University of Twente

Bachelor Thesis

Artificially intelligent collective decision-making: A systematic review

---

Author:
Beāte Hermansone (s2207028)

Supervisors:
Dr. René Torenvlied
Dr. Ringo Ossewaarde

Management, Society and Technology

Word count: 10835

Enschede
June 30th, 2021

ABSTRACT

This Bachelor Thesis aims to study the relationship between Artificial Intelligence and collective decision-making models in order to understand how Artificial Intelligence could contribute to non-cooperative and cooperative social choice theories. The relationship between AI and two cooperative decision-making theories namely, Nash bargaining solution and vote trading is examined as well as AI's relatedness to three non-cooperative group decision-making theories, namely, Condorcet's paradox, Arrow's impossibility theorem and Black's Median Voter theorem, is studied. As the literature relating these concepts is scarce, a systematic literature review following PRISMA guidelines is performed to aim to fill in the existing gaps. The initial dataset incorporated 1,619 documents, which eventually led to a final corpus of 51 relevant articles after applying the exclusion criteria. Results show that AI can be applied two one of the selected cooperative decision-making models, Nash bargaining solution, and the non-cooperative decision-making model Condorcet's paradox. However, there are no studies indicating how Artificial Intelligence algorithms could facilitate the other examined social choice theories.

Keywords: *Social choice theories, collective decision-making, Condorcet's paradox, Arrow's impossibility theorem, Black's median voter theorem, Nash bargaining solution, Vote trading*

TABLE OF CONTENTS

ABSTRACT 2
1. INTRODUCTION 5
1.1. Problems in preference aggregation 5
1.2. Artificial Intelligence and decision-making 6
1.3. Research problem 6
2. BACKGROUND AND RELATED WORK 8
2.1. Collective decision-making 8
2.1.1. Condorcet's Paradox 8
2.1.2. Arrow's impossibility theorem 9
2.1.3. Black's Median voter theorem 9
2.1.4. Nash bargaining solution 10
2.1.5. Vote trading 10
2.2. Artificial Intelligence 11
3. RESEARCH METHOD: SYSTEMATIC LITERATURE REVIEW 12
3.1. Preparing the Systematic Literature Review 12
3.2. Conducting the Systematic Literature Review 17
4. FINDINGS 18
4.1. Description of the Corpus 18
4.2. Summary of findings 25
4.3. Approaches of AI 30
4.3.1. Reliability 30
4.3.2. Complexity 30
4.3.3. Cognitive abilities 31
4.3.4. Efficiency 31
4.3.5. Operationalization 31
4.3.6. Filling in gaps 31
4.3.7. Providing new insight and strengthening evidence 32
4.3.8. Human behavior imitation 32
4.3.9. Interdisciplinarity 32
4.4. Benefits from AI to modes of collective decision-making 33
4.4.1. Condorcet's paradox 33
4.4.2. Arrow's Impossibility theorem 33
4.4.3. Black's median voter theorem 33
4.4.4. Nash bargaining solution 34
4.4.5. Collective decision-making generally 34
5. CONCLUSION AND DISCUSSION 35
5.1. Discussion 35
5.2. Conclusion 36
5.3. Practical Implications and Future Work 36
5.4. Limitations 37

List of tables

Table 1: *Preference ordering among the three decision makers*

Table 2: *Overview literature sourcing and selection protocol*

Table 3: *Research, methodology and approach in the corpus consisting of 51 articles*

Table 4: *Summary of research, methodology and approach in the corpus consisting of 51 literature reports*

Table 5: *Journal distribution of the 51 articles related to the literature combining collective decision-making theories and various aspects of AI.*

Table 6: *Types of collective decision-making theories applied to Artificial Intelligence in documents*

Table 7: *summary of the findings*

List of figures

Figure 1: *Illustration of Black's median voter theorem*

Figure 2: *Overview data selection*

Figure 3: *Distribution of the 51 selected articles (corpus) by year*

Figure 4: *Distribution of 51 selected articles (corpus) by sector*

1. INTRODUCTION

Humans have proven to be outstanding cognitive information processors, conflict resolvers, and rational decision-makers since the dawn of time. When participating in collective decision-making that incorporates more than one autonomous decision-making body, individuals must share their decision-making power. The process by which groups of logical human beings reach binding choices without the use of dictatorial leadership is known as collective decision-making (Aikenhead, 1985). The aim of group decision-making processes consisting of autonomous individuals is different from government collective decision-making investigated in this paper. First, because the guiding principle for the actors must be serving public's interests in various ways (e.g., through working around the challenges, providing services and facilities, maintaining legislation, and guiding behaviors of safety, well-being, and prosperity of the community) as opposed to simply focusing on personal benefits (Knill & Tosun, 2020). Second, it is important for public officials to follow guidelines and theories discussed in the next section to ensure equal decision-making power distribution and a fair outcome of the decision-making (Bindseil & Hantke, 1997). Technocratic knowledge has shown to be powerful enough to help society prosper in a variety of ways, but there is no clear understanding of how AI's potential may help overcome decision-making difficulties and paradoxes from the nineteenth century (Riles, 2004).

Collective decision-making is a complex process involving the aggregation of individual preferences into a collective preference ordering (Lindblom, 1965). This aggregation process is far from trivial. There are four main formal collective decision-making systems consensus reaching methods, voting-based methods, Delphi method and dotmocracy (Sen, 1986). The focus on this thesis is on the two former methods. Consensus or cooperative decision-making methods avoid "winners" and "losers", Nash bargaining solution and vote trading will be the two methods included. The former occurs when a threat point exists far beyond the policy positions of the decision-makers, the decision-makers will give in on the basis of salience and power. (Nash, 1950). The latter is another cooperative collective bargaining strategy that involves an individual decision-maker casting their vote in favor of another individual decision-maker in exchange for them returning the favor (Riker & Brams, 1973).

1.1. Problems in preference aggregation

When it comes to the non-cooperative voting-based methods, majority voting, precisely, ranked voting encounters a few paradoxes found by mathematicians in the 19^{th} century. The first one is "Condorcet paradox" which occurs in a Condorcet method. It is an election technique that elects the candidate who receives a majority of the votes in every head-to-head election against all other candidates, that is, a candidate who is preferred by more voters than all others (Shepsle, 2010). Condorcet's paradox demonstrates that the majority rule can lead to a situation in which the decision-makers strictly ranking three preferences (A; B; C) can develop a cycle without a Condorcet winner if they collectively prefer A to B, B to C, and C to A. These pairwise preferences form a cycle producing an irrational outcome (Shepsle, 2010). Next, Arrow's Impossibility Theorem asserts that dictatorship is the only possible voting system that can occur under certain conditions when there are (A) at least three decision alternatives, (B) the unanimity, and (C) independence of irrelevant alternatives principles are met. In other words, every non-dictatorial social choice gives rise to a non-rational choice function (Shepsle, 2010).

A different approach is taken when using a spatial representation of preferences over a policy scale (Black, 1958). Preferences are single-peaked among a group of autonomous agents when the set of possible outcomes can meet two requirements (a) each decision-maker has their "best outcome" in the set and (b) the outcomes that are further from an agent's best outcome are preferred less (Black, 1958). Furthermore, Duncan Black proposed the median voter theorem in 1948 in connection with ordered preference voting. If agents and alternatives are distributed along a one-dimensional continuum, with voters rating alternatives in order of proximity, any voting method that meets the Condorcet criterion would elect the candidate who is nearest to the median voter (Black, 1958). This thesis seeks to understand if there is a way for Artificial Intelligence to intervene and work around these theories.

1.2. Artificial intelligence and decision-making

Motivated by the belief that the human intellect, logic, decision-making, and imagination do not have to be mysterious. Herbert A. Simon was one of the founding fathers of artificial intelligence, alongside John McCarthy, Alan Turing, Marvin Minsky, and Allen Newell (Haenlein & Kaplan, 2019). Simon worked on "thinking" robots and came to consider human intuition as a type of subconscious pattern recognition. He showed that intuition does not have to be associated with magic or mysticism, and that it can be combined with rational thinking (Frantz, 2003). Artificial Intelligence was invented at a pivotal period in the history of replicating the capabilities of the human brain, and it has evolved since then from the construction of physical advancements to the utilization of the human brain's intellectual capacity to assist decision-making. The ability of AI to evaluate a large volume of data and a diversity of data using high-performance computing and construct algorithms that detect patterns and correlations explains its utility and validity in the decision-making process (Haenlein & Kaplan, 2019). Artificial intelligence can theoretically be used in communal decision-making processes, however there is only a small body of literature that connects these ideas. Collective decision-making is limited by Herbert Simon's bounded rationality principle, competing interdependent tactics among decision-makers, and a focus on one's own merits (Simon, 1990).

1.3. Research problem

The scientific relevance of this thesis is twofold. First it lies in the aim to both identify and fill in the gaps in the literature when relating collective decision-making theories and Artificial Intelligence. Second, this thesis seeks to contextualize the various aspects of AI that can potentially contribute to cooperative and non-cooperative collective decision-making strategies. The societal relevance lies in the potential for the research to be used by policy makers to understand the current possibilities for AI to be integrated in decision making processes as well as help them decide what kind of group decision-making strategy to choose based on the paradoxes and theories involved. A systematic literature review is performed to grasp the aspects of AI which have the potential to contribute to collective decision-making and to investigate the research question "*How could the different consensus reaching, and voting-based models of collective decision-making be improved through the incorporation of Artificial Intelligence*?" There are three main sub-questions established that will contribute to answering the research question:

1. What are the paradoxes of cooperative and non-cooperative decision-making strategies?
2. What aspects of Artificial Intelligence, as reported in the literature, have the potential to contribute to collective decision-making?
3. How do models of collective decision-making processes benefit from Artificial Intelligence?

This thesis is organized in three main sections. First, the theoretical background is provided to provide further insight into the examined cooperative and noncooperative group decision-making models. Next, the preparation of the systematic literature review is described along with the results presented in figures and tables. In the last section the key findings are explicitly stated and a follow-up discussion and conclusion with an answer to the research question is given. The limitations of both the research topic and the systematic review are highlighted.

2. BACKGROUND AND RELATED WORK

2.1. Collective decision making

At the core of collective decision-making lies social choice theory, a study in the social science and economic field related to collective decision processes and procedures. The theory is made up of a set of frameworks and findings relating to the set of individual inputs through actions such as voting; preference ordering; judgment making; welfare establishment into collective outputs. Researching how a group of individuals can choose a winning outcome from a given set of options; finding evidence about the possibilities of a group arriving at coherent collective preferences and analyzing the properties of different voting systems are all fundamental examination topics for social choice theorists, who not only try to find answers but also develop models and provide theorems. As discussed in the introduction, there are four formal group decision-making systems, namely, consensus decision-making, voting-based methods, Delphi method and dotmocracy (Sen, 1986).

Consensus decision-making and voting-based methods have been chosen for the research as it ensures the opportunity to reflect on the remarkable and therefore widely known research done by societal choice theorists. Consensus-building or, to put it another way, cooperative decision-making is a model that aims to prevent conflict. Attempts to stay away from "winners" and "losers." Consensus necessitates that a majority of people agree on a course of action while the minority agrees to go along with it. In other words, if a minority object to a course of action, consensus necessitates that it be amended to remove the undesirable features (Xu, 2009). Nash bargaining solution is one of the consensuses reaching theories, which is often used in games, it was selected for this analysis. Another cooperative method selected is vote trading. When it comes to the non-cooperative decision-making models, one of the voting-based models, specifically, majority voting was selected for the systematic review. Majority voting requires support from more than 50% of the members of the group. Thus, the bar for action is lower than with unanimity and a group of "losers" is implicit to this rule (Penrose, 1946). Although a common method of majority voting is ranking the alternatives, it does not come without its pitfalls found by various mathematicians and social choice theorists.

2.1.1. Condorcet's Paradox

Condorcet's paradox is among one of those ranking method theories identified that hinder the collective decision-making process. Specifically, it was developed in the 18th century by French philosopher Nicolas de Condorcet in his Essay on the Application of Analysis to the Probability of Majority Decisions (1785). Condorcet's Jury theorem states that if each member of a jury has an equal and independent chance better than random, but worse than perfect, of making a correct judgment on whether a defendant is guilty (or on some other factual proposition), the majority of jurors is more likely to be correct than each juror and the probability of a correct majority judgment approaches as the jury size increases (Boland, 1989). Thus, Condorcet's paradox developed from Condorcet's jury theorem and it is the observation that majority preferences can be regarded as irrational (transitive) even when individual preferences are rational. For example, a decision has to be made between three alternatives among a group of three decision-makers and one-third of a group prefers alternative A to B to

C, a second third prefers *B* to *C* to *A*, and a final third prefers *C* to *A* to *B* (Table 1). These majorities (of two-thirds) for *A* against *B,* for *B* against *C,* and *C* against *B* develop a cycle that violates transitivity. Another important aspect of this cycle is that none of the alternatives is a Condorcet winner, namely, an alternative that beats or ties with every other alternative in pairwise majority contests (Shepsle, 2010).

Table 1. Preference ordering among the three decision makers

1	2	3
A	B	C
B	C	A
C	A	B

2.1.2. Arrow's Theorem

Arrow's Theorem is another ranking voting method theorem that was developed in the 20th century by Kenneth Arrow, who introduced a general approach to the study of preference aggregation. He proved that there exists no method of aggregating the preferences of two or more individuals over three or more alternatives into collective preferences, where this method satisfies five seemingly plausible axioms: (1) universal domain; (2) ordering; (3) weak Pareto principle; (4) independence of irrelevant alternatives and (5) non-dictatorship. Universal domain requires the aggregation rule to cope with any level of pluralism in its inputs. Ordering requires it to produce "rational" social preferences, avoiding Condorcet cycles. The weak Pareto principle requires that when all individuals strictly prefer alternative *A* to alternative *B*, so does society. Independence of irrelevant alternatives requires that the social preference between any two alternatives *A* and *B* depend only on the individual preferences between *A* and *B*, not on individuals' preferences over other alternatives. Non-dictatorship requires that there is no "dictator" who always determines the social preference, regardless of other individuals' preferences (Shepsle, 2010).

2.1.3. Black's median voter theorem

The last ranking voting theorem selected for the literature review was developed by Duncan Black in 1948, which states that if voters and policies are spread along a one-dimensional spectrum, with voters ranking alternatives in order of closeness, any voting mechanism that meets the Condorcet criterion will elect the candidate who is closest to the median voter ((Shepsle, 2010). A majority vote between two possibilities will accomplish this. Figure 1 is presented to illustrate an example of the theorem.

Figure 1. Illustration of Black's median voter theorem

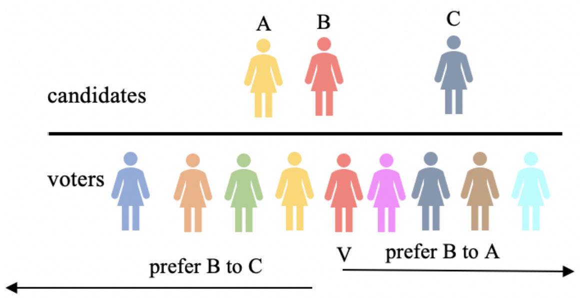

Figure 1 shows that assuming there are three candidates and an odd number of voters (9) whose opinions are distributed along a spectrum, and assuming that each voter ranks the candidates in an order of proximity such that the candidate closer to the voter receives their first preference, the next closest receive their second preference and so on. Then there is a median voter and the election be won by the candidate closest to the median voter. Consider that the median voter is Vivian. The candidate closest to her will receive her first preference vote. Suppose that this candidate is Beāte and that she lies to Vivian's left. Then Vivian and all voters to her left will prefer Beāte to all candidates to her right, and Vivian and all voters to her right will prefer Beāte to all candidates to her left. Referring to the Condorcet theorem, that any candidate who is preferred to every other candidate by a majority of the electorate will be the winner, suggests that Beāte will win any election using a Condorcet method, hence under any voting method which satisfies the Condorcet criterion, the winner will be the candidate preferred by the median voter (Gehrlein & Valognes, 2001).

2.1.4. Nash Bargaining Solution

Nash Bargaining Solution is among the two cooperative collective decision-making techniques selected for further investigation. It is a cooperative collective decision-making strategy presented by John Forbes Nash in 1950. If there exists a threat point far outside the range of the decision-makers' policy positions, (also called the disagreement point), the value that the decision-makers can expect to receive if the negotiations break down, then the decision-makers will give in on the basis of the salience (steepness of utility functions) and power (fairness). It is called the Nash bargaining solution, which can be approximately computed as a weighted mean of the policy positions, considering that the weights are salience and power. There are a few conditions that must be met in order for the Nash bargaining solution to work. The first is that the rescaling of the linear utility functions does not affect the outcomes, the second called pareto-optimality is fulfilled when an outcome is only viable if no actor suffers utility losses. The third condition called anonimity is met when the outcome does not change even when the policy positions are mixed in the utility functions. Last, independence of the irrelevant alternatives has to be fulfilled, meaning that between any two alternatives *A* and *B* depend only on the individual preferences between *A* and *B*, not on individuals' preferences over other alternatives (Nash, 1950).

2.1.5. Vote Trading

Vote trading is a cooperative collective-decision making model which involves casting a vote on a proposal, a position on a more general topic, or a preferred candidate in the manner desired by the other person in return for the other person's vote on another bill, plan, or candidate (Riker & Brams, 1973). Vote trading is not a formal procedure in almost all voting systems, so it is mostly unofficial and often not binding. The Compromise of 1790 was one of the earliest examples of vote-trading in the United States, when Thomas Jefferson made a bargain with James Madison and Alexander Hamilton to move the capital from New York to a location along the Potomac River after it had been in Philadelphia for too long, in return for the federal government taking on the states' debts from the Revolutionary War (Kiewiet, 2003).

2.2. Artificial intelligence

Relating group decision-making theories to Artificial Intelligence requires an explanation of what it includes. Artificial intelligence (AI) is a computer system or algorithm that can perform many human mental tasks that require intelligence, such as creating computer programs, arithmetic, common sense reasoning, language comprehension, and even driving a car (Nilsson, 2014). There are different domains of Artificial Intelligence that were included in the systematic review to broaden the scope of the analysis, these aspects include, machine learning, expert systems, knowledge engineering and agent-based modeling. Machine learning aims to answer the question of how to create machines that learn on their own (Jordan & Mitchell, 2015). An expert system is a computer program that simulates the judgment and behavior of a human or an organization with expert knowledge and expertise in a particular field using artificial intelligence (AI) technologies (Jackson, 1986).

Knowledge engineering is a branch of artificial intelligence (AI) that develops rules to apply to data in order to mimic a human expert's cognitive process. It examines the structure of a task or a decision in order to determine how a result is arrived at (Studer et al., 1998). Computer models that seek to represent the behavior of individuals in a given context are known as agent-based models. They are more intuitive than mathematical or statistical models because they represent items as we experience them in the world: as distinct individuals (Janssen & Ostrum, 2006).

Computational social choice is an interdisciplinary area of research that bridges the gap between social choice theory and computer science, allowing for a two-way exchange of ideas. On one side, it is related to the application of computer science principles to the study of social choice processes such as voting procedures or equal division algorithms, such as complexity analysis or algorithm design. Computational social choice, on the other side, is concerned with bringing ideas from social choice theory into computing. In other words, computational social choice combines concepts from a variety of fields, including computer science, artificial intelligence, logic, political science, and economic theory. Despite a few forerunners experimenting with algorithms in the 1960s to find secure matches between two groups of people with preferences, and strategic manipulation prevention by machine in voting systems being studied in the 1980s, the computational social choice is a relatively new research area that arose in the early 2000s (Brandt et al., 2016).

3. RESEARCH METHOD: SYSTEMATIC LITERATURE (REVIEW)

The main research method was a Systematic Literature Review (SLR), which is a method for locating, appraising, and collating all relevant and available studies on a specific research question, topic, or phenomenon (Kitchenham, 2004). This research technique will provide a systematic and unambiguous overview of the evidence that is currently accessible. It will also aid in identifying research gaps in current knowledge of the subject investigated. This method was also chosen because of its ability to eliminate researcher bias and the potential to expose any methodological flaws in research papers that may be used to improve future work in the field. The methods of the PRISMA systematic literature review statement is used. First, the identification of information sources. All databases, registers, websites, organizations, reference lists, and other sources searched or consulted to identify studies and the date when each source was last searched or consulted will be specified. Second, the full search strategies for all databases, registers, and websites, including any filters and limits used will be presented. The methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process will be specified. The methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process will be specified. All outcomes for which data were sought will be listed and defined. All results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses) will be specified. The methods used to assess the risk of bias in the studies will be described. The results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, will be described. Included studies will be cited and their characteristics presented. (Moher et al., 2009). The purpose of analyzing a range of scientific literature is to highlight the disparities in perspectives that the analysts have when associating Artificial Intelligence and collective decision- making, as well as examining how common it is for the two concepts to be associated.

An overview of the data selection method is provided in Figure 2. The number of articles that were included and excluded can be seen in this overview. A brief and general explanation of the reasons for these decisions has also been provided. The sections that follow provide a full explanation of how the articles were chosen.

3.1. Preparing the Systematic Literature Review

Stage 1: Preliminary search

The preliminary search was conducted to grasp the core ideas of the concepts studied and to gain insight in order to construct the search string. In addition, this step also offered relevant literature for the introduction and theory chapters of this thesis. Mainly two academic databases: Scopus and Web of Science were used to conduct this search. Furthermore, sources such as blogs, media articles and reports were frequently used to study the concepts from various perspectives.

Stage 2: Search string:

The review was performed using two academic databases Scopus and Web of Science following the Systematic Literature Reviews (PRISMA) guidelines. Two primary search terms Artificial Intelligence (AI) and collective decision-making were used to find articles tying these two concepts together. Various secondary search terms discussed in theoretical framework chapter serving as alternative wording of collective decision-making such as social choice; Condorcet's Paradox, Arrow's theorem; Black's Single-Peakedness Theorem; Nash bargaining solution; Vote Trading and Expert Systems; Machine Learning; Agent-Based Modelling; Knowledge Engineering were used as alternative wording to AI. This inclusion resulted in different types of articles concerning the implementation of the two concepts in various contexts.

The following search queries were used
Scopus: TITLE-ABS-KEY ((“collective decision-making” OR “social choice” OR “Condorcet's paradox” OR “Arrow's Theorem” OR “Black's Single-Peakedness Theorem” OR “Nash Bargaining Solution” OR “Vote Trading”) AND (“Artificial Intelligence” OR “AI” OR “Expert System*” OR “Machine Learning” OR “Agent-Based Modelling” OR “Knowledge Engineering”))

Web of Science: AB= ((collective decision-making OR social choice OR Condorcets paradox OR Arrows Theorem OR Blacks Single-Peakedness Theorem OR Nash Bargaining Solution OR Vote Trading) AND (Artificial Intelligence OR AI OR Expert System* OR Machine Learning OR Agent-Based Modelling OR Knowledge Engineering))

The asterisk (*) is applied for including articles that use the plural denomination. The search strings were applied on the 1st of June 2021, in the title, abstract, and keywords on two of the most used search platforms for peer review scientific articles in this context: Scopus and Web of Science (Falagas et al., 2008). This search resulted in total of 450 documents in Scopus and 1.169 documents in Web of Science. Nonetheless, the majority of the documents in the collection were extraneous to this literature study, necessitating screening. The article source and selection methodology used in this study is summarized in Table 3.

Figure 2
Overview data selection

Filters:
- Document types: conference papers; articles, conference reviews, reviews
- Language: English
- Area: social sciences, decision sciences, business, arts and humanities, computer sciences, mathematics, engineering
- Publication years: everything up to June 2021

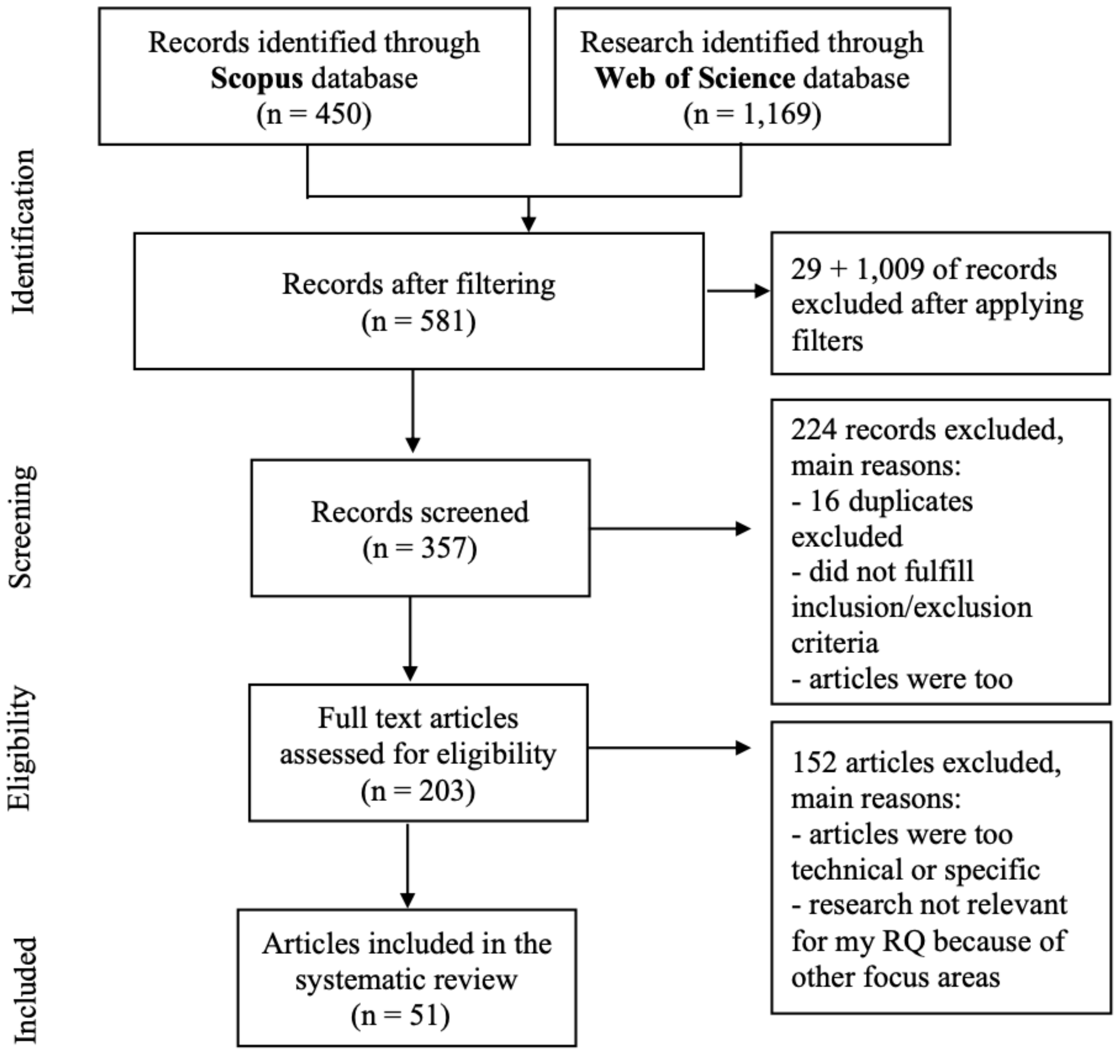

Table 2
Overview literature sourcing and selection protocol

Selection	Inclusion/exclusion criteria	Rationale
1. Search string	• social choice	To gain understanding about different social choice theory paradigms and their relatedness to AI
Inclusion	• Condorcet's paradox	This term views the collective decision-making from another approach
	• Arrow's Theorem	This term provides an additional insight in the complex collective decision-making process
	• Black's Single Peakedness Theorem	This term was used as an addition to Condorcet's paradox.
	• Nash Bargaining solution	This term considers another cooperative collective decision-making strategy.
	• Vote Trading	To explore and examine yet another cooperative collective decision-making technique.
	• Expert system*	Necessary to broaden the spectrum of AI search results.
	• Machine learning	Used to obtain knowledge of a specific AI subsector and broaden the scope of research.
	• Agent-based modelling	Necessary as it covers the exact dimension of AI responsible for decision-making.
	• Knowledge engineering	Used as an alternative wording for AI to broaden the search results.
Exclusion	• Artificial Intelligence/ Collective decision-making (on its own)	Too broad with too many results, more specific in combination with other selected search terms.
	• Artificial decision-making	Including this term resulted in many off-topic literature.
	• Decision making software	Including this term resulted in literature that did not help answering the RQ.
2. Selection of literature	English language literature	The systematic literature must be written in English.

		Peer-reviewed journals, conference papers, conference reviews, reviews	Due to the concerns that the research regarding the topic is limited and the aim to analyze various opinions, “grey” literature was included as well.
3.	Selection of time range	All available published literature from databases Scopus and Web of Science up to June 2021	This time span encompasses all possible literature from the start of the paradigms through the conclusion of the review. This time span was thought to be adequate for capturing all key factors, including paradigm evolution.
4.	Literature selected from the search results	Literature discussing different approaches and aspects of Artificial Intelligence for collective decision-making	This criterion will identify the first sub question to answer the RQ.
		Literature related to the practices of using AI for collective decision-making	The practices show how the use of AI is implemented in the decision-making process. It is interesting to explore and identify which theories and paradigms of collective decision-making are replaced by AI.
		Literature related to solving the collective decision-making problems through the use and application of AI	This criterion will identify the second part of the research question and help to grasp how the use of AI help solving the complex issues that arise in collective decision-making.

Stage 3: Filtering:

The document type has been filtered to article, conference paper, conference review and review in both databases Scopus and Web of Science. There were mainly two reasons for including literature published outside the traditional academic publishing (grey literature) that is considered to have lower credibility levels. The first is the concern that due to the relatively novel concept of AI and its implementation in different fields as well as the specification of the field, there might not be many articles to review. The second reason is the aim to analyze the two concepts from as various perspectives as possible. The thesis is written in accordance with Management, Society, and Technology Bachelor program. Therefore, a deliberate choice was made to focus on the different areas of social sciences, decision sciences, business and management, arts and humanities to study the collective decision-making aspect. On the other hand, computer sciences, mathematics and engineering were all filtered areas to cover the AI aspect.

All documents that were not in the English language were excluded as this thesis must be written in English. First, all the citation information of the dataset after applying filters is exported to an Excel file covering both Scopus and Web of Science literature. It resulted in a total of 581 records. Within this excel data set 16 records were identified as duplicates between Scopus and Web of Science, they were removed.

3.2 Conducting the Systematic Literature Review

Stage 4: First reading (screening):

In this stage, a total of 581 articles have been assessed with the inclusion and exclusion criteria (Table 2). Then the title, abstract and keywords were screened for 357 articles. When reading the title, keywords and abstract of the records, relevant articles were marked with ‘1’, whereas not relevant articles that did not fulfill the selection criteria were marked with ‘0’. In case when there was not enough information provided in the title, abstract or keywords to fully assess whether this document is useful for this research, it was marked with ‘2’for further full text reading in the next stage of this review. Additionally, a brief description oft the reasons for the inclusion or exclusion of each article was made.

Stage 5: Second reading (eligibility):

The second reading involves the full-text reading of 203 documents out of which 51 potential sources of literature were identified for this study. This corpus of qualifying articles was thoroughly read and analyzed based on the introduction, methodology, findings, and other sections as needed. In addition, each paper has been summarized in order to identify and underline the most important aspects. A publication was included in the final corpus if it met the inclusion criteria and provided useful information for answering the research question. In total, 51 records were included whereas 16 articles appeared in both searches and are therefore seen as double.

4. FINDINGS

The systematic literature review was carried out to answer the research question of how Artificial Intelligence could be used to improve existing models of collective decision making. A mixture of hard- and soft aspects will be shown to describe what are the approaches of AI that could potentially improve collective decision-making and how exactly would the collective decision-making models could benefit from the introduction of AI. First, an overview with descriptive methods of the resulting papers will be displayed. Second, the aspects of AI and the different collective decision methods tied with AI in literature will be described.

4.1. Description of the Corpus

Various tables and figures are offered in the next part to help visualize the results of the systematic literature review. Table 3 was created to categorize the items in the corpus. This table is based on the format used by Bhamra et al. (2020); changes have been made to emphasize the thesis' classification relevance. Table 4 shows an overview of the corpus' articles, specified by research type, methodology and research approach.

The sub-heading 'Mixed' refers to a mixed research approach. According to Johnson et al. (2007), a mixed research approach is one that merges principles of both qualitative and quantitative research methods, for instance by using qualitative data collection methods and analysis to develop a broader insight of the topic.

To ensure transparency of the findings, the data in Table 4 is summarized in additional Table 4 below. Table 5 identifies the number of reports used and their percentage. As each article may contribute to one or more areas, the totals do not add up to 100% for each area. The differences between the types of research chosen are not remarkable. However, there are significant differences in the types of methodology and approach used. The most widely utilized methodology is conceptual (90 percent) The reason for this can be attributed to AI's complexity as a concept; as stated in the introduction, it lacks a clear definition, making it difficult to connect with social choice theories and generate case studies or comparative analyses. The most widely applied research approach is quantitative (80%). This may be based on the fact that AI is a concept widely investigated in computer science and mathematical domains, therefore researchers are more likely to deal with quantitative data rather than qualitative data.

Table 3
Research, methodology and approach in the corpus consisting of 51 articles

Research				Methodology			Approach		
Authors	Exploratory	Descriptive	Explanatory	Conceptual	Case study	Comparative	Qualitative	Quantitative	Mixed
(Airiau, et al., 2017)		x		x				x	
(Amodio et al., 2016)			x	x				x	
(Azzini & Munda, 2020)			x	x				x	
(Bistarelli et al., 2019)		x		x				x	
(Borodin et al., 2019)			x	x				x	
(Brandl et al., 2018)	x					x		x	
(Bredereck et al., 2021)		x		x				x	
(Caragiannis et al., 2017)			x	x				x	
(Chen et al., 2019)	x			x				x	
(Chevaleyre et al., 2008)	x			x					x
(Conitzer, 2019)		x		x				x	
(de Callaos, 1994)		x		x				x	
(de Haan et al., 2020)		x		x			x		
(Dehghanpour & Nehrir H, 2018)			x	x				x	
(Dehghanpour & Nehrir, 2019)			x	x				x	

(Elkind E et al., 2021)	x			x				x	
(Elkind & Leyton-Brown, 2010)		x		x					x
(Endriss, 2011)	x			x				x	
(Fain et al., 2019)			x	x				x	
(Filatova & Baratgin, 2018)	x			x					x
(Fitzsimmons & Hemaspaandra, 2016)			x	x				x	
(Garcia & Riedl, 2013)	x			x				x	
(Gershtein et al., 2019)		x		x				x	
(Grandi & Endriss, 2011)			x	x				x	
(Haret et al., 2018)	x			x				x	
(Jiao et al., 2017)			x	x					x
(Kimelfeld et al., 2018)			x	x				x	
(Kirsch, 2019)		x		x				x	
(Kucakowski, 2016)	x			x				x	
(Lepskiy et al., 2018)			x	x				x	
(Li & Vo, 2012)			x	x				x	
(Madani et al., 2014)	x			x				x	
(Maushagen & Rothe, 2020)	x			x				x	
(Maynard-Zhang & Lehmann, 2003)		x		x				x	

(McHugh et al., 2016)	x				x				x
(Mogos et al., 2015)	x					x		x	
(Mossel & Racz, 2012)			x	x				x	
(Neveling & Rothe, 2021)	x			x				x	
(Novaro et al., 2018)	x			x				x	
(Pal & Bandyopadhyay, 2019)	x				x				x
(Petcu et al., 2008)		x		x				x	
(Pigozzi, 2006)		x		x			x		
(Pigozzi et al., 2016)		x		x				x	
(Pournaras, 2020)			x	x				x	
(Prasad, 2019)	x			x			x		
(Pujari & Kanawati, 2012)		x		x				x	
(Rossi, 2014)			x	x				x	
(Teng et al., 2018)			x	x				x	
(Werbin-Ofir et al., 2019)	x			x				x	
(Zhang et al., 2019)			x	x				x	
(Zucker, 2020)	x					x			x

Table 4

Summary of research, methodology and approach in the corpus consisting of 51 literature reports

Research			Methodology			Approach		
Exploratory	Descriptive	Explanatory	Conceptual	Case study	Comparative	Qualitative	Quantitative	Mixed
19 (37%)	14 (27%)	18 (35%)	46 (90%)	2 (3%)	3 (5%)	3 (5%)	41 (80%)	7 (13%)

Figure 3 shows the distribution of collective decision making and Artificial Intelligence articles in the corpus in all publication years up and to June 2021. The study shows that before 1994 no relevant papers were published within our defined research boundaries. Interestingly, most articles were found between the years 2016 and 2020, especially in year 2019, a significant amount of 12 articles was found. This finding stresses the relevance of this thesis's topic by other scholars.

Figure 3
Distribution of the 51 selected articles (corpus) by year

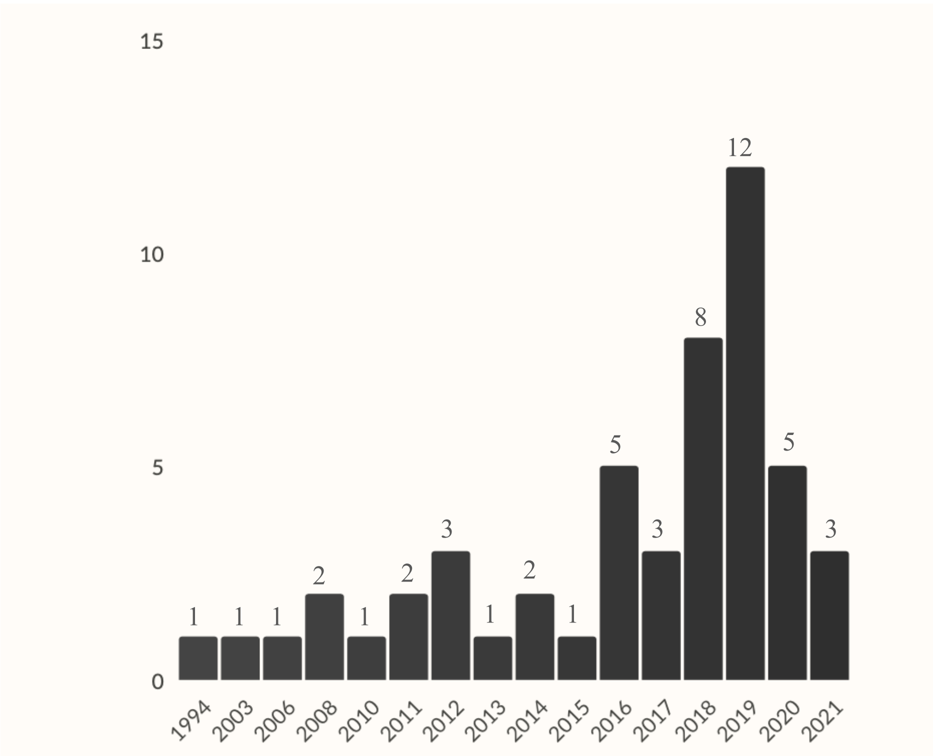

Figure 4 presents the distribution of articles in the subject domains. As expected, most articles (47) were related to the computer sciences sector since AI has its roots in computer science and is still active within this sector. Besides, in total, two articles were also in the context of the two articles were written in the mathematics sector, which is strongly related to the computer science. In addition, two articles were chosen from the decision sciences area, thereby indicating that AI and decision making are related.

Figure 4
Distribution of 51 selected articles (corpus) by sector

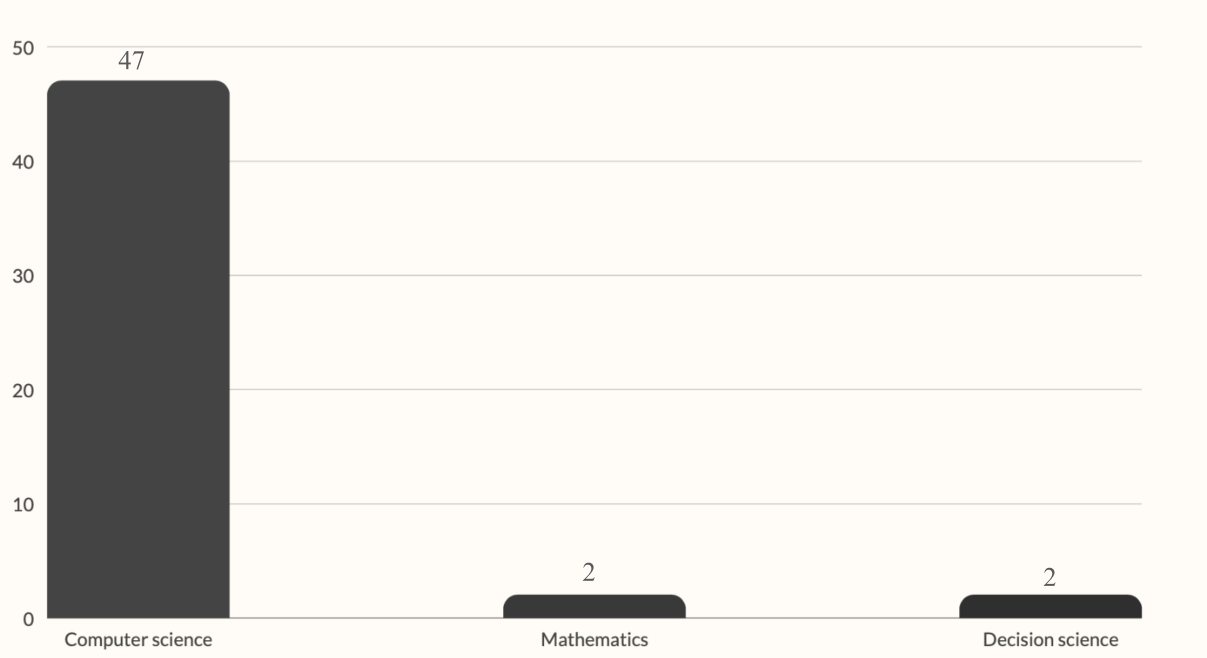

Table 5 shows an overview of the distribution of articles relating collective decision-making and AI, specified per document and source type. The journals and conference papers are shown in a descending way. Most articles were found in the 'Journal of Artificial Intelligence Research' (3), followed by 'Journal of Artificial Intelligence' (3) and 'AI Magazine' (3). The other journals cover two or fewer articles. Most conference papers were retrieved from 'The Thirty-Third AAAI Conference on Artificial Intelligence 2019' (5), followed by 'Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence 2018' (4) and 'Frontiers in Artificial Intelligence and Applications' (3). The rest of the selected conference proceedings cover just 1 conference paper.

Table 5
Journal distribution of the 51 articles related to the literature combining collective decision-making theories and various aspects of AI.

Document type	Source	Total
Article	Journal of Artificial Intelligence Research	5
	Journal of Artificial Intelligence	3
	AI Magazine	3
	European Journal of Operational Research	2
	IEEE Transactions on Smart Grid	2
	Annals of Mathematics and Artificial Intelligence	2
	Cognitive Processing	1
	Combinatorica	1
	Constraints	1
	Episteme	1
	Expert Systems with Applications	1
	Journal of Parallel and Distributed Computing	1
	Mobile Networks and Applications	1
	The Leadership Quarterly	1
		25
Conference paper	The Thirty-Third AAAI Conference on Artificial Intelligence 2019	5
	Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence 2018	4
	Frontiers in Artificial Intelligence and Applications	3
	34th AAAI Conference on Artificial Intelligence	1
	31st International Conference on Tools with Artificial Intelligence	1
	ACM International Conference Proceeding Series	1
	Proceedings of the 2018 IEEE Symposium Series on Computational Intelligence	1
	2018 11th International Conference on Human System Interaction	1
	Proceedings of 2018 11th International Conference Management of Large-Scale System Development	1
	The 2016 3rd International Conference on Systems and Informatics	1
	20th International Conference on Control Systems and Science	1
	2014 IEEE International Conference on Systems, Man, and Cybernetics	1
	2013 IEEE 25th International Conference on Tools with Artificial Intelligence	1
	2012 IEEE 24th International Conference on Tools with Artificial Intelligence	1
	The European Future Technologies Conference and Exhibition 2011	1
	Proceedings of the Twenty-Second International Joint Conference on Artificial Intelligence	1
	Proceedings of the IEEE International Conference on Expert Systems for Development	1
		26

4.2. Summary of findings

Table 6 was created to categorize the selected documents by the type of collective decision-making theory used to related them to various aspects of AI. Condorcet's paradox (21) is the most commonly collective decision-making theory applied to AI algorithms, followed by Election theories (15) and Arrow's Impossibility theorem (10). Documents related to multiple collective decision-making theories are included. Collective decision-making refers to articles that do not make use of specific theories. Others refer to other social choice theories that were not discussed in the theoretical framework of this thesis.

Table 6

Types of collective decision-making theories applied to Artificial Intelligence in documents

Collective decision-making theory

Authors	Collective decision	Condorcet's paradox	Arrow's theorem	Black's theorem	Nash bargaining	Others
(Airiau, et al., 2017)	x					
(Amodio et al., 2016)		x	x			
(Azzini & Munda, 2020)		x				
(Bistarelli et al., 2019)						x
(Borodin et al., 2019)		x		x		x
(Brandl et al., 2018)		x				
(Brederek et al., 2021)						x
(Caragiannis et al., 2017)			x			
(Chen et al., 2019)						x
(Chevaleyre et al., 2008)			x			
(Conitzer, 2019)						x
(de Callaos, 1994)			x			
(de Haan et al., 2020)	x					
(Dehghanpour & Nehrir H, 2018)					x	

	Collective decision	Condorcet's paradox	Arrow's theorem	Black's theorem	Nash bargaining	Others
(Dehghanpour & Nehrir, 2019)					x	
(Elkind E et al., 2021)						x
(Elkind & Leyton-Brown, 2010)						x
(Endriss, 2011)		x				
(Fain et al., 2019)	x				x	
(Filatova & Baratgin, 2018)			x			
(Fitzsimmons & Hemaspaandra, 2016)		x		x		x
(Garcia & Riedl, 2013)		x				
(Gershtein et al., 2019)		x				
(Grandi & Endriss, 2011)			x			
(Haret et al., 2018)		x		x		
(Jiao et al., 2017)		x				
(Kimelfeld et al., 2018)		x				
(Kirsch, 2019)		x				
(Kucakowski, 2016)		x	x			x
(Lepskiy et al., 2018)	x					
(Li & Vo, 2012)		x				
(Madani et al., 2014)					x	

	Collective decision	Condorcet's paradox	Arrow's theorem	Black's theorem	Nash bargaining	Others
(Maushagen & Rothe, 2020)						x
(Maynard-Zhang & Lehmann, 2003)		x	x			
(McHugh et al., 2016)	x					
(Mogos et al., 2015)		x	x	x		x
(Mossel & Racz, 2012)		x	x			
(Neveling & Rothe, 2021)						x
(Novaro et al., 2018)	x					
(Pal & Bandyopadhyay, 2019)					x	
(Petcu et al., 2008)					x	
(Pigozzi, 2006)		x				
(Pigozzi et al., 2016)	x					
(Pournaras, 2020)	x					
(Prasad, 2019)		x				
(Pujari & Kanawati, 2012)		x				x
(Rossi, 2014)						x
(Teng et al., 2018)	x					
(Werbin-Ofir et al., 2019)						x
(Zhang et al., 2019)	x					
(Zucker, 2020)		x				
Total	10	21	10	4	6	15

Table 7 summary of the findings

provides a summary of the findings to help answer the research question. In five separate columns, the findings of how approaches of Artificial Intelligence can employ Condorcet's paradox, Arrow's theorem, Black's Theorem, Nash bargaining solution and election theories will be shown. The gaps in the table indicate that there was no application of a specific AI approach to a collective decision-making theory reported in the literature.

	Modes of collective decision-making				
Approaches of AI	**Condorcet's Paradox**	**Arrow's Theorem**	**Black's Theorem**	**Nash Bargaining**	**Others**
Reliability	Condorcet winner used as a desired property to develop and algorithm for carrying out tests of approval voting (Gershtein et al., 2019).	Using Arrow's theorem to find factors in AI algorithms that cause biases in reasonings (Filatova & Baratgin, 2018).	Making use of Black's single-peakedness theorem to investigate the reliability of direct and primary voting systems (Borodin et al., 2019).	Using the theory of Nash bargaining solution to develop algorithms to aim for a consensus reaching (Pal & Bandyopadhyay, 2019)	Combining search with dynamic programming to develop algorithms that can predict whether election has a winning committee (Bredereck et al., 2021).
Complexity	Artificial Intelligence algorithms typically consist of many components which ensures the ability to work with complex problems (Neveling & Rothe, 2021).				
Cognitive ability	Artificial Intelligence possesses higher cognitive abilities than humans which can help all modes of decision making (Pournaras, 2020).				
Efficiency	The efficiency aspect of AI ensures its ability to solve Condorcet cycles (Azzini & Munda, 2020).	The use of Arrow's Theorem basis to develop algorithms which make pair wise comparisons more efficient to enhance priority deriving procedure (Kucakowski, 2016).	Using Black's single-peakdness theorem to study social ranking and aim to develop an efficient solution (Haret et al., 2018).	Nash bargaining solution is employed to develop a model for optimized decision-making power distribution (Dehghanpour & Nehrir, 2019).	Using AI algorithms to make various analyzes and tests less time-consuming (Maushagen & Rothe, 2020).
Operationalization	Using AI to operationalize large	Using Arrow's impossibility theorem to develop an algorithm to change the			

	numbers of alternatives in ranking procedure which help solving Condorcet's paradox (Azzini & Munda, 2020).	normative approach of voting aggregation into a quantitative one (Caragiannis et al., 2017).			
Filling in gaps			Using Black's single peakedness theorem to develop and algorithm that helps solving a tie between the most preferred alternatives (Fitzsimmons & Hemaspaandra, 2016).		
Providing new insight and strengthening evidence	Developing algorithms to solve messy voter sets and, in that way, strengthen the evidence that has been already proved (Zucker, 2020).	Using Arrow's Impossibility theorem to interpret the results of a comparison between three AI algorithms (Mogos et al., 2015).	Making use of Black's single-peakdness theorem to develop an algorithm for comparing algorithms (Mogos et al., 2015).		Making use of Borda count to develop algorithms that help comparing different voting strategies and outcomes (Werbin-Ofir et al., 2019).
Human behavior imitation	Condorcet theories offer useful insights on solving the value alignment problem of successfully aligning AI behavior with human values (Prasad, 2019).				Using game theory to develop argumentation algorithms to model human behavior in simulations (Bistarelli et al., 2019).
Interdisciplinarity	AI in collective decision-making consists of a combination of multiple academic disciplines (Fain, 2019). Experts from multiple scientific domains are cooperating to develop algorithms for optimized collective decision-making (Pournaras, 2020).				

4.3. Approaches of AI

Having thoroughly analyzed the 51 documents in this literature review that relate Artificial Intelligence and collective decision-making, nine key approaches of AI that either have the potential to contribute to collective decision-making or have already proven to be beneficial have been identified. It could be argued that all of them are interrelated and what refers to reliability can be similarly applicable to complexity or vice versa which is largely true. The reason for distinguishing these individual approaches is to provide additional insight and reflect more accurately on the information gathered in the systematic review.

4.3.1. Reliability

The more data you gather for developing deep learning algorithms the more advanced and reliable they become. What makes AI particularly reliable is the notion that reliability is grounded on predicting future actions based on the past (Ryan, 2020). This is particularly relevant to decision-making strategies as algorithms are able to look at the preferred alternatives or candidates based on, for instance, the decision-maker political beliefs, interests or aims in the past to predict their desired outcome in the future. Similarly, the algorithms could develop patterns about the outcome of the election based on different factors (e.g. candidate's standpoint on the political spectrum) to try to determine the outcome of the election. Systematic algorithm development, computation, and application to various decision-making strategies is in its nature transparent, allowing room for close investigation of previously used algorithms, their pitfalls and it provides room for improvement. Next, AI is reliable due to its ability to combine the search process with dynamic programming to perform tests and find correlations, assessing whether there is truth to the algorithms (Bredereck et al., 2021). These tests could help could contribute to the development of better algorithms suitable for more optimal decision-making, for instance, they could potentially advance to work around Arrow's impossibility theorem.
Furthermore, AI assesses large quantities of data systematically, following a consistent pattern that completely excludes cognitive biases and avoids human error. Cognitive biases and human errors are important pitfalls of collective decision-making strategies, the voters might accidentally confuse, mix up or misinterpret the information that is significant for preference order, which, in turn results in biased outcomes.

4.3.2. Complexity

In this case, complexity as an approach of AI refers not only to the notion that Artificial Intelligence is a very complex computer science subfield that involves many different facets, but also its ability to detect, analyze and investigate complicated problems and aim to develop algorithms to derive solutions. A general notion has been made Neveling and Rothe, stating that Artificial Intelligence algorithms typically consist of many components which ensure the ability to work with complex problems (Neveling & Rothe, 2021). These components involve AI's ability to understand and work with both spoken and written language, the ability to form concepts, perceive and analyze visual data, model the representation of algorithms, follow established rules and others (Pannu, 2015). All of the above mentioned components can be perceived as requirements for AI that must be fulfilled in order to develop algorithms that can assist the decision-making process. There is the necessity for language skills to determine what the preferred alternatives are, visual data analysis to interpret the schemes and tables of different preference orderings (e.g. linear and spatial), for following the rules to ensure fairness. This wide scope of AI complexity is what makes it particularly applicable to collective decision-making.

4.3.3. Cognitive abilities

Cognitive skills are central nervous system capabilities that are required to complete every task, from the basic to the most difficult. They have less to do with actual information but everything to do with the processes of how we absorb, memorize, resolve issues, and pay any attention. Answering calls, for example, requires perception (hearing the ring tone), decision-making (answering or not), motor skill (raising the receiver), language abilities (speaking and understanding language), and social skills (interpreting tone of voice and interacting properly with another human being) (Ones et al., 2010). According to Pournaras, due to its nature, Artificial Intelligence possesses higher cognitive abilities than humans which can help all modes of decision making (Pournaras, 2020). This aspect of AI can be applied to collective decision-making since it implies that algorithms serve as a tool to absorbing and memorizing information crucial for either choosing the preferred alternative/ candidate or ordering these preferences, as well as paying close attention to what the other involved parties have decided.

4.3.4. Efficiency

Efficiency is usually used to assess the performance of an outcome. It comes as no surprise that AI based decisions would be considered more efficient in every aspect. First, time efficiency could be considered. AI can be very helpful in improving the data analyzing speed and increasing the reporting time. In case group decision-making (e.g., parliamentary elections) were computer-based, the process of counting the votes would not exist, the results would be immediate. Second, unlike humans, AI does not need to rest, and they can provide their service 24 hours a day. Third, this is also strongly tied to resource efficiency. If different decision-making bodies from every involved subfield to make a strategic decision would have to be involved, the costs would be high, luckily, we can replace it with an algorithm. These are the most important factors indicating why the efficiency approach would have the potential to contribute to AI.

4.3.5. Operationalization

While in the scientific research domain, operationalization refers to the process of turning abstract data into measurable variables, it has a different connotation in this context. The collective decision-making models involve mathematical calculations which get more and more complex with every additional decision-maker involved and every alternative presented. While it might not be difficult to compute them when there is, for example, a set of three alternatives to choose from, there are cases when the numbers of alternatives are so large, they must be operationalized using AI algorithms to ensure that either the human brain can work with them, or they can be further used to perform tests or analyze the results of the mathematical calculations (Azzini & Munda, 2020).

4.3.6. Filling in gaps

Filling in gaps is another indirectly implied approach of AI found in the documents. In this case, it refers to the ability of AI to use one or multiple of its many aspects to fill in the missing information for successful execution of a plan. An example is provided by Zucker (2020) when the author presents an algorithm that deals with the intransitivity property. In short, intransitive sets of votes produce cycles that cannot be typologically sorted to produce a unique order.

Another aspect highlighted by Zucker is the AI's ability to resolve incompleteness through finding patterns to work around missing information (Zucker, 2020).

4.3.7. *Providing new insight and strengthening evidence*

Developing new algorithms based on mathematical decision-making theories to either broaden the knowledge about a specific topic, sort the information in transparent categories, use it to solve problems or even to perform tests and simulations for comparison lie at the core of the 51 selected documents in the literature review. Teng (2018) shows the different aspects of providing insight that AI could take by using algorithms to express the degree of voter satisfaction with the presented outcomes (Teng et al., 2018). On the other hand, AI could also contribute to strengthening the already existing evidence through performing new tests and comparisons. To give an example, Werbin-Ofir et al., propose an aggregation method for comparing the best voting rule to be used in each setting (Werbin-Ofir et al., 2019).

4.3.8. *Human behavior imitation*

Although human behavior imitation might sound like it is overlapping cognitive abilities, the researchers take a slightly different approach. In this case, the focus is moved from incorporating cognitive abilities in AI to describing and examining ways in which AI serves as a tool of overcoming human limitations. This approach was selected due to Lepskiy et al., defining Artificial Intelligence as a tool for supplementing the human brain (Lepskiy et al., 2018). As reported by Rossi (2014), there is a possibility to apply machine learning algorithms to game theory to contribute to optimized conflict resolution. Humans can remember every step of the game and there is no way to force them to forget the past steps which result in complicated situations, whereas it is possible to make an algorithm disregard the past moves of the players (Rossi, 2014).

4.3.9. *Interdisciplinarity*

The last key approach potentially contributing to collective decision-making as identified in multiple literature review sources is interdisciplinarity. In this context, interdisciplinarity is referred to as the practice of combining knowledge from different fields. Artificial Intelligence is capable of creating instant bridges between the experts of one research field to another to synthesize relevant information develop specific algorithms. According to Lepskiy et al., fields such as philosophy, sociology, law, quantum physics, mathematics are just a small part of all the required knowledge bases involved to successfully synthesize information and achieve collective decision-making (Lepskiy et al., 2018).

4.4. Benefits from AI to modes of collective decision-making

Various ways in which modes of collective decision-making could benefit from the application of AI have been found in the literature. Descriptions of how exactly AI facilitates the decision-making process through each social choice theory are provided.

4.4.1. Condorcet's paradox

As discussed earlier in the theory section of this thesis, Condorcet method refers to an election technique that elects the candidate who receives most votes and is favored by more voters than all others called the Condorcet winner (Shepsle, 2010). According to de Haan et al. (2020) algorithms can be used to determine the outcome of this election technique (de Haan et al., 2020). However, there are instances when the winner of a pair wise comparison is not clear. These cases are referred to as Condorcet paradox, which occurs when there is no winner alternative, and the collective preferences develop a cycle even when the individual preferences are not cyclic (Shepsle, 2010). Multiple authors have presented how AI algorithms can solve this paradox (Azzini & Munda, 2020) (Zucker, 2020). One way to achieve it is by using algorithms to fill in information for incomplete voters sets or solve the messy ones (Zucker, 2020). Furthermore, the theory of Condorcet can be used as a desired property for algorithm development to carry out tests and investigate other voting methods (Gershtein et al., 2019).

4.4.2. Arrow's impossibility theorem

Arrow's impossibility theorem, as indicated in the theoretical section, is a social choice paradox that illustrates the impossibility of establishing an optimal voting structure. In a nutshell, it asserts that a clear order of preferences cannot be established when fair voting norms are upheld (Shepsle, 2010). There is no evidence in the analyzed literature that AI can provide a way to get around Arrow's Impossibility theorem, resulting in a gap in the literature. However, there have been scientific literature studied that executes the theorem to develop further AI algorithms. It might not be beneficial for this mode of collective decision-making, but it contributes to optimization of social choice. Filatova & Baratgin (2018) used the premises of Arrow's theorem to find factors in AI algorithms that cause biases in reasonings and consequences (Filatova & Baratgin, 2018). Kucakowski (2016) made use of the roots of the theorem to develop algorithms for more efficient pair wise comparisons to enhance priority deriving procedure (Kucakowski, 2016).

4.4.3. Black's median voter theorem

If voters and policies are spread along a one-dimensional spectrum, with voters ranking alternatives in order of closeness, any voting mechanism satisfying the Condorcet criterion will elect the candidate closest to the median voter (Shepsle, 2010). There is again no clear solution to this theorem provided in the literature of Artificial Intelligence. Same as with Arrow's impossibility theorem, there are ways mentioned in which this theorem can be applied to improve collective decision-making as such. Borodin et al. (2019) prove that it could be used to investigate the reliability of different voting methods, direct and primary in their case (Borodin et al., 2019). Haret et al., (2018) have investigated how the application of this theory can facilitate the solution of social ranking (Haret et al., 2018). Other authors have analyzed how the use of Black’s theorem can help developing an algorithm that solves a tie between the most preferred alternatives (Fitzsimmons & Hemaspaandra, 2016).

4.4.4. Nash bargaining solution

As opposed to the other three non-cooperative decision-making theories, Nash bargaining solution is a cooperative social choice theory. It is a concept stating that when a threat point exists far beyond the policy positions of the decision-makers, the decision-makers will give in on the basis of salience and power (Nash, 1950). There is only one way reported in literature in terms of how the application of AI can improve this theorem. Algorithms could be applied to identify this threat point (Zhang et al., 2019). Oh the other hand, Nash bragining solution is a desired property in consensus reaching processes as it satisfies the fairness principle (everyone opts to equal benefits). This is the main reason why the theory is applied to algorithm development. Some authors employ the Nash bargaining solution to develop a model for optimized decision-making power distribution (Dehghanpour & Nehrir, 2019).

4.4.5. Collective decision-making generally

This section will provide a brief insight in ways how collective decision-making in general can benefit from the application of Artificial intelligence as reported in the literature. Some reports have examined the application of algorithms to group decision making to first reduce manipulation where an external authority seeks to influence the outcome of elections and second to avoid bribery (Neveling & Rothe, 2021). Other authors have examined the application of algorithms to recounting votes in manipulated districts (Elkind E et al., 2021). Novaro et al., (2018) have studied the possibilities of AI application to provide the ability to make unique decisions and ensure the fairness principle (Novaro et al., 2018). Rossi (2014) has investigated the use of social media platform algorithms (Facebook, Twitter) for collective decision-making (Rossi, 2014).

5. DISCUSSION AND CONCLUSION

5.1. Discussion

This research will allow us to understand what Artificial Intelligence approaches have the potential to contribute to collective decision-making processes, as well as how AI may be used to overcome various social choice theories or to enhance group decision-making generally. We conducted a systematic literature review since it is essential for constructing a unified body of knowledge and guiding future research efforts (Danese et al., 2018). Previous research relating AI and collective decision-making, are scarce, as most of them focus on explaining the ethics and fairness principles, aiming to find how trustworthy Artificial Intelligence is to be used for decision-making (e.g., Baum, 2020; Kim & Song, 2021) while largely neglecting the advantage factor. This study aimed to fill this gap by conducting a systematic literature review with an initial dataset of 1,619 articles that eventually led to a final corpus of 51 relevant articles which were all selected from Scopus database. The results indicate that the research topic has become a point of interest in the last 5 years. Most of the documents have been chosen in the timeframe from 2016 to 2021 (36 documents), as opposed to just 15 documents selected from the years 1994 to 2015. In a broad sense, there were a very few research reports (9) found on the benefits of incorporating AI in group decision-making as such. Furthermore, there were no reports explicitly stating ways in which AI could improve specific decision-making models, hence they were derived from the aims and results of these documents. In the section below, the implications that have been considered as most interesting are highlighted.

There was a lot less literature concerning cooperative decision-making theories than non-cooperative. Vote trading is the practice of voting on a policy, position, or favored candidate in the way of another person's wishes in exchange for them returning the favor (Riker & Brams, 1973). This technique of collaborative social choice technique was included in the search query, however, out of all the scanned and analyzed documents, there was nothing found on this decision-making model. In addition, the other cooperative technique investigated is Nash bargaining solution, although five selected articles had included this theory, the extent was expected to be larger compared to, for instance, Condorcet's paradox which was extensively mentioned in total of 21 documents.

There were 9 key aspects of Artificial Intelligence that have the potential to contribute to collective decision-making recognized the selected documents, namely, reliability, complexity, cognitive abilities, efficiency, operationalization, gap filling, providing, and strengthening evidence, human behavior imitation and interdisciplinarity. All these key aspects are interrelated and could potentially be categorized as one aspect. However, the aim of the distinction is to reflect the exact specifications the authors make and derive the contributions of those aspects to group decision-making. Considering that most of the documents were done in mathematics or computer science fields, there was often no clear transparency found as to how each of the mentioned aspects contribute to either a specific social choice theory or collective decision-making in general. The texts were interpreted and concepts that make up the idea of Artificial Intelligence, for example, machine learning, agent-based modeling, algorithms, and others were closely searched for to derive conclusions.

5.2. Conclusion

This systematic literature review not only revealed ways on how the current theories of collective decision making be improved through inclusion of Artificial Intelligence, but also ways how the theories could be used to enhance the non-cooperative group decision-making process. As reported in the selected literature, out of the three non-cooperative collective decision-making models investigated, Condorcet's paradox, Arrow's impossibility theorem and Black's median voter theorem, Condorcet's paradox or cycles is the only theory that can be solved with the involvement of AI. This is where mainly the previously discussed gap filling characteristic comes in to play as it contributes to the ability of algorithm manufacturing. To answer the research question on how could the different consensus reaching, and voting-based models of collective decision-making be improved through the incorporation of Artificial Intelligence, it was concluded that the algorithms can help the consensus reaching model (Nash bargaining solution), through identifying the threat point and the non-cooperative model (Condorcet's paradox) through solving messy voter sets and filling in missing information (Zucker, 2020, Zhang et al., 2019). AI might not be able to facilitate a solution for these social choice theories, but there are various opportunities discussed how the preliminaries of these group decision theories can contribute to algorithm development to enhance collective decision-making as such. Condorcet's theory can be used as desired property for algorithm development to carry out tests and investigate other voting methods (Gershtein et al., 2019). Arrow's impossibility theorem is helpful in to finding factors in AI algorithms that cause biases in reasonings and consequences (Filatova & Baratgin, 2018). Black's median voter theorem can be used to investigate the reliability of different voting methods, direct and primary in their case (Borodin et al., 2019). And facilitate the solution of social ranking (Haret et al., 2018).

5.3. Practical Implications and Future Work

The findings of this thesis can contribute to a deeper understanding of Artificially Intellect collective decision-making. By mainly incorporating empirical articles in our systematic literature review, practical examples of what the key aspects of AI potentially facilitating the decision-making process are, how they differ and in what ways can AI aim to working around decision-making theories and paradoxes. The practical implications of the results are mainly for policy makers aiming to either understand ways how the decision-making could benefit from the integration of AI or to introduce algorithms for more efficient group decisions. Now, they have a better understanding of where the current progress of AI in decision-making lies; therefore, policy makers are better able to decide whether the research on AI is ripe enough to be integrated or there are whether there still is the potential for improvement.

The future research could be conducted aiming to investigate the relationship between different aspects of Artificial Intelligence and other formal decision-making systems such as range or plurality voting methods, the Delphi method or the dotmocracy to grasp whether the research relating AI and these group decision-making strategies has advanced further. There is also a potential for a qualitative research design that involves interviews with experts on both sides of the research problem, algorithm designers (e.g., computer scientists) and policy makers, to determine whether it is possible to work around the other cooperative and non-cooperative theories and paradoxes.

5.4. Limitations

The limitations of the AI and collective decision-making analysis and the systematic review are discussed separately.

Although the AI and collective decision-making analysis is initiated to be an analysis with limited data available and assumptions that there exist gaps in the literature, there are a few limitations worth mentioning. One of the limitations is that complex mathematical and computer science reports were analyzed which both exceed the scope of my knowledge to accurately assess the reasoning behind the algorithmic calculations and as well as the scope of this research. Another closely tied limitation is that parallels were drawn between two very different fields of research. The theoretical potential from a computer scientist's or mathematician's viewpoint to use AI in collective decision-making or apply it to social choice theories might be very different from the practical opportunities for politicians to use it. This can cause a discrepancy in the appropriateness of the findings.

For the systematic review, the limitation of this thesis arises from the analysis of not only peer reviewed journal articles but also the inclusion of conference papers or "grey literature". This can significantly decrease the credibility of the research since the information provided in conference papers is vaguely put a discussion of research and development by academics rather than a solid, reliable source of the current opportunities provided by AI in collective decision-making. The reliability of the research is negatively affected due to the limited time to conduct the systematic literature review if the time frame was longer, there would have been a possibility to include documents from more databases (e.g., google scholar).

REFERENCES

References with an asterisk (*) are the selected articles of the corpus.

Aikenhead, G. S. (1985). Collective decision making in the social context of science. *Science education*, *69*(4), 453-75.

*Airiau, S., Bonzon, E., Endriss, U., Maudet, N., & Rossit, J. (2017). Rationalisation of profiles of abstract argumentation frameworks: Characterisation and complexity. *Journal of Artificial Intelligence Research*, *60*, 149-177.

*Amodio, S., D'Ambrosio, A., & Siciliano, R. (2016). Accurate algorithms for identifying the median ranking when dealing with weak and partial rankings under the Kemeny axiomatic approach. *European Journal of Operational Research*, *249*(2), 667-676.

Austen-Smith, D. and J. S. Banks, 1996, "Information Aggregation, Rationality, and the Condorcet Jury Theorem." *American Political Science Review,* 90: 34–45

*Azzini, I., & Munda, G. (2020). A new approach for identifying the Kemeny median ranking. *European Journal of Operational Research*, *281*(2), 388-401.

Baum, S. D. (2020). Social choice ethics in artificial intelligence. *AI & SOCIETY*, *35*(1), 165-176.

Bhamra, R., Nand, A., Yang, L., Albregard, P., Azevedo, G., Corraini, D., & Emiliasiq, M. (2020). Is leagile still relevant? A review and research opportunities. *Total Quality Management and Business Excellence*, *0*(0), 1–25. https://doi.org/10.1080/14783363.2020.1750360

Bindseil, U., & Hantke, C. (1997). The power distribution in decision making among EU member states. *European Journal of Political Economy*, *13*(1), 171-185.

*Bistarelli, S., Faloci, F., & Taticchi, C. (2019, November). Implementing Ranking-Based Semantics in ConArg. In *2019 IEEE 31st International Conference on Tools with Artificial Intelligence (ICTAI)* (pp. 1180-1187). IEEE.

Boland, P. J. (1989). Majority systems and the Condorcet jury theorem. *Journal of the Royal Statistical Society: Series D (The Statistician)*, *38*(3), 181-189.

*Borodin, A., Lev, O., Shah, N., & Strangway, T. (2019, July). Primarily about primaries. In *Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 33, No. 01, pp. 1804-1811).

*Brandl, F., Brandt, F., & Stricker, C. (2018, June). An Analytical and Experimental Comparison of Maximal Lottery Schemes. In *IJCAI* (pp. 114-120).

Brandt, F., Conitzer, V., & Endriss, U. (2012). Computational social choice. *Multiagent systems*, 213283.

Brandt, F., Conitzer, V., Endriss, U., Lang, J., & Procaccia, A. D. (Eds.). (2016). *Handbook of computational social choice*. Cambridge University Press.

*Bredereck, R., Faliszewski, P., Kaczmarczyk, A., Niedermeier, R., Skowron, P., & Talmon, N. (2021). Robustness among multiwinner voting rules. *Artificial Intelligence*, *290*, 103403.

Campitelli, G., & Gobet, F. (2010). Herbert Simon's decision-making approach: Investigation of cognitive processes in experts. *Review of General Psychology*, *14*(4), 354-364.

*Caragiannis, I., Nath, S., Procaccia, A. D., & Shah, N. (2017). Subset selection via implicit utilitarian voting. *Journal of Artificial Intelligence Research*, *58*, 123-152.

*Chen, L., Xu, L., Xu, S., Gao, Z., & Shi, W. (2019, July). Election with bribed voter uncertainty: Hardness and approximation algorithm. In *Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 33, No. 01, pp. 2572-2579).

*Chevaleyre, Y., Endriss, U., Lang, J., & Maudet, N. (2008). Preference handling in combinatorial domains: From AI to social choice. *AI magazine*, *29*(4), 37-37.

*Conitzer, V. (2019, July). Designing preferences, beliefs, and identities for artificial intelligence. In *Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 33, No. 01, pp. 9755-9759).

Danese, P., Manfè, V., & Romano, P. (2018). A systematic literature review on recent lean research: State-of-the-art and future directions. *International Journal of Management Reviews*, *20*(2), 579–605. https://doi.org/10.1111/ijmr.12156 Edition),

*de Callaos, B. (1994, March). Artificial organizational intelligence. In *Proceedings of International Conference on Expert Systems for Development* (pp. 55-62). IEEE.

*Dehghanpour, K., & Nehrir, H. (2017). An agent-based hierarchical bargaining framework for power management of multiple cooperative microgrids. *IEEE Transactions on Smart Grid*, *10*(1), 514-522.

*Dehghanpour, K., & Nehrir, H. (2017). Real-time multiobjective microgrid power management using distributed optimization in an agent-based bargaining framework. *IEEE Transactions on Smart Grid*, *9*(6), 6318-6327.

Edward N. Zalta (ed.), Retrieved from

*Elkind, E., & Leyton-Brown, K. (2010). Algorithmic game theory and artificial intelligence. *AI Magazine*, *31*(4), 9-12.

*Elkind, E., Gan, J., Obraztsova, S., Rabinovich, Z., & Voudouris, A. A. (2021). Protecting elections by recounting ballots. *Artificial Intelligence*, *290*, 103401.

*Endriss, U. (2011). Computational social choice: Prospects and challenges. *Procedia Computer Science*, *7*, 68-72.

*Endriss, U., de Haan, R., Lang, J., & Slavkovik, M. (2020). The Complexity Landscape of Outcome Determination in Judgment Aggregation. *Journal of Artificial Intelligence Research*, *69*, 687-731.

*Fain, B., Goel, A., Munagala, K., & Prabhu, N. (2019, July). Random dictators with a random referee: Constant sample complexity mechanisms for social choice. In *Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 33, No. 01, pp. 1893-1900).

Falagas, M. E., Pitsouni, E. I., Malietzis, G. A., & Pappas, G. (2008). Comparison of PubMed, Scopus, Web of Science, and Google Scholar: strengths and weaknesses. *The FASEB Journal*, *22*(2), 338–342. https://doi.org/10.1096/fj.07-9492lsf

*Filatova, D., & Baratgin, J. (2018, July). Multi-agent social choice model and some related questions. In *2018 11th International Conference on Human System Interaction (HSI)* (pp. 425-431). IEEE.

*Fitzsimmons, Z., & Hemaspaandra, E. (2016). Modeling single-peakedness for votes with ties. *arXiv preprint arXiv:1604.08191*.

Frantz, R. (2003). Herbert Simon. Artificial intelligence as a framework for understanding intuition. *Journal of Economic Psychology*, *24*(2), 265-277.

*Garcia, D., & Riedl, A. (2013, November). On the Development of Voter Transition Models for Social Choice Markov Decision Processes. In *2013 IEEE 25th International Conference on Tools with Artificial Intelligence* (pp. 811-817). IEEE.

Gehrlein, W. V., & Valognes, F. (2001). Condorcet efficiency: A preference for indifference. *Social Choice and Welfare*, *18*(1), 193-205.

*Gershtein, M., Sarne, D., & Aumann, Y. (2019, October). Approval voting with costly information. In *Proceedings of the First International Conference on Distributed Artificial Intelligence* (pp. 1-8).

*Grandi, U., & Endriss, U. (2011). Binary aggregation with integrity constraints.

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California management review*, *61*(4), 5-14.

*Haret, A., Khani, H., Moretti, S., & Ozturk, M. (2018, July). Ceteris paribus majority for social ranking. In *27th International Joint Conference on Artificial Intelligence (IJCAI-ECAI-18)* (pp. 303-309).

https://plato.stanford.edu/archives/win2013/entries/social-choice/

Jackson, P. (1986). Introduction to expert systems.

Janssen, M. A., & Ostrom, E. (2006). Empirically based, agent-based models. *Ecology and society*, *11*(2).

*Jiao, P., Xu, K., & Sun, L. (2016, November). Diversity voting and its application in real-time strategy games multi-objective optimization decision-making behavior modeling. In *2016 3rd International Conference on Systems and Informatics (ICSAI)*(pp. 552-559). IEEE.

Johnson, B. R., Onwuegbuzie, A. J., & Turner, L. A. (2007). Toward a definition of mixed methods research. *Journal of Mixed Methods Research*, *1*(2), 112–133.

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, *349*(6245), 255-260.

Keller, R. (2012). *Doing discourse research: An introduction for social scientists*. Sage.

Kiewiet, D. R. (2003). Vote Trading in the First Federal Congress? James Madison and the Compromise of 1790.

Kim, T., & Song, H. (2021). How should intelligent agents apologize to restore trust? Interaction effects between anthropomorphism and apology attribution on trust repair. *Telematics and Informatics*, *61*, 101595.

*Kimelfeld, B., Kolaitis, P. G., & Stoyanovich, J. (2018). Computational social choice meets databases. *arXiv preprint arXiv:1805.04156*.

*Kirsch, A. (2019). A unifying computational model of decision making. *Cognitive processing*, *20*(2), 243-259.

Kitchenham, B. (2004). Procedures for performing systematic literature reviews. In *Keele University*.

Knill, C., & Tosun, J. (2020). *Public policy: A new introduction*. Red Globe Press.

*Kułakowski, K. (2016). Notes on the existence of a solution in the pairwise comparisons method using the heuristic rating estimation approach. *Annals of Mathematics and Artificial Intelligence*, *77*(1), 105-121.

*Lepskiy, V. E., Avdeeva, Z. K., & Raikov, A. N. (2018, October). Disruptive situation management in digital economy. In *2018 Eleventh International Conference" Management of large-scale system development"(MLSD* (pp. 1-4). IEEE.

*Li, M., & Vo, Q. B. (2012, August). Choosing Combinatorial Social Choice by Heuristic Search. In *ECAI* (pp. 528-533).

Lindblom, E. (1965). *The intelligence of Democracy: Decision Making through Mutual Adjustment.* New York: The Free Press.

List, C. (2013) "Social Choice Theory", *The Stanford Encyclopedia of Philosophy* (Winter 2013

*Madani, K., Hooshyar, M., Khatami, S., Alaeipour, A., & Moeini, A. (2014, October). Nash-reinforcement learning (N-RL) for developing coordination strategies in non-transferable utility games. In *2014 IEEE International Conference on Systems, Man, and Cybernetics (SMC)* (pp. 2705-2710). IEEE.

Maskin, E. (1999). Nash equilibrium and welfare optimality. *The Review of Economic Studies*, *66*(1), 23-38.

*Maushagen, C., & Rothe, J. (2020). The Last Voting Rule Is Home: Complexity of Control by Partition of Candidates or Voters in Maximin Elections. In *ECAI 2020* (pp. 163-170). IOS Press.

*Maynard-Zhang, P., & Lehmann, D. (2003). Representing and aggregating conflicting beliefs. *Journal of Artificial Intelligence Research*, *19*, 155-203.

*McHugh, K. A., Yammarino, F. J., Dionne, S. D., Serban, A., Sayama, H., & Chatterjee, S. (2016). Collective decision making, leadership, and collective intelligence: Tests with agent-based simulations and a Field study. *The Leadership Quarterly*, *27*(2), 218-241.

*Mogos, A. H., Mogos, B., & Florea, A. M. (2015, May). A voting approach for comparing several swarm intelligence algorithms. In *2015 20th International Conference on Control Systems and Computer Science* (pp. 287-293). IEEE.

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & Prisma Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *PLoS medicine*, *6*(7), e1000097.

*Mossel, E., & Rácz, M. Z. (2015). A quantitative Gibbard-Satterthwaite theorem without neutrality. *Combinatorica*, *35*(3), 317-387.

Nash, J. (1950). The Bargaining Problem. *Econometrica* (18): 155-62

Nash, J. F. (2016). *8. Two-Person Cooperative Games* (pp. 99-116). Princeton University Press.

*Neveling, M., & Rothe, J. (2021). Control complexity in Borda elections: Solving all open cases of offline control and some cases of online control. *Artificial Intelligence*, *298*, 103508.

Nilsson, N. J. (2014). *Principles of artificial intelligence*. Morgan Kaufmann.

*Novaro, A., Grandi, U., Longin, D., & Lorini, E. (2018). Goal-based collective decisions: Axiomatics and computational complexity. International Joint Conference on Artificial Intelligence (IJCAI).

Ones, D. S., Dilchert, S., Viswesvaran, C., & Salgado, J. F. (2010). Cognitive abilities

*Pal, M., & Bandyopadhyay, S. (2018, November). Consensus of subjective preferences of multiple occupants for building energy management. In *2018 IEEE symposium series on computational intelligence (SSCI)* (pp. 1815-1822). IEEE.

Pannu, A. (2015). Artificial intelligence and its application in different areas. *Artificial Intelligence*, *4*(10), 79-84.

Penrose, L. S. (1946). The elementary statistics of majority voting. *Journal of the Royal Statistical Society*, *109*(1), 53-57.

*Petcu, A., Faltings, B., & Parkes, D. C. (2008). M-DPOP: Faithful distributed implementation of efficient social choice problems. *Journal of Artificial Intelligence Research*, *32*, 705-755.

*Pigozzi, G. (2006). Two aggregation paradoxes in social decision making: the ostrogorski paradox and the discursive dilemma. *Episteme*, *2*(2), 119-128.

*Pigozzi, G., Tsoukias, A., & Viappiani, P. (2016). Preferences in artificial intelligence. *Annals of Mathematics and Artificial Intelligence*, *77*(3), 361-401.

*Pournaras, E. (2020). Proof of witness presence: blockchain consensus for augmented democracy in smart cities. *Journal of Parallel and Distributed Computing*, *145*, 160-175.

*Prasad, M. (2019). Nicolas de Condorcet and the First Intelligence Explosion Hypothesis. *AI Magazine*, *40*(1), 29-33.

*Pujari, M., & Kanawati, R. (2012, November). Link prediction in complex networks by supervised rank aggregation. In *2012 IEEE 24th International Conference on Tools with Artificial Intelligence*(Vol. 1, pp. 782-789). IEEE.

Riker, W. H., & Brams, S. J. (1973). The paradox of vote trading. *The American Political Science Review*, *67*(4), 1235-1247.

Riles, A. (2004). Real time: Unwinding technocratic and anthropological knowledge. *American ethnologist*, *31*(3), 392-405.

*Rossi, F. (2014). Collective decision making: a great opportunity for constraint reasoning. *Constraints*, *19*(2), 186-194.

Ryan, M. (2020). In AI We Trust: Ethics, Artificial Intelligence, and Reliability. *Science and Engineering Ethics*, *26*(5), 2749-2767.

Sen, A. (1986). Social choice theory. *Handbook of mathematical economics*, *3*, 1073-1181.

Shepsle, K. A. (2010). *Analyzing politics: Rationality, behavior, and institutions*. New York: W.W.

Simon, H. A. (1990). Bounded rationality. In *Utility and probability* (pp. 15-18). Palgrave Macmillan, London.

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, *104*, 333-339.

Studer, R., Benjamins, V. R., & Fensel, D. (1998). Knowledge engineering: Principles and methods. *Data & knowledge engineering*, *25*(1-2), 161-197.

*Teng, L., Zhu, J., Li, B., & Jiang, Y. (2018). A voting aggregation algorithm for optimal social satisfaction. *Mobile Networks and Applications*, *23*(2), 344-351.

*Werbin-Ofir, H., Dery, L., & Shmueli, E. (2019). Beyond majority: Label ranking ensembles based on voting rules. *Expert Systems with Applications*, *136*, 50-61.

Xu, Z. (2009). An automatic approach to reaching consensus in multiple attribute group decision making. *Computers & Industrial Engineering*, *56*(4), 1369-1374.

*Zhang, H., Cheng, Y., & Conitzer, V. (2019, July). A better algorithm for societal tradeoffs. In *Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 33, No. 01, pp. 2229-2236).

*Zucker, J. (2020, April). Position-Based Social Choice Methods for Intransitive Incomplete Pairwise Vote Sets (Student Abstract). In *Proceedings of the AAAI Conference on Artificial Intelligence*(Vol. 34, No. 10, pp. 14001-14002).