Google Patents yielded approximately 20,000 patents. Following the scanning of the initial 50 pages of results, the search was halted due to the attainment of saturation (Garousi et al., 2019). From Google patents, a total of 25 patents was selected for further analysis. In the Espacenet database, the search string yielded 53 results, of which 10 patents were selected based on the predetermined exclusion criteria. The finalized dataset encompassed patents from the following years: 2010 (7), 2012 (4), 2014 (5), 2015 (6), 2016 (5), 2017 (7), 2018 (9), 2019 (12), 2020 (14), 2021 (25), 2022 (35), 2023 (41), 2024 (33). Following the application of the search criteria, we determined that no patents from the years 2011 and 2013 were found to be relevant. Consequently, they have not been included in the following listing. The process of searching and selecting patents was conducted between May and October 2024.

Second, following the selection of relevant patents from the three databases, each patent was analyzed individually using OpenAI’s chatbot ChatGPT-4o. The decision to utilize AI for the execution of the patent analysis was made based on its proven accuracy and substantial data processing capabilities, thereby facilitating a more comprehensive and representative examination of the AI advancements in DM. To guarantee the veracity of the results, a manual analysis of the steps requested from ChatGPT was conducted for a selection of patents. The findings of these tests were consistent with the results generated by ChatGPT. In the initial prompt, the number, year of publication and a concise overview of each patent were requested from ChatGPT. Subsequently, we incorporated inquiries pertaining to the participation of artificial intelligence and human operators at each stage of the ODM process. The results obtained from ChatGPT were then extracted and arranged into a tabular format. As the third step in the patent analysis, a synthesis of the results for all patents was conducted to ascertain the number of patents published per country, year, and industry. In addition, an analysis was conducted to ascertain the extent to which AI had been implemented to execute human tasks within each step of the DM process. To synthesize the results from the initial round of analysis, we utilized ChatGPT to generate an overview of the analyzed patents, categorized according to the respective publishing year and industry. This overview was then compiled into a tabular format. This step of the analysis revealed a variety of use cases for AI support in ODM. For example, the patent KR 000102663455 B1 from 2024 describes an analysis and decision support system for franchise managers which collects, stores, and analyzes various store data to deliver customized recommendations to managers allowing them to make more efficient decisions. In patent US 020180075384 A1 from 2018, a data-driven innovation decision support system visualizes an innovation entity within a network map of various technology domains. The system further assesses the level of strength of the innovation entity in each technology domain and provides one or more strategic suggestions for at least two nodes of the network map.

Third, an evaluation of the extent of AI involvement per step across all the patents was necessary. To accomplish this objective, ChatGPT was prompted to generate a table that exhibited the seven DM steps as column headings, with each row corresponding to a specific publishing year. In the present study, the inclusion criteria for patents were specified as those instances where AI is involved in the execution of a specific DM process step to an equal extent as human decision makers or more.

Results

Qualitative Insights into the Evolution of Artificial Intelligence on Decision Making

In the following section, the results of the MLR are presented, examining the current body of scientific and grey literature on AI-driven DM. The analyzed articles primarily address the repercussions of AI on strategic ODM in domains such as leadership, clinical DM, or finance. In addition, an extant corpus of literature has examined possible models of collaborative human-AI ODM with varying forms of task allocation (e.g. Jarrahi, 2018; Ivanov, 2023; Vincent, 2021; Shrestha et al., 2019; Trunk et al., 2020). This is consistent with our research focus, which is targeted at strategic ODM. The extent to which AI can be regarded as a decision maker is a matter of some debate. As elucidated in the background section, scholars differentiate between three levels of AI involvement in ODM: (1) Decision Support or Assisted Intelligence, (2) Decision Augmentation or Augmented Intelligence, and (3) Decision Automation (Ahdadou et al., 2023; Hilb, 2020). In the current stage of AI development in DM, scholars have identified a tendency towards AI realism, which can be considered to encompass the initial two stages, Assisted Intelligence and Augmented Intelligence (Ahdadou et al., 2023; Hilb, 2020). Hilb (2020) asserts that the subsequent stage of AI realism is characterized by the adoption of AI systems to perform DM tasks with increasing autonomy levels. This approach has been shown to minimize human interference in data handling and analysis, thereby reducing the number of decisions made by executives (Watson, 2018). This development is already evident in the field of AI, with technology increasingly assuming a proactive role in advising human decision makers (Van Quaquebeke and Gerpott, 2023; Ahdadou et al., 2023).

Key finding 1: The current role of AI in ODM seems to be assisted and augmented intelligence. Furthermore, AI is taking more and more a proactive role in the ODM process.

In contrast, other authors from both academia and practice adopt a more cautious stance when assessing the current impact of AI on ODM. The prevailing perspective among experts in the field is that the absence of intuitive capabilities and ethical judgment in AI represents a significant deficiency. Consequently, they evaluate AI-based DM systems as inherently incapable of making autonomous decisions, necessitating the incorporation of a holistic, subjective perspective that is characteristic of a human decision maker (Trunk et al., 2020; Bolander, 2019). Despite the advancement of AI as a DM tool from executing merely analytical tasks based on pre-defined process rules, research assesses these systems as unable to imitate human behavior and learning (Borges et al., 2021; Shrestha et al., 2019). Humans have the capacity to access contextual knowledge and formulate solutions in uncertain and dynamic decision making scenarios, drawing upon prior experiences (Jarrahi, 2018; van Krogh, 2018; Bolander, 2019). The human cognitive abilities of flexibility, abstract thinking, and intuitive judgment enable superior performance in ill-structured DM settings when compared with AI (Bolander, 2019). However, human decision makers possess limited information processing capacities, and thus tend to rely on heuristics to deal with complex problem settings (Bolander, 2019; Simon, 1987). In this regard, most scholars concur that AI exhibits superior analytical and information processing capabilities (Jarrahi, 2018; van Krogh, 2018). The employment of AI as a DM tool necessitates the utilization of extensive data inputs, the capacity for explanation, and a distinctly delineated decision objective, given the inability of AI to manage overly complex scenarios (van Krogh, 2018; Trunk et al., 2020; Shrestha et al., 2019). It is evident that machines demonstrate optimal performance when confronted with scenarios that are unambiguously delineated. In such circumstances, they can produce precise and methodically structured resolutions, thereby facilitating analytical reasoning over intuitive decision making (Jarrahi, 2018).

Key finding 2: Despite the development described in Key finding 1, researchers recognize that AI has limited capabilities when it comes to intuition and ethical judgement. By contrast, humans can perform well even in poorly structured ODM settings due to their prior experience. However, AI performs better when the situation is clear and requires analytical and information processing capabilities.

In a sub-stream of research on AI in ODM, scholars have attempted to design human-AI collaboration models. The aim of these models is to exploit analytical DM capabilities of AI and human intuition whilst limiting the harmful effects of their respective weaknesses (Vincent, 2021). Depending on the ODM scenario, a range of collaboration modes have been proposed. A solely AI-based approach is considered suitable in programmed decision settings where the following criteria are met: (1) The search space is clearly defined, (2) the decision is standardized, frequently occurring and low-risk, and (3) many alternatives exist (Ivanov, 2023; Vincent, 2021; Shrestha et al., 2019). Conversely, complex, non-programmed decision settings are characterized by the following: (1) high outcome uncertainty; (2) ethical complexity; (3) infrequent occurrence; and (4) a lack of predefined DM process rules (Ivanov, 2023; Vincent, 2021). Such decision making processes necessitate the implementation of a "human in the loop" or "on the loop" approach (Ivanov, 2023). In the field of human-AI ODM, researchers have proposed a framework known as hybrid sequential DM, which can be executed in either a confirmatory or exploratory manner (Shrestha et al., 2019). In the confirmatory method, the human decision maker arrives at a solution that is then either confirmed or altered based on an evaluation by AI (Vincent, 2021). As posited by Shrestha (2019), a related set of recommendations entails the selection of a predetermined number of alternatives by human means, with the ultimate evaluation and selection of the optimal solution being conducted by means of AI. In the exploratory method, AI is utilized to identify potential solutions, which are subsequently conveyed to a human decision maker for further consideration (Vincent, 2021). In the field of data science, a framework has been developed by Mentzas et al. (2022) that integrates prescriptive analytics and machine learning (ML) based on reinforcement learning, guided by human experience. The latter approach is adopted, with AI delivering data-driven predictions that serve as input for the human-AI DM process (Mentzas et al., 2022). Another form of hybrid DM is known as aggregated DM, in which decision tasks are performed simultaneously by humans and AI. This results in a combined solution (Shrestha et al., 2019). Trunk et al. (2020) developed a framework for the usefulness of AI in each DM process step, which states that AI outperforms humans for information collection tasks, but remains in a merely supportive role when researching, evaluating, and deciding for solution alternatives. In the concluding steps, the involvement of artificial intelligence is entirely excluded.

Key finding 3: Research mainly differentiates between two collaboration modes in ODM: First, a solely AI-based approach, which is feasible if the search space is clearly defined, low-risk, frequently occurring and many alternatives exist. Second, a human in or human on the loop approach, which is feasible if there exists a high outcome uncertainty, ethical complexity, infrequent occurrence and a lack of predefined rules.

Despite AI playing an increasingly important role in ODM, several issues regarding the adoption of AI in organizational and managerial decision scenarios remain. For instance, managers tend to prefer human-AI collaboration scenarios in which humans retain a major role (Haesevoets et al., 2021). In alignment with this finding, Solberg et al. (2022) state that people display higher levels of trust in AI-based DSS systems with low autonomy and lower levels of trust for systems with high autonomy, regardless of the reliability of the decision automation systems. Furthermore, research has emphasized a lack of clear guidance on organizational AI uptake through regulatory frameworks (Leyer & Schneider, 2021; Martin & Waldman 2023; Orwat et al., 2022). Lüthi et al. (2023) state that the autonomous DM capability of AI systems enables both, the providing organization and the using organization, to shift responsibility to the system, thus they suggest a mechanism to distribute accountability for the actions of a DM system between the entities. Besides regulatory frameworks imposed by governments, such as the EU AI Act, organizations need to develop and implement governance mechanisms for the adoption of AI in ODM (Araujo et al., 2019; Breidbach, 2024), also outlined in Art. 9 (1) and 14 in the EU AI Act (Regulation 2024/1689).

Key finding 4: Scientific literature has shown that managers prefer human-AI collaboration modes in ODM with humans retaining a major role, especially in high-risk decision scenarios. The development and implementation of guidelines for governance and risk management of AI in ODM positively influences managerial trust in AI systems.

In summary, most scholars from this field concur with the complementarity of the unique strengths of AI and humans in ODM (Jarrahi, 2018; Shrestha et al., 2019; Hemmer et al., 2023). The suggested frameworks focus on hybrid human-AI DM throughout the middle part of the ODM process (Vincent, 2021; Trunk et al., 2020). The process flow can be categorized as either sequential AI-to-human (Mentzas et al., 2019; Shrestha et al., 2019), sequential human-to-AI (Vincent, 2021), or aggregated DM without task specialization (Choudhary et al., 2023; Metcalf, 2019). However, scholars do not consider AI to be a suitable method for the preliminary step of the DM process, Problem Understanding (Shrestha et al., 2019; Trunk et al., 2020). However, only a limited number of authors have argued for the plausibility of full human-to-AI delegation (Trunk et al., 2020; Agrawal et al., 2019; Ahdadou et al., 2023).

Quantitative Insights into the Impact of Artificial Intelligence on Decision Making

The present study aims to assess the current state of AI in DM quantitatively through a structured patent analysis (Borges et al., 2021). As illustrated in Figure 2, the DM process is depicted alongside the progression of AI integration over time. First, the analysis reveals an overall increase in the number of patents filed for AI-based DSS. The number of patents from this field identified as such grew from 7 in 2010 to 41 in 2023. However, it should be noted that this growth was not linear. The number of published patents exhibited fluctuations between 2010 and 2018, ranging from a minimum of four to a maximum of nine, with no instances exceeding ten. The percentages in brackets indicate the share of patents within each year column. In 2019 and 2020, we observe a slow growth in the number of published patents up to 14. Between 2020 and 2021, the number significantly increased to 25 published patents.

Total Number of Patents: 203

Number of patents per year that indicate the involvement of AI

	Step 1	*Step 2*	*Step 3*	*Step 4*	*Step 5*	*Step 6*	*Step 7*
2010	7 (100%)	7 (100%)	7 (100%)	7 (100%)	7 (100%)	6 (86%)	1 (14%)
2012	4 (100%)	4 (100%)	4 (100%)	4 (100%)	4 (100%)	3 (75%)	1 (25%)
2014	5 (100%)	5 (100%)	5 (100%)	5 (100%)	5 (100%)	5 (100%)	2 (40%)
2015	6 (100%)	6 (100%)	6 (100%)	6 (100%)	6 (100%)	6 (100%)	3 (50%)
2016	5 (100%)	5 (100%)	5 (100%)	5 (100%)	5 (100%)	5 (100%)	3 (60%)
2017	7 (100%)	7 (100%)	7 (100%)	7 (100%)	7 (100%)	7 (100%)	3 (43%)
2018	9 (100%)	9 (100%)	8 (89%)	9 (100%)	9 (100%)	6 (66%)	6 (66%)
2019	12 (100%)	12 (100%)	12 (100%)	12 (100%)	12 (100%)	11 (92%)	8 (66%)
2020	14 (100%)	14 (100%)	14 (100%)	14 (100%)	14 (100%)	12 (86%)	7 (50%)
2021	24 (96%)	25 (100%)	25 (100%)	25 (100%)	25 (100%)	21 (84%)	10 (40%)
2022	33 (94%)	35 (100%)	34 (97%)	35 (100%)	35 (100%)	31 (89%)	11 (31%)
2023	39 (95%)	41 (100%)	39 (95%)	40 (98%)	40 (98%)	32 (78%)	12 (29%)
2024	31 (97%)	32 (100%)	31 (97%)	32 (100%)	31 (97%)	26 (81%)	16 (50%)

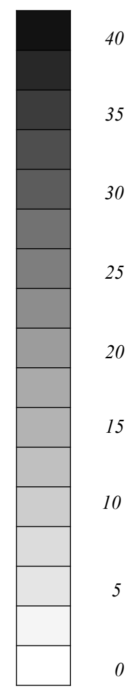

Figure 3. Results of Patent Analysis

Second, we find an increasing allocation of DM tasks to AI in each step and a progressing shift of AI involvement toward the final steps over time. As explained in the method section, when analyzing AI involvement per step in each patent, we differentiate between patents where AI is involved less than human decision makers, and cases where AI takes over the same as or more responsibilities than humans. The latter represents the shift from descriptive to prescriptive analytics which our analysis focuses on. Across the entire timeframe from 2010 to 2024, we observed equal or major participation of AI in comparison to humans in the first up to the fifth process step. In *Problem Understanding,* AI is involved to a large extent in 100% of the analyzed patents published between 2010 and 2020. Between 2021 and 2024, 97% of analyzed patents suggest that AI plays a major role in *Problem Understanding*.

For the subsequent step *Search for Information*, 100% of the analyzed patents across the years 2010 to 2024 allocate a large share of the DM step to AI. The third step *Define Alternatives* involves AI to a large extent in 100% of the analyzed patents published between 2010 and 2021, except 2018 where this was the case for eight out of nine patents. In the subsequent years, the share drops slightly to 97% in 2022 and 95% in 2023 but increases again up to 97% in 2024. For the fourth step *Screen Alternatives,* 100% of the analyzed patents published between 2010 and 2024 suggest an equal or major task allocation to AI in comparison to humans. The only exception is the year 2023 where this share decreases slightly to 98%. We observe the exact same development for the fifth step of *Evaluate Alternatives*, with AI playing a major role in the DM step in 100% of the patents from 2010 to 2022, 98% from 2023, and 97% from 2024. In summary, in five out of seven steps of the ODM process, the involvement of AI is either equal or larger than human involvement in almost 100% of patents published since 2010. For the sixth step *Decide*, the extent of AI involvement in comparison to humans is almost equal to the extent of involvement in step 1 to 5, with an exceptional decrease in 2018 where AI is largely involved in the sixth step in only two-thirds of all patents. Hence, patents for AI-based DSS suggested at least a partial automation of the DM step of deciding on a solution alternative. From 2021 on, the total number of patents suggesting a large involvement of AI in the final decision still grows steadily. However, the relative share of patents allocating this task to AI across all examined patents slightly decreases to an average of 84% between 2021 and 2024.

The analysis reveals a similar development for the seventh DM step *Execute*. Across all patents between 2010 and 2024, AI involvement in the final step is significantly lower than in the previous six steps. From 2010 up to 2017, among all seven patents, the share of patented DSS with AI playing a major role in *decision execution* remains below 50%. For instance, in 2010, only one out of seven patents suggested utilizing AI mostly for decision execution. From 2017 on, the total number of patented DSS including AI in the last DM step increased steadily, from six patents allocating decision *execution* to AI in 2017 up to 16 patents in 2024. Between 2020 and 2023, the share fluctuates between 60% in 2020 and 40% in 2023 of patents augmenting the final DM step with AI. Only lately, in 2024, the share increased to 60%. In summary, from 2010 until 2024 the involvement of AI in the final process step of decision execution increased, despite fluctuations in the development.

Discussion

Theoretical Implications

This work constitutes three primary contributions, which give rise to several implications for researchers in the fields of strategic management and information systems.

First, we examine the current body of literature on AI in ODM and include the perspectives of different research streams. We contribute to these by providing an overview of existing scientific literature and laying the foundation for connecting their findings. For instance, we find that most of the suggested human-AI collaboration models for ODM are based on the notion of complementarity of the analytical DM and information processing capabilities of AI and human judgment, experience, and intuition (Hemmer et al., 2024; Jarrahi, 2018; Vincent, 2021; Shrestha et al., 2019). Hence, current research mostly assesses AI as capable of taking full decision authority in confined, structured decision spaces where many alternatives exist (Shrestha et al., 2019; Vincent, 2021). Furthermore, the results of studies on human trust in AI such as the survey conducted by Araujo et al. (2019) implicate the ideal ratio of responsibility for DM tasks between humans and AI in collaboration models and suggest “human in the loop” designs to increase managerial acceptance (Ivanov, 2023; Metcalf, 2019).

Second, we fill the research gap of quantitative studies on AI progress in ODM by analyzing published patents in the field of AI-based DSS within the past 14 years. Scholars found that most publications on AI in ODM are based on conceptual research approaches (Trunk et al., 2020). This is confirmed by the findings of our MLR. Hence, our work addresses calls from researchers for more quantitative studies on the progress of AI in ODM (Trunk et al., 2020; Gruetzemacher et al., 2021). In our findings, we observe a significant growth in the number of patents on AI-based DSS from 14 patents in 2020 to 25 in 2021. A possible explanation for this is the announcement of the release of GenAI and transformer models like ChatGPT in the previous year, implying the increasing importance of GenAI technology for ODM (Baabdullah, 2024). Furthermore, the results of the patent analysis implicate a significant extent of AI involvement from the first until the fifth step of the ODM process. This confirms insights from scientific literature regarding AI’s capability to process large amounts of data, extract the requested information (descriptive analytics), and deliver forecasts and recommendations (prescriptive analytics) (Philipps-Wren, 2013; Raisch and Kraikowski, 2021).

Furthermore, the findings from the patent analysis outline that AI is increasingly involved in the sixth step of the ODM process and takes final decisions with growing autonomy. In the results of the patent analysis, we observe slight decreases in the relative share of patents suggesting a strong involvement of AI in the

Decide step (e.g. in the years 2020 to 2023). This could be traced back to the fact that traditionally, DSS played a supporting role in ODM providing insights from descriptive analytics (Simon, 1987). The logical reasoning capabilities of decision support technology made it suitable for low-stakes, formalized DM scenarios (Howard, 2019; Philipps-Wren, 2013; Haenlein and Kaplan, 2019). More recently, AI has started to take responsibility for more complex DM tasks (Vincent, 2021; Giachino et al., 2024; Ahdadou et al., 2023), which has not been the case in previous predictions (Trunk et al., 2020). However, this also results in an increased risk of the system taking decisions that are possibly harmful or detrimental to the goals of an organization, which makes a larger weight of human judgment in the final ODM steps to monitor the outcomes more desirable (Breidbach, 2024). The findings further demonstrate that in contrast to the ODM process steps 1 to 6, AI is involved to a significantly lower extent in the final *Execution* step. A possible explanation could be the difficulty of holding an AI system accountable for the decisions it makes; thus it cannot execute strategic decisions autonomously without human involvement (Breidbach, 2024). However, the decision execution is a complex part of the ODM process involving a variety of stakeholders and organizational factors (Haenlein and Kaplan, 2019). Thus, we observe from our patent analysis that AI has been increasingly supporting the *Execution* step to guide human decision makers in obtaining authorization and implementing decisions (Storey et al., 2024). Figure 4 shows the evolution of AI in the ODM in comparison to a prediction from 2020.

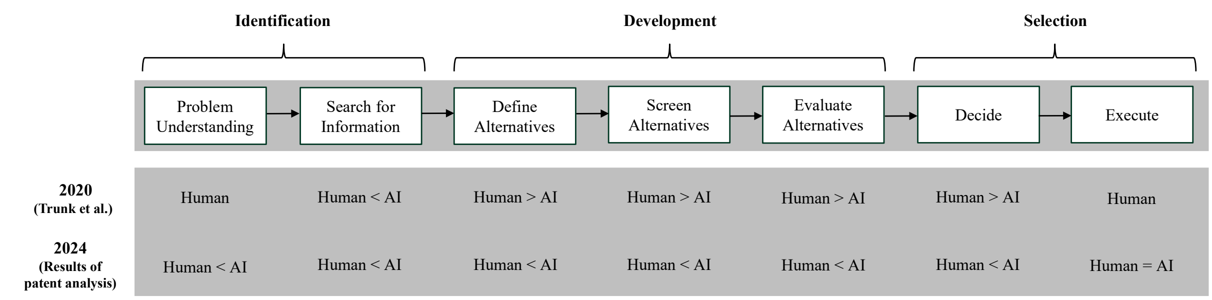

Figure 4. Evolution of the Influence of AI in ODM

Third, based on our findings, we infer predictions of the future evolution of the ODM process under the influence of AI including which steps of the ODM process will be augmented or automated by AI in the future. Our results indicate a trend toward an increasing augmentation of human intelligence with AI in the final two steps *Decide* and *Execute* in the ODM process, under the constraint that an entire automation of these steps for strategic decisions is neither desirable due to AI lacking access to implicit knowledge nor in compliance with regulatory guidelines (e.g. EU AI Act) (Breidbach, 2024; Metcalf, 2019; Bolander, 2019). In addition, our results indicate changes in the ODM process and its organizational context. On the one hand, our results contribute to answering the question of how the increasing involvement of AI in the ODM process affects organizational knowledge management structures (von Krogh, 2018). For instance, the outcomes of AI decisions can be more easily stored in organizational knowledge databases, whilst human expert knowledge can be retained with the help of the technology and used as input for AI-based DSS (Gil et al., 2020). On the other hand, the first stage of the patent analysis implies that the traditional ODM process (see Theoretical Background) is complemented with an additional process step *Quality Control* in the ODM process due to the increasing responsibility of AI. This step enables human decision makers to retain control over the ODM process by monitoring AI's decision outcomes and taking corrective actions, if necessary (Booyse and Scheepers, 2024; Ivanov, 2023; Vincent, 2021). Thus, we suggest an enhanced model of the ODM process complemented by the process step *Quality Control* resulting from the decision outcome and impacting new iterations of the ODM process.

Managerial Implications

Besides theoretical implications, our work provides two practical implications for managers and decision makers in organizational contexts.

First, our findings envision a future increase in the use of AI in the final two steps within ODM processes, implying the necessity to adapt organizational structures and redefine the role of managers. Through changes in the ODM process driven by AI, different capabilities from organizations and managers will be needed (Mayer et al., 2024). With AI increasingly taking over the cognitive workload from human managers and automating repetitive tasks, communication skills as well as leadership capabilities of managers will become more important (Van Quaquebeke and Gerpott, 2023; Ahdadou et al., 2023; Hao et al., 2024; Huang et al., 2019). Furthermore, managers will need to improve their data and AI literacy (Watson et al., 2021; Gimpel et al., 2024). Organizational structures need to adapt to accommodate these changes of the workplace. We find that a complete replacement of humans in ODM and a resulting abolition of the manager's role in organizations is unlikely due to two reasons. First, strategic decision scenarios characterized by ambiguity and uncertainty still require human intuition and implicit knowledge which AI cannot access. Second, regulatory guidelines and ethical values require humans to retain veto rights and a certain decision responsibility to be ultimately accountable for decision outcomes. Instead of AI substituting humans in ODM, we expect AI-based DSS to restructure the process and improve its efficiency, increasing the managerial focus on other leadership tasks (Watson et al., 2021; Gimpel et al., 2024).

Second, our findings indicate discrepancies between (i) human preference for limited AI involvement on the level of Decision Support and Decision Augmentation, (ii) the observable trend toward Decision Automation as displayed in patents for AI-driven DSS, and (iii) the lack of practical guidance for organizations in adopting responsible AI DM. As demonstrated by scientific literature, managers tend to trust human judgment more than AI judgment, especially in high-risk decision scenarios (Martin and Waldman, 2023). Furthermore, questions regarding the division of accountability between system providers and decision makers remain unanswered (Lüthi et al., 2023), and regulatory frameworks such as the EU AI Act lack binding regulations and practical advice for organizations to mitigate AI risks (Orwat et al., 2022). Hence, organizations need to develop guidelines for governance and risk management practices to responsibly adopt AI-driven DM and increase trust from managers in AI systems (Araujo et al., 2019; Breidbach, 2024), also outlined in Art. 9 (1) and 14 in the EU AI Act (Regulation 2024/1689). The additional ODM process step *Quality Control* as suggested in the theoretical implications becomes even more important for AI adoption in DM to continuously monitor the quality of algorithmic decisions (Breidbach, 2024).

Limitations and Future Research

The present study is subject to some limitations that provide avenues for future research. First, one limitation is attributable to the exclusionary criteria, which are focused on English publications and patents. To facilitate the reproduction of our research, we deliberately chose to exclude non-English patents. Future research endeavors may address this through an analysis of patents published in other languages, with a view to identifying insights on AI progress in ODM (e.g. in non-Western countries). Second, the quality of the patents is not assessed as a measure in the heatmap but the quantity of the patents per year. Given the increase of involvement of AI in daily life across various industries, the number of patents will continue to rise, even if the relevance of the contribution of the patent might be questionable. Third, the absence of a clear differentiation between the terms 'decision support systems', 'decision making systems' and 'decision automation systems' in research is a limitation to the study. The ambiguity of the definitions of DSS resulted in a lower number of search results for relevant scientific contributions that yielded with the search string. Prior to conducting our review, we undertook a comprehensive examination of the theoretical underpinnings of DSS and AI in managerial DM, thereby delineating the scope of our work to encompass AI-based DSS for organizational and strategic decision making. Nonetheless, further research is required to establish a clear conceptualization of contemporary AI-based DSS, with a view to enhancing scientific understanding of the utilization of AI in ODM (Duan et al., 2019). Fourth, as outlined in the managerial implications, incongruity was identified between the increasing utilization of AI in the ODM process and the actual propensity of human decision makers to adopt AI. It is recommended that future research focuses on the strategies employed by organizations regarding the incorporation of AI-based DSS or other AI tools within ODM, and on the question of whether they intend to assign decision making authority to AI. Fifth, a further research avenue concerning future studies, as implied by the present study, concerns evaluations of the individual technologies and their associated risks underlying future AI-based DM systems. For instance, subsequent research could investigate the limitations and risks intrinsic to LLM implementation and the integration of LLMs with other AI models to develop systems for strategic DM systems in organizational contexts (Changeux and Montagnier, 2024). Recent technical developments, including the release of OpenAI's latest reasoning model GPT o3 and the rise of multi-agent systems (Baird and Maruping, 2021), give rise to questions concerning the composition of future AI-based DSS and DM systems. Specifically, there is a need to ascertain whether such systems will be composed of multiple autonomous agents collaborating within an ecosystem. We recommend that further research is conducted on the possibilities and limitations of these emerging technologies to assess their potential use in strategic ODM.

Conclusion

The objective of this work was to examine the evolution of AI-driven decision support, from both a qualitative and a quantitative point of view, to derive trends for the future development of AI alongside the ODM process. To answer the research question posed, an MLR was conducted to identify the principles and challenges of AI-driven DM. Furthermore, an analysis of patents on AI-based DSS was conducted to address the research gap concerning quantitative studies on AI in ODM. In conclusion, the present study contributes to the existing body of research on AI-based DM by providing a comprehensive overview of the current research discourse in the field and laying the foundation for connecting their findings. The results of the patent analysis indicate a trend towards an augmentation of human intelligence with AI in the final two steps of the ODM process: *Decide* and *Execute*. This facilitates the capacity of managers to predict the future evolution of ODM under the influence of AI, thereby enabling them to adapt organizational structures and redefine the role of decision makers. This study ultimately demonstrates inconsistencies between human preferences concerning the limited integration of AI in ODM, the prevailing tendency towards decision automation, and the absence of organizational guidance regarding the adoption of responsible AI DM.

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