Reactions on Algorithms:
a systematic Literature Review of
Algorithm Aversion and Algorithm Appreciation

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Dr. Oliver KOLL

Department of Strategic Management, Marketing and Tourism

The University of Innsbruck School of Management

Submitted by

Johannes SCHWIENBACHER

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Johannes Schwienbacher

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Abstract

The implementation of algorithms offers various new possibilities in the marketplace. However, relatively little is known about how people react towards algorithmic advice. The major part of research supports the phenomenon of algorithm aversion, which increasingly received attention in the twenty-first century. Despite that, recent research has also shown that people are not always averse to algorithms. This phenomenon is called algorithm appreciation. With the purpose of systematically reviewing people's reactions towards algorithms, 128 peer-reviewed articles from various fields, published between 1954 and 2020, are taken into consideration. The consulted academic literature is categorized into four themes: causes of algorithm aversion and appreciation, individual differences, areas in which algorithms are rejected or appreciated, and strategies on how to overcome algorithm aversion. Each of the presented themes deals with different factors regarding decision aids, reactions from decision-makers and users as well as environmental influences. Therefore, overlapping and conflicting results are highlighted. This systematic literature review provides implications for decision-makers, especially for the field of marketing. It is suggested that there exists a research need for a clearer understanding of how people react towards algorithms. This review can serve as a basis for further investigations.

KEYWORDS

algorithm appreciation, algorithm aversion, decision aids, human-algorithm interaction, human–automation interaction, human vs. nonhuman, reactions on algorithms

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1. Introduction

"I would recommend this movie to you. I think it suits your preferences. It's exciting and very funny. The story is all about love, friendship & relationships. "The screenplay contains scenes that we found so charming." - James Lander / Film Critic" ("content-generator," n.d.)

At first sight, this movie recommendation appears to be similar to every other existing one. It seems personalized as it includes the user's preferences and a credible positive opinion from a professional film critic. However, there is something extraordinary about this recommendation. It is not, as assumed, a personalized advice by a person, but it is a recommendation provided by a computer. To be precise, an online artificial intelligence (AI) has generated this recommendation by processing various data. Big data has become one of the groundbreaking technological advancements in the last decades. Many companies invested in software to take advantage of this technology. Nowadays, companies collect and store a large amount of data with the ambition to benefit from it in the future (Mohamad, Rahim & Abughazaleh, 2018). The global data share will increase to 175 zettabytes by 2025 (Reinsel, Gantz & Rydning, 2018). In order to handle the tremendous amount of data and simultaneously benefit from it, different types of algorithm systems, such as automation or AI are considered. Various forms of algorithms, such as recommender and forecast systems, chatbots, content-creators, speech recognition, ad targeting, etc. are increasingly becoming an integral part of modern companies. They are used as tools for various decision-making processes (Prahl & Van Swol, 2017). Therefore, the use of algorithms in various contexts is also becoming increasingly important in the field of marketing, as users and marketers more and more interact with this technology. In marketing, algorithms might help to support various processes up to complete automation. Automation is highly appreciated when considering efficiency (e.g. productivity) and effectiveness (e.g., allocation decisions) (Bucklin, Lehmann & Little, 1998). In marketing and sales, 40% of the teams state that the use of AI software is crucial to accomplish their goals (Dresner, 2019). Therefore, marketers make use of algorithms as an aid to make decisions more often (Prahl & Van Swol, 2017). Algorithmic tools might often be cheaper, faster, and less prone to making errors compared to humans. Slowly people get used to algorithmic-based recommender systems which needs to be considered something companies benefit from. For example, Netflix, a company that is well-known for its streaming service, is able to save about $1 billion each year by using recommender systems. What kind of series or movies Netflix users choose to watch after they have completed another is largely dependent from the recommendations that are provided by the algorithm. In 80% of the cases, the decision of the user can be lead back to the mentioned recommendation (Gomez-Uribe & Hunt, 2015). Despite the increasing utilization of algorithms in various domains, in practice, decision-makers can choose between two different ways on how to make a decision. On the one hand, decision-makers could rely on the advice provided by the traditional method, in which available information is considered and decisions are made based on intuition. On the other hand, they could also rely on the advice from a data-based algorithm (Dietvorst, Simmons & Massey, 2015). Dietvorst et al. (2015) call the first possibility "human method" and the second "algorithm method". Such scenarios are often challenging for decision-makers, as it is difficult to decide which advice they should rely on – algorithm or human advice.

Back to the movie recommendation example mentioned above. This example shows the potential of algorithms. If the person affected is not aware of the fact that the recommendation was created by an AI, s/he is likely to assume that it was created by a human. The use of algorithms shows various advantages in decision-making, however, also relying on algorithmic advice can result in weak outcomes. For example, when the algorithm includes faulty data, resulting from biases or data errors. Furthermore, algorithms operate with collected data from the past, and therefore, unexpected situations might lead to wrong advice. Nevertheless, the utilization of algorithms in decision advice taking increases in various domains. This clearly shows that the rise of this new technology as a decision-aid is a current topic and makes it increasingly important to understand the underlying effects of it on users and decision-makers. For decision-makers and especially for marketers, it would be of interest to understand how people react to such algorithm-based advice in various situations and how they judge algorithmic-based decision aids.

1.1 Problem Statement

Nowadays, individuals rely on different types of algorithmic advice, such as product (Amazon), movie (Netflix), or music recommendations (Spotify), spell-check (Grammarly), financial advice (Betterment) or even for finding the right partner (Parship), the right clothing style (Stitch Fix), the right job or suitable employees (LinkedIn), only to mention a few examples. These examples might indicate that decision-makers react positively towards algorithmic advice and thus, often rely on algorithmic judgment instead of human judgment. However, the assumption that people rely on algorithms in a wide variety of areas stands in conflict with a research stream has received more attention throughout the twenty-first century. The major part of academic research supports the popular assumption which shows that people often do not rely on algorithmic decision aids and prefer to rely on human judgment (e.g. Dietvorst et al., 2015; Yeomans, Shah, Mullainathan & Kleinberg, 2019). This behavior is called algorithm aversion (Dietvorst et al., 2015). However, academic literature has also shown that individuals are not always averse to algorithms (e.g. Logg, Minson & Moore, 2019; Thurman, Moeller, Helberger & Trilling, 2019). The countercurrent research stream, which received more attention in recent years and shows that people are inclined to rely on algorithmic advice in certain scenarios, is called algorithm appreciation (Logg et al., 2019). Both research streams, algorithm aversion, and algorithm appreciation show how people react towards algorithmic advice in various situations. However, academic research on these two phenomena is rather sparse, unconnected, and includes contradictory findings from different areas. This applies to different research streams regarding these phenomena. Algorithm aversion could occur because people expect an algorithmic system to operate perfectly and when the algorithmic model unexpectedly makes an error, it leads to a decreased use (Madhavan & Wiegmann, 2007b). However, another approach indicates that individuals have mistrust in algorithms because they think that only humans are capable of making perfect forecasts (e.g. Dawes, 1979; Highhouse, 2008). Furthermore, individuals rely more heavily on advice when they realize that the decision is based on intuition rather than on an algorithm (Arkes, Shaffer & Medow, 2007; Önkal, Goodwin, Thomson, Gönül & Pollock, 2009). According to Dijkstra, Liebrand & Timminga (1998), however, individuals find algorithms as more objective and rational compared to humans. Both algorithm aversion and appreciation occur in different areas. In the area of medicine, the research on algorithm aversion has been conducted since 1954. Meehl (1954), for instance, published his work about people's perception of clinical versus statistical methods. In contrast to the field of medicine, in the field of marketing, little research has been conducted in this context up to the present day. According to Castelo, Bos & Lehmann (2019), humans are inclined to rely on algorithms to a greater extent when tasks are perceived as objective and rely less on algorithmic advice for tasks that are perceived as subjective. However, Logg et al. (2019) showed that people rely on algorithms even when it comes to highly subjective tasks. Furthermore, a great amount of research has proved that algorithms are capable to outperform human advice (e.g. Dietvorst et al., 2015; Yeomans et al., 2019). Therefore, academic literature also provides approaches on how to decrease algorithm aversion, such as motivating and training managers to ensure that they become more used to operate with algorithms (Burton, Stein & Jensen, 2020). In addition to these main research streams regarding these phenomena, scholarly sources offer also approaches that are important to mention in this context. This includes individual differences and different biases. Regarding individual differences, research reveals some contradictory insights about different variables (e.g. gender or age) that influence peoples' reactions towards algorithms (Hoff & Bashir, 2015). Regarding biases, people are often overconfident about their judgments and therefore prefer to rely on their judgement more heavily compared to the judgement made by an algorithm (Arkes, Dawes & Christensen, 1986). As opposed to this statement, Mosier & Skitka (1996) claim that people also show the behavior of overreliance on algorithmic decision aids.

Summing up, academic literature on algorithm aversion and algorithm aversion provides various findings in different contexts. However, many findings of these phenomena are contradictory. This makes it difficult to link the different findings of several sources and to derive appropriate value out of them. It becomes clear that, compared to other areas, especially in the area of marketing little is known about how people react to algorithm advice. Consequently, more research in this field needs to be conducted to get a deeper understanding of these phenomena.

1.2 Research Objectives

In response to the contradicting and unconnected findings of peoples' reactions towards algorithms, this thesis provides a broad and detailed overview targeting this topic. As a methodological approach in order to close the research gap, a systematic literature review was chosen. All in all, 128 peer-reviewed papers from 1954 until 2020, from which the major part was published in academic journals and a small part contains conference papers, are included in this thesis. This review primarily focuses on the phenomena of algorithm aversion and algorithm appreciation in various contexts. A systematic literature review does not aim to generate new knowledge but rather enhances new insights, by structuring and ordering existing scholarly sources in a new way. This approach helps to discover research gaps which generates a base for future research (Webster & Watson, 2002; Wee & Banister 2015). This thesis adds more insights to the human vs. nonhuman literature by showing research efforts over the years and the growing interest in the reactions towards algorithms. As a result, the existing state of research from 1954 until 2020 is identified and different research streams are detected which help to understand the factors influencing these phenomena and to uncover the areas in which they occur. Furthermore, approaches from various scholarly sources are found which suggest different possibilities on how to reduce aversion towards algorithms.

To sum up, research regarding algorithm aversion has been carried out since 1954 but became more relevant in the twenty-first century whereas algorithm appreciation is a rather new area of research. Both research streams provide conflicting and accordingly confusing findings, as well as many unanswered questions. Consequently, research regarding peoples' reactions towards algorithms and implications for the area of marketing is rather scarce. Nevertheless, through the emerging development and utilization of these kind of technologies, such as decision-aids in practice, a need for more research in this field arises. To provide an overview of the state of research regarding algorithm aversion and algorithm appreciation which potentially presents a starting point for future research, the following research question is focused on in this thesis:

RQ1: *What causes peoples' aversion and appreciation towards algorithms and in which areas do these phenomena occur?*

Moreover, many scholarly sources support the assumption that algorithms are capable to outperform humans in various domains (e.g. Einhorn, 1986; Grove & Meehl, 1996; Grove, Zald, Lebow, Snitz & Nelson, 2000; Yeomans et al., 2019). Therefore, to provide an overview of different suggestions from academic literature on how to reduce algorithm aversion towards algorithms, the following research question is developed:

RQ2: *What are strategies to overcome the phenomenon of algorithm aversion?*

By reviewing these research questions, the present thesis contributes to a more comprehensive understanding of humans' reactions towards algorithms. The findings included in this systematic literature analysis have its origin in various areas, such as medicine, law, or management. The objective of this review is to provide a broad and deep overview of algorithm aversion and algorithm appreciation regarding different contexts. As a result, different research streams were detected. Therefore, an overview of the state of research regarding different causes and individual differences concerning algorithm aversion and algorithm appreciation is provided. Further, investigated areas, such as medical, management, or law, in which these phenomena occur are presented. Finally, different strategies mentioned in academic literature to reduce algorithm aversion are highlighted. By presenting a systematic overview, existing research gaps are identified and implications for managers on how decision-makers and users react towards algorithmic-based decision aids are shown.

1.3 Structure of the Thesis

The following chapter provides a short theoretical input to differentiate the terms of algorithm, automation, and AI which serves as a basis for the upcoming literature review. Whereupon, the chapter describing the method of systematic literature review with the process of literature search and analysis follows. Afterwards, the phenomenon of algorithm aversion is reviewed. This chapter includes the section of different causes found in academic literature regarding this phenomenon. Furthermore, it contains the section of individual differences with regards to both topics, algorithm aversion, and algorithm appreciation, as well as the section of different areas in which algorithms are rejected. The chapter of algorithm aversion ends with strategies which can be applied in order to overcome the aversion towards algorithms. After the chapter focusing on algorithm aversion, the chapter algorithm appreciation follows. In this chapter the causes of this phenomenon as well as areas in which algorithms are appreciated, are reviewed. Lastly, a general discussion, managerial and theoretical implications, as well as avenues for future research are provided.

2. Theoretical Background

2.1 Algorithm

Due to the increasing available amount of data, companies are increasingly using algorithms to process and benefit from this data. Based on this, operational decisions are made (McAfee & Brynjolfsson, 2017). According to the oxford dictionaries, an algorithm is as “a process or set of rules to be followed in calculations or other problem-solving operations, especially by a computer” (“Oxford Dictionaries,” n.d.). This means that algorithms are capable of making autonomous decisions. Algorithms are based on statistical models and make decisions without explicit human influence (Lee, 2018). As previously mentioned, algorithms are increasingly used for various tasks. From suggesting the most time-efficient route to reach a specific place to making financial investment decisions, almost everything is possible. For marketing purposes, companies such as Facebook, Google, or Airbnb use advertising algorithms, that include a huge amount of data from users to identify potential target groups for a specific service or product. As a result, users are provided with ads that are tailored on their preferences (Liu & Mattila, 2017). Academic literature, which was published decades ago already showed that basic, uncomplicated algorithms are capable of making superior predictions than human experts (e.g. Dawes, at al., 1989; Meehl 1954). While basic, uncomplicated algorithms were used in this period of time, this technology has developed a lot in the last decades. Nowadays, algorithms are even able to learn from experiences (Castelo et al., 2019). In this context of algorithms, the technologies of automation and AI, which are based on algorithms, should also be considered, and are explained in the following sections.

2.2 Automation

First of all, Parasuraman & Riley (1997) define automation as “the execution by a machine agent (usually a computer) of a function that was previously carried out by a human” (p.231). Automation can be used for various purposes, such as for selecting data, information gathering, for decision-making as well as for control processes, where the automation level can vary, from no to complete automation (Lee & See, 2004; Parasuraman et al., 2000). Automation provides the opportunity to perform tasks with a higher level of accuracy, efficiency, reliability, and cost-effectiveness than humans (Parasuraman & Riley, 1997). Furthermore, this technology is capable of carrying out complex tasks quickly and repetitively (Hoff & Bashir, 2015). Automated technologies have the potential to increase human performance and provide a higher safety standard for different tasks (Lee & See, 2004). They are applied in different areas, such as for GPS systems, flight & ship management systems, or even automated driving (Hoff & Bashir, 2015; Liu et al., 2019). In the field of marketing, automation can be used for different tasks, such as for interactions with customers through welcome and reminder e-mails, or newsletters.

2.3 Artificial Intelligence

Due to rapid technological growth, artificial intelligence (AI) has become increasingly relevant for both theory and practice in the recent years. Kaplan & Haenlein (2019) define AI as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (p.15). AI refers to the idea that algorithms are capable to perform tasks that would normally require acting and thinking of a human being. AI creates the possibility to automate various activities related to the collection, storage, analyzing as well as the retrieval of data. AI enables machines to detect different patterns in large amounts of data (Kumar, Rajan, Venkatesan & Lecinski, 2019) and it helps to save time and effort and therefore also to reduce costs (Yang, Ozbay & Xuegang, 2017). Nowadays, AI is applied in various areas of daily usage, e.g. as a personal assistant (Alexa), smart home solutions (Nest), or language translation (Deepl), to mention a few examples. In the field of marketing AI offers various new opportunities, such as for content-creation, forecast systems, chatbots, speech recognition or ad targeting.

In conclusion, a short theoretical input was provided to differentiate the three terms of algorithm, automation, and AI, to enhance a better understanding about algorithms. Algorithms and the related automation and AI offer various new possibilities in the marketplace. They have the potential to reduce time, effort, and costs (Parasuraman & Riley, 1997). In the following chapters, as automation and artificial intelligence are based on algorithms, these terms will not be differentiated from one another. Therefore, it needs to be mentioned that in this systematic literature review the umbrella terms of "algorithm" and "decision aid" are taken into account, for different paradigms, such as for AI, automation, expert systems and decision support systems. After a short theoretical input, the following chapter describes the method used for this master thesis.

3. Method

To provide a well-structured and up-to-date overview of the state of research regarding the topics of algorithm aversion and algorithm appreciation a conceptual method was chosen, namely a systematic literature review. According to Denney & Tewksbury (2013), a systematic literature review "[…] is a comprehensive overview of prior research regarding a specific topic. The overview both shows the reader what is known about a topic, and what is not yet known, thereby setting up the rationale or need for a new investigation, which is what the actual study to which the literature review is attached seeks to do" (p.218). This method does not primarily generate new knowledge, but provides various benefits for researchers. It helps to structure and order existing research in a new way to discover research gaps and thus to determine future research needs (Webster & Watson, 2002; Wee & Banister, 2015). A literature analysis consists of literature search and analysis, which are described in the following.

3.1 Literature Search Process

The overall literature search process in this systematic literature review, including search in databases and forward/backward search, resulted in the discovery of 128 relevant research papers that are used to describe the topics of algorithm aversion and algorithm appreciation (Appendix, Table 31). In the following paragraphs, the literature search regarding both topics is described. This includes the search terms used, the inclusion criteria as well as databases and forward/backward search. Table 1 illustrates the whole search process of scholarly sources for algorithm aversion and algorithm appreciation.

3.1.1 Search Terms

For the literature search the keywords "algorithm aversion" and "algorithm appreciation" were utilized separately. Despite the fact that these specific keywords only appear moderately in the existing literature, they specify these phenomena most accurately for the review. The research paper by Dietvorst et al. (2015) showed that trust plays an important role in describing the reactions on algorithms. However, trust is a very broad concept and is described in various contexts which are not relevant for this review. Therefore, it not suitable as a keyword. Consequently, using other keywords has been deliberately avoided since the most relevant sources regarding these topics could be found in databases if the search terms “algorithm aversion” and “algorithm appreciation” were taken into account. Through the additional extensive forward and backward searches and querying of recommended articles in databases, appropriate articles were found to complement the insights provided from the most relevant papers found in databases. The literature search in databases and forward/backward search resulted in a satisfying number of scholarly sources, and thus, no additional search method was taken in consideration.

Results of Search	Number of Articles
EBSCO Host	22
Web of Science	11
Wiley Online Library	21
Sage Journals	6
ScienceDirect	17
Total Articles	**77**
Reasons for Exclusion	
Duplicates	24
Working Papers/Dissertations/Theses	1
No relation to the Topic	40
Excluded Articles	**65**
Results of Search in Databases	12
Forward/Backward Search	116
Total Articles included for this Literature Review	**128**

Table 1: Literature Search Process of Algorithm Aversion and Algorithm Appreciation

3.1.2 Inclusion Criteria

In order to provide a comprehensive overview of the development and state of research in algorithm aversion and algorithm appreciation, comparatively fewer restrictions were defined for articles to be included in this literature review. Regarding inclusion criteria, search results were limited to peer-reviewed scholarly sources written in English. The main focus was lain on information provided by several scientific journals. Nevertheless, some conference papers were included which were used to support some approaches. Scholarly sources like working papers, theses, and dissertations were excluded. The papers which were used as a basis for this review were not chosen based on when they were published, so regarding time, no restriction needed to be considered. Therefore, appropriate articles from 1954 (in 1954 Meehl published the first research regarding algorithm aversion) until 2020 were included in this review. For the research design used in articles, no qualification was specified. Scholarly sources included had to describe either algorithm aversion, algorithm appreciation, or both topics, or else, to support an appropriate approach to further address these topics.

3.1.3 Databases & Forward/Backward Search

As stated by Webster & Watson (2002), a literature search involves the use of scientific databases with keywords as well as backward and forward searches based on relevant articles. The literature search involving databases was conducted with EBSCO Host, Web of Science, Wiley Online Library, Sage Journals, and ScienceDirect. Regarding the Ebsco Host literature search, the databases of Business Source Premier, APA PsycInfo, PSYNDEX Literature with PSYNDEX Tests, APA PsycArticles, EconLit, MEDLINE, SocINDEX as well as Library, Information Science & Technology Abstracts were included. This variety of databases, e.g. in areas of business, psychology and medicine, was chosen because algorithm aversion does not only affect decision-making in management and economics, but also occurs in other areas. Research findings from different areas can provide insightful approaches to the field of marketing. The literature search through databases resulted in 77 research papers regarding the keywords "algorithm aversion" and "algorithm aversion". After screening each abstract and the content of these papers, excluding duplicates and papers which do not fulfill the inclusion criteria, 12 relevant sources regarding these topics were found.

In addition to the literature search in databases, a backward and forward search was conducted. Backward search is the search for relevant literature from the cited sources of the article. The search for literature citing the article in question is referred to as forward search. This means that one considers aspects such as who cites the author and from whom the author cites (Webster & Watson, 2002). After an extensive forward and backward search through relevant papers and recommended articles from databases, another 116 scholarly sources were discovered to complement the articles found by the search in databases. In the end, a total of 128 academic papers were found through the search in databases and through forward and backward search to review the topics of algorithm aversion and algorithm appreciation. After the selection process of relevant articles, the next step is the analysis of the research papers.

3.2 Analysis

The analysis of the scholarly sources found in literature began with coding the sources by the author, published year, research design, topic (aversion or appreciation or aversion and appreciation) as well as key findings of every article (Appendix, Table 31). This categorization allowed to identify different aspects of algorithm aversion and algorithm appreciation. It resulted in four different research streams that were drawn out of the articles: causes of algorithm aversion and appreciation, individual differences, areas in which algorithms are rejected or appreciated, as well as strategies to overcome algorithm aversion.

As previously mentioned, in sum, 128 papers from 1954 until 2020 are used in this literature review. Table 2 shows a timeline from 1951 until 2020 and lists the articles sorted by the year they were published. It illustrates the development of the scholarly sources consulted for every research stream, as well as in sum, over time. The amount of papers illustrated in the table also includes duplicates. Therefore, also the amount of papers ranked by year, excluding duplicates is provided. As illustrated, the number of articles regarding the published years for each research stream has changed over time, and therefore also the attention towards them. It can be seen that for the research stream "areas in which algorithm are rejected & appreciated" research began early. Whereas for the causes of these two topics, individual differences, as well as strategies to overcome algorithm aversion, the attention towards them and thus, investigations began later. The largest amount of papers (42,2%) was consulted in order to review the causes of algorithm aversion and appreciation. Whereas, for the research stream of individual differences, however, the fewest scholarly sources (15%) were consulted. As becomes apparent in the table, the amount of papers for every research stream as well as the sum of the amounts used for this review indicate that the number of published papers increased with time. The major part (66%) of scholarly sources, without duplicates, used in this review was published between 2001 and 2020. It can be seen that the topics algorithm aversion and algorithm appreciation became more the subject of investigation in the twenty-first century. After explaining the characteristics of the method applied for this thesis, in the following chapter the topic algorithm aversion is reviewed.

Year	Causes of Algorithm Aversion & Appreciation	Individual Differences	Areas in which Algorithms are rejected & appreciated	Overcoming Algorithm Aversion	Sum including Duplicates	Sum excluding Duplicates
1951-1955			1		1	1
1961-1965			1		1	1
1966-1970		1	1		2	2
1971-1975		1			1	1
1976-1980	2		1		3	2
1981-1985	1	1	1	1	4	4
1986-1990	6		2	2	10	7
1991-1995	5	3	1	2	11	9
1996-2000	11		6		17	16
2001-2005	10	3	6	2	21	16
2006-2010	12	6	7	4	29	21
2011-2015	7	7	6	8	28	21
2016-2020	22	5	13	12	52	27
Total	**76**	**27**	**46**	**31**	**180**	**128**
%	**42,2%**	**15%**	**25,6%**	**17,2%**	**100%**	

Table 2: Articles of Algorithm Aversion and Algorithm Appreciation over Time

4. Algorithm Aversion

The past and present research shows that people often rely more heavily on human than on algorithmic advice (e.g. Diab, Pui, Yankelevich & Highhouse, 2011; Dietvorst et al., 2015; Meehl, 1954; Önkal et al., 2009). Especially when it comes to creating forecasts in different areas, e.g. employee and academic performance (Dawes, 1979; Highhouse, 2008), for recommendations, e.g. for jokes (Yeomans et al., 2019), as well as management decisions and medical diagnoses (Grove et al., 2000; Sanders & Manrodt, 2003a), algorithmic advice appears to be a more reliable tool. Additionally, people evaluate experts using decision-support-systems as less professional with a lower level of ability than experts who make an aid free prediction (Arkes et al., 2007).

Regardless of many pieces of evidence (e.g. Einhorn, 1986; Grove & Meehl, 1996; Grove et al., 2000; Yeomans et al., 2019) demonstrating the accuracy of algorithm judgment, people trust in less accurate judgments of individuals more which is a phenomenon called algorithm aversion (Dietvorst et al., 2015). The first pioneer research on algorithm aversion belongs to Meehl (1954) who investigated the topic of clinical (human) versus statistical (algorithm) forecasts. Meehl (1954) presenting a review of studies, showed that a statistical model outperforms skilled people relying on their intuition in prediction making. The first researches already showed that basic, uncomplicated algorithms can outperform experts e.g. in medical diagnoses (Dawes, Faust & Meehl, 1989). From then on, technology and increased automation and artificial intelligence have developed a lot. Slowly, algorithms were able to analyze and learn from past data (Yeomans et al., 2019) and therefore, they were even able to understand human emotions (Castelo et al., 2019). However, it was only now, in the twenty-first century, that the aversion towards algorithms became more relevant and scholars finally tested it empirically more often (e.g. Dietvorst et al., 2015; Promberger & Baron, 2006).

To sum up, people often rely more heavily on human than on algorithmic predictions, even though algorithmic predictions are more accurate (Dietvorst et al., 2015). This phenomenon was first studied by Meehl (1989) and became more important in the last decades. Nowadays, companies are worried that consumers or employees do not rely on their own generated algorithms even if they outperform humans (Haak, 2017). Algorithm aversion of any type of stakeholder is costly and it is important for companies to understand this phenomenon (Dietvorst et al., 2015).

To enhance a better understanding of algorithm aversion, this chapter gives, firstly, a broad overview of the causes of algorithm aversion and, secondly, individual differences with regards to both topics, algorithm aversion and algorithm appreciation are reviewed. Thirdly, it shows the areas in which people do not rely on algorithms. Finally, methods on how to overcome this phenomenon are described.

Table 3 gives a comprehensive overview of the distribution of the sources found in the academic literature, across the four subchapters. All in all, 118 scholarly sources are used to describe the topic of algorithm aversion. As illustrated, most papers were found for the review of the subchapter "Causes of Algorithm Aversion" with 57 sources, compared to the other subchapters. Whereas for the subchapter "Individual Differences", which refers to both topics, algorithm aversion and algorithm appreciation, with 27 papers, the fewest scholarly sources could be found. After a short introduction which aims at providing a better understanding of this phenomenon, a more detailed explanation is going to follow in the next part of this thesis. The following subchapter focuses on the identified causes of this phenomenon.

Topic	Sources	
Causes of Algorithm Aversion	57	Alexander et al. (2018); Arkes et al. (1986); Arkes et al. (2007); Arkes et al. (2016); Armstrong (1980); Banker & Khetani (2019); Baron (2000); Burton et al. (2020); Camerer & Johnson (1991); Castelo et al. (2019); Commerford et al. (2019); Corey & Merenstein (1987); Croskerry & Norman (2008); Dane & Pratt (2007); Dane et al. (2012); Dawes (1979); Dawes et al. (1989); Dietvorst et al. (2015); Dzindolet et al. (2001); Dzindolet et al. (2002); Efendić et al. (2020); Einhorn (1986); Green & Hughes (1986); Grove et al. (2000); Hafenbrädl et al. (2016); Highhouse (2008); Hoff & Bashir (2015); Kahneman (2003); Kaplan (2000); Lee (2018); Lee & Moray (1992); Lee & See (2004); Lim & O'Connor (1995); Liu et al. (2019); Logg et al. (2019); Longoni et al. (2019); Luo et al. (2019); Luong et al. (2020); Madhavan & Wiegmann (2007a); Madhavan & Wiegmann (2007b); Madhavan et al. (2006); Manzey et al. (2012); Meehl (1986); Montazemi (1991); Moore & Healy (2008); Nass & Lee (2001); Nass et al. (1996); Önkal et al. (2009); Parasuraman & Riley (1997); Prahl & Van Swol (2017); Promberger & Baron (2006); Shaffer et al. (2013); Sieck & Arkes (2005); Todd & Gigerenzer (2007); Whitecotton (1996); Workman (2005); Yeomans et al. (2019);
Individual Differences	27	Araujo et al. (2020); Bhattacharya et al. (2012); Blankenship et al. (1984); Byrne & Griffitt (1969); Duck (1973); Ho et al. (2005); Hoff & Bashir (2015); Huerta et al. (2012); Lee (2008); Li et al. (2010); Logg et al. (2019); Lourenço et al. (2020); Lundeberg et al. (1994); McBride et al. (2012); Merritt & Ilgen (2008); Naef et al. (2008); Nass et al. (1995); Nass & Lee (2001); Nomura et al. (2008); Pak et al. (2012); Prince (1993); Rau et al. (2009); Sanchez et al. (2004); Szalma & Taylor (2011); Thurman et al. (2019); Thurman & Fletcher (2019); Tung (2011);
Areas in which Algorithms are rejected	41	Arkes et al. (2007); Bennett & Hauser (2013); Bigman & Gray (2018); Buckley et al. (2000); Bucklin et al. (1998); Castelo et al. (2019); Cortina et al. (2000); Dawes (1979); Dawes et al. (1989); Diab et al. (2011); Dietvorst et al. (2015); Eastwood et al. (2012); Fildes & Goodwin (2007); Fitzsimons & Lehmann (2004); Gough (1962); Grove & Meehl (1996); Grove et al. (2000); Highhouse (2008); Jakesch et al. (2019); Kleinmuntz (1990); Komaroff (1982); Kuncel et al. (2013); Lee (2018); Lievens et al. (2005); Liu et al. (2019); Lodato et al. (2011); Longoni et al. (2019); Luo et al. (2019); Marchese (1992); Meehl (1954); Önkal et al. (2009); Patel et al. (2009); Promberger & Baron (2006); Rynes et al. (2002); Sanders & Manrodt (2003°); Sanders & Manrodt (2003b); Sawyer (1966); Schmidt & Hunter (1998); Shaffer et al. (2013); Sinha & Swearingen (2001); Yeomans et al. (2019);
Overcoming Algorithm Aversion	31	Alexander et al. (2018); Arkes et al. (1986); Arkes et al. (2007); Brown (2015); Burton et al. (2020); Carbone et al. (1983); Castelo et al. (2019); Diab et al. (2011); Dietvorst et al. (2015); Dietvorst et al. (2018); Goodwin et al. (2013); Green & Hughes (1986); Hafenbrädl et al. (2016); Hagmann et al. (2019); Kahneman (2003); Kuncel (2008); Lee (2018); Lim & O'Connor (1995); Liu et al. (2019); Lodato et al. (2011); Martini et al. (2015); Mullins & Rogers (2008); Nass & Lee (2001); Nass et al. (1995); Önkal et al. (2009); Patterson (2017); Prahl & Van Swol (2007); Westin et al. (2015); Wiese et al. (2012); Wiese et al. (2017); Yeomans et al. (2019);
Sum	**156**	
Excluding Duplicates	38	
Total Articles	**118**	

Table 3: Sources of Algorithm Aversion

4.1 Causes of Algorithm Aversion

People are inclined to rely on human advice to a greater extent than on algorithmic ones, even though algorithms are more accurate than humans (Dietvorst et al., 2015). This brings disadvantages to companies. Algorithm aversion is costly and, consequently, it is fundamental to understand the causes of this phenomenon (Dietvorst et al., 2015). When looking at various scholarly sources on algorithm aversion, five causes can be identified. This subchapter starts, firstly, with the cause of algorithm error, where algorithmic errors play an important role (Dietvorst et al., 2015). Secondly, divergent rationalities are described, which have a strong impact on decision-making (Croskerry & Norman, 2008). Thirdly, the domain of judgment, where the area of relationship plays a role is focused on (Alexander, Blinder & Zak, 2018). Finally, the disuse of algorithms, where people's erroneously underutilization of unnecessary perceived algorithmic models plays a role (Arkes et al., 1986), is explained in detail. As illustrated in table 4, excluding duplicates, 57 papers are used to describe the causes of algorithm aversion. Most papers used describe the causes of "Divergent Rationalities" and "Disuse of Algorithms", whereas, in comparison, fewer academic sources describe "Algorithm Error" and "The Domain of Judgment".

Results of Search	Number of Articles
Algorithm Error	12
Divergent Rationalities	24
The Domain of Judgment	12
Disuse of Algorithms	19
Sum	**67**
Excluding Duplicates	10
Total Articles	**57**

Table 4: Causes of Algorithm Aversion

4.1.1 Algorithm Error

Algorithm error is one of the investigated reasons that influences the aversion towards algorithms (e.g. Dietvorst et al., 2015; Dzindolet, Pierce, Beck & Dawe, 2002; Prahl & Van Swol, 2017). Dietvorst et al. (2015) conducted a research on student performance about student performance forecasting and found out that people are averse to algorithmic forecasts after seeing them making an error, even when they notice that the algorithmic model outperforms a human forecast. The following straightforward example underlines this tendency. When someone drives to work via a normal route and runs into traffic, s/he predicts that another route will be faster. In the end, s/he arrives 20 minutes late. A coworker might say to her/him that the original route would have been faster. Many people have already made such mispredictions in their lives, but only very few would decide to never trust their judgment in situations like this again. If s/he had used a traffic-sensitive GPS in the same scenario, the case would be different. The GPS would have made a mistake, and, because of this, many people would lose confidence in the machine (Dietvorst et al., 2015). As shown in the example, humans' tendency to rely on algorithmic forecast decreases after noticing it making an error, but humans' tendency to rely on people forecasts does not decrease if a human makes a mistake (Dietvorst et al., 2015). People are prone to believing that human mistakes are random and therefore correctable and statistical errors occur systematically (Dietvorst et al., 2015; Highhouse, 2008). They are more sensitive towards algorithm errors and due to that, their level of trust decreases after they notice errors made by the algorithm (Dzindolet et al., 2002; Madhavan & Wiegmann, 2007a). For example, traffic accidents involving self-driving vehicles are perceived more negatively than traffic accidents involving human-driven vehicles, even though the self-driving vehicles do not cause the accident (Liu, Du & Xu, 2019). Additionally, people's usage of algorithmic decision aids decreases more than on human decision aids after experiencing bad advice (Prahl & Van Swol, 2017). As a result, people are more likely to abandon algorithmic advice than advice given by humans when each of them makes mistakes, although the algorithm outperforms the human forecast (Dietvorst et al., 2015).

In order to describe the cause of algorithm error, the following paragraphs explain the approaches which influence this cause. This includes approaches such as the desire for perfect predictions, the error rate, the timing of the error, the difficulty of the task, and the role of confidence. Finally, it includes the belief that algorithms are dehumanizing and not able to learn from mistakes. Research papers investigating this cause are illustrated in table 5.

Cause	Sources	
Algorithm Error	12	Dawes (1979); Dietvorst et al. (2015); Dzindolet et al. (2002); Einhorn (1986); Highhouse (2008); Hoff & Bashir (2015); Madhavan & Wiegmann (2007a); Madhavan & Wiegmann (2007b); Madhavan et al. (2006); Manzey et al. (2012); Liu et al. (2019); Prahl & Swol (2017);

Table 5: Algorithm Error

The first approach presented here is that humans have a desire for perfect forecasts. A reason for this kind of behavior could be human beliefs (Dietvorst et al., 2015). In the area of medical diagnosis, Einhorn (1986) investigated clinical (human) versus statistical (machine) methods. The clinical method (human judgment) is based on the optimistic goal of ideal forecasts (Einhorn, 1986). In this case, people want future actions to be predictable. This impossible desire is transformed into the belief that future actions are indeed highly predictable. Because of the desire for perfect forecasts, people are inclined to switch the forecast method. If one method (e.g. the algorithmic method) makes a small mistake and is therefore evaluated as a bad predictor by humans, they might assume that an alternative method might be superior. Therefore, they switch to another method (e.g. human judgment) being convinced that this kind of behavior would increase the probability of a better forecast (Dawes, 1979). Furthermore, two parallel running, mutually exclusive streams could be used to explain this behavior, namely the perfection schema (Madhavan & Wiegmann, 2007b) and the human belief that people are more likely of being perfect than algorithms (Dawes, 1979; Einhorn, 1986; Highhouse, 2008). The first stream, the perfection schema states that people usually expect an algorithmic forecast model to work perfectly. As a result, when the algorithmic model makes an error, it feels particularly negative because it was unexpected for the user and decreases the level of trust. Human mistakes do not feel that negative for the user because people believe that humans are imperfect. Therefore, people are more likely to forgive the human forecaster than the algorithmic model (Madhavan & Wiegmann, 2007b). The second stream is peoples' belief that humans are able to be perfect (Dawes, 1979; Einhorn, 1986; Highhouse, 2008). Although individuals may know that algorithmic forecasts are more accurate, they rely on human forecasts more heavily because of the belief that humans are more likely to give a perfect forecast (Einhorn, 1986). For example, in the area of employee selections, managers think that they are capable to predict the potential employee success and to rely on their intuitive expertise (Highhouse, 2008). The role of intuition is going to be explained in more detail in the following cause of "Divergent Rationalities". Although both streams run into a completely opposite direction, they provide important insights into the way people might think when interacting with algorithms.

Furthermore, the error rate plays a role. The error rate plays an important role when it comes to the way in which people perceive algorithms. If machines are wrong only occasionally humans are inclined to overestimate the perceived error rate (Dzindolet et al., 2002; Hoff & Bashir, 2015). Consequently, people have less tolerance for errors caused by algorithmic systems than for errors caused by humans (Dietvorst et al., 2015).

Next, the approach of error timing and the difficulty of the task have an influence on the role of trust in algorithm advice (Hoff & Bashir, 2015). At the beginning of the usage, perceived algorithmic errors have a more negative effect on trust than errors which occur later in the usage. Errors occurring at the beginning of the usage can have a lasting negative effect on the user (Manzey, Reichenbach & Onnasch, 2012). Therefore, the first impression of the algorithmic model is crucial, especially for unfamiliar algorithms (Hoff & Bashir, 2015). Additionally, algorithmic models that make errors on easy-perceived tasks influence the level of trust more negatively than algorithmic models that make errors on difficult-perceived tasks. When an algorithm fails to perform an easy task, people's level of trust decreases more because they believe that the algorithmic model is not capable to solve more challenging tasks at all (Madhavan, Wiegmann & Lacson, 2006).

The approach of confidence plays also an interesting role. Confidence in the algorithmic model already decreases when people see a model make small mistakes but interestingly, confidence in human forecasts does not decrease when a human makes major mistakes (Dietvorst et al., 2015). Even though, in the experiment of Dietvorst et al. (2015), human forecasters made more errors than the algorithm model, people preferred the human forecast. People only choose the statistical model when they are more confident in algorithms. They choose the human forecast when people are more confident in the human judgment or indifferent between human or algorithmic judgment (Dietvorst et al., 2015).

Finally, the ethical approach is also important to mention. Individuals think that algorithms are dehumanizing. When data-based models choose the right candidate for a job, people think that such an important decision without a personal face to face interview is dehumanizing (Dawes, 1979). Also the phenomenon of dehumanizing will be discussed in the following cause of "Divergent Rationalities". Additionally, people rely on human judgments because they erroneously think that unlike algorithms, only individuals are able to improve over time and to learn from mistakes (Dawes, 1979; Dietvorst et al., 2015; Highhouse, 2008). Therefore, they punish algorithms more than humans when they notice that a mistake has been made (Dietvorst et al., 2015).

Summing up, humans' choice of relying on decision aids decreases after noticing the algorithm making an error but does not decrease if a human makes a mistake (Dietvorst et al., 2015). Individuals believe that human mistakes are random and therefore correctable and decision aids errors occur systematically (Dietvorst et al., 2015; Highhouse, 2008). Several factors, such as the desire for perfect forecasts, the error rate, the timing of the error, the difficulty of the task, the role of confidence, and the perception of dehumanizing, influence the cause of algorithm error.

4.1.2 Divergent Rationalities

A further cause of algorithm aversion which needs to be taken into consideration are divergent rationalities. In this relation, the heuristic and bias program as well as the fast-and-frugal heuristics should be mentioned. With regards to the heuristic and bias program, people are biased by overconfidence judgment which influences rational decision-making. It is a bias that has a strong impact on decision-making and prevents people from using decision-making tools in a correct manner (Croskerry & Norman, 2008). This behavior appears when people show extreme confidence (Baron, 2000) and leads to illogical and irrational decisions (Croskerry & Norman, 2008). According to Moore & Healy (2008), the overconfidence bias can be categorized into three different types: overestimation, overplacement, and overprecision. The first type, overestimation, occurs when an individual is overconfident in, or, in other words, overestimates its abilities. The second type, overplacement, takes place when individuals think that they are superior to others. Most of the individuals assess themselves as being better than the average. The last type, overprecision, occurs when people are highly certain of the truthfulness of their own beliefs (Moore & Healy, 2008). Another approach concerning rationality is that scholars have strongly focused on the heuristics-and-biases program although other approaches as the fast-and-frugal heuristics also offer value in which algorithm aversion could occur (Burton et al., 2020).

In decision-making, people often overestimate their abilities in comparison to algorithms (Banker & Khetani, 2019). The different approaches described below include the overconfidence bias and the associated intuition, as well as the perception of dehumanization. Additionally, the approach of fast-and-frugal heuristics in relation to algorithm aversion is explained. Scholarly sources investigating divergent rationalities in algorithm aversion are illustrated in table 6.

Cause	Sources	
Divergent Rationalities	24	Arkes et al. (1986); Arkes et al. (2007); Arkes et al. (2016); Banker & Khetani (2019); Baron (2000); Burton et al. (2020); Camerer & Johnson (1991); Croskerry & Norman (2008); Dane et al. (2012); Dane & Pratt (2007); Dawes (1979); Dawes et al. (1989); Grove et al. (2000); Hafenbrädl et al. (2016); Highhouse (2008); Kahneman (2003); Lee (2018); Lim & O'Connor (1995); Longoni et al. (2019); Meehl (1986); Moore & Healy (2008); Önkal et al. (2009); Sieck & Arkes (2005); Todd & Gigerenzer (2007);

Table 6: Divergent Rationalities

The overconfidence bias has a negative impact on decision aids. Individuals believe that they do not dependent on decision-making tools, such as automation or artificial intelligence because they do not need any support in making decisions (Arkes et al., 1986). People with higher knowledge of the subject tend to lower the usage of decision aids than less knowledgeable ones. Consequently, the decision maker's overconfidence leads to the erroneous underutilization of unnecessary perceived algorithmic models (Arkes et al., 1986), which is explained in more detail in the fourth and last approach mentioned in this subchapter "Disuse of Algorithms".

A major part of decisions that are made is not based on the collection and analysis of information, but rather on the subconscious level of intuition (Dane, Rockmann & Pratt, 2012).

Therefore, one reason for decision-makers to be overconfident is intuition. According to Dane & Pratt (2007), intuitions are “affectively charged judgments that arise through rapid, nonconscious, and holistic associations” (p.40). People often link intuitive decision making with creativity and insights, whereas algorithmic models appear opaque and boring (Arkes et al., 2007). For example, many people have the opinion that there is something like a “selection expertise”. This means that humans are able to become increasingly skilled in intuitive decision-making about a potential employee’s success. Nevertheless, research shows that experience does not lead to improved intuition-based forecasts (Camerer & Johnson, 1991; Dawes, Faust & Meehl, 1989; Grove et al., 2000; Highhouse, 2008). As a result, the welfare of decision-makers may decrease due to suboptimal decisions if they rely on their intuition rather than algorithmic judgment (Banker & Khetani, 2019). Moreover, people find experts which do not use decision aids more professionally, and therefore, they rely on experts more heavily when they realize that the decision is based on intuition and experience rather than on decision-making tools (Arkes et al., 2007; Önkal et al., 2009).

In relation to algorithmic decision aids, people are concerned about ethics. Individuals perceive algorithmic decision aids as “dehumanizing” and decision-makers which rely on their intuition and experience as more caring (Sieck & Arkes, 2005). According to Meehl (1986), abandoning algorithmic methods and the associated advantages such as accuracy and efficiency in order to get a warmer and more personal feeling when receiving human advice is a bad exchange. When people believe that an expert has high-level knowledge at his/her disposal, they are inclined to abandon decision aids. Such a perception is rather imprecise (Sieck & Arkes, 2005). As Dawes (1979) points out, people’s memory of major decisions without decision aids can be a factor. An individual’s memory of good decisions may overshadow the bad decisions. Therefore, people tend to suppress bad decisions based on intuition and to focus on the good ones. In the context of job interviews, individuals perceive algorithmic-based decision aids as less trustworthy, less fair, and feel more negatively towards them than towards human advice (Dawes, 1979; Lee, 2018). People believe that algorithmic methods are not capable to choose good candidates or to analyze employee performance. Different from human decisions, algorithms are perceived as tools that can only measure quantitative data, are not able to analyze social topics or to handle exceptions, and have lack of intuition (Lee, 2018). Additionally, people believe that algorithmic tools do not consider their unique individual characteristics in the same extent as human experts (Longoni, Bonezzi & Morewedge, 2019). Individuals feel that such important social choices, like judging a person, based on algorithms are "dehumanized" (Dawes, 1979).

Furthermore, the plurality of individuals' decision making in practice, such as fast-and-frugal heuristics, is often ignored in research and a stronger focus is lain on the heuristics-and-biases program (Kahneman, 2003; Burton et al., 2020). This includes the suggestion that humans are not able to make rational calculations (Kahneman, 2003) and the algorithmic decision aid could fix this issue to reduce the bounds of rationality (Burton et al., 2020). Research in heuristics-and-biases program has provided valuable insights for a better understanding of the relationship between humans and algorithms by identifying an individual's motivation deficits (e.g. Hafenbrädl, Waeger, Marewski & Gigerenzer, 2016; Lim & O'Connor, 1995). However, by focusing on this research they have neglected the research about fast-and-frugal heuristics. This includes simple heuristics which are used by human decision-makers for uncertainty. For this type of decision-making beneficial decisions are specified as ecological rational (Arkes, Gigerenzer & Hertwig, 2016). Ecological rationality is an approach that refers to the real world (to the practice). It states that the level of rationality regarding a decision depends on the environment in which the decision is made. This representation stands in contrast to the rational-choice-theory (Todd & Gigerenzer, 2007). On the one hand, regarding ecological rationality, people making decisions in practice often find themselves in a scenario of uncertainty, where probabilities and alternatives are unknown. On the other hand, regarding rational-choice theory, algorithms run in risky scenarios where probabilities are known (Hafenbrädl et al., 2016; Todd & Gigerenzer, 2007). When people are faced with decisions in certain scenarios, making a decision under risk is often not the best choice under uncertainty. Therefore, if an individual or an algorithm is not able to determine whether a decision under risk or uncertainty is superior, aversion towards algorithm could emerge (Burton et al., 2020).

To conclude, the overconfidence bias has a great influence on algorithm aversion. Individuals still prefer to rely on their or other people's intuition instead of an algorithm (Arkes et al., 2007). They believe that an algorithm lacks capabilities in decision-making in comparison to humans (Lee, 2018). Additionally, scholars have neglected research about alternative decision-making methods, such as fast-and-frugal heuristics. Aversion towards algorithms could emerge when individuals or algorithms are not able to determine if a decision under uncertainty or risk is superior in a specific scenario (Burton et al., 2020).

4.1.3 The Domain of Judgment

The third approach that influences the skepticism of individuals towards algorithms, even though algorithms are often superior to humans (Dawes, 1979), is the domain of judgment (Logg et al., 2019). To describe this cause, it is important to include the area of the relationship between humans and between humans and algorithms. Research papers investigating this cause are illustrated in table 7.

Cause	Sources	
Domain of Judgment	12	Alexander et al. (2018); Armstrong (1980); Castelo et al. (2019); Dawes (1979); Efendić et al. (2020); Logg et al. (2019); Madhavan & Wiegmann (2007b); Nass & Lee (2001); Nass et al. (1996); Prahl & Van Swol (2017); Shaffer et al. (2013); Yeomans et al. (2019);

Table 7: The Domain of Judgment

One reason why individuals react differently to advice from humans or algorithms is the people's habit to seek a social relationship with the medium of judgment (Alexander et al., 2018; Prahl & Van Swol, 2017). People are convinced that they have more in common with human-based recommendations in comparison to algorithmic-based recommendations (Prahl & Van Swol, 2017). Moreover, social proof has a high impact on the usage of algorithmic models. If people know that others have already successfully used the algorithm, they are more likely to use it too (Alexander et al., 2008).

In daily situations where people are obliged to make decisions, e.g. when deciding which book to read, which restaurant to eat at, they look for recommendations from people close to them. Therefore, when making decisions about personal taste, people tend to rely on recommendations from people close to them, such as friends and family, rather than relying on an algorithmic model (Yeomans et al., 2019). When individuals think that the advice comes from humans, they can make sense of why someone gave such a recommendation. However, when individuals think that the advice comes from an algorithm, they perceive it as opaque (Yeomans et al., 2019). Additionally, in contrast to most algorithmic models, human advisors are able to explain their recommendations (Armstrong, 1980; Castelo et al., 2019) and it is easier for individuals to blame other humans for mistakes than algorithmic models (Shaffer, Probst, Merkle, Arkes & Medow, 2013). As a result, individuals believe to have a better understanding of human advice than of algorithmic advice. Therefore, individuals are more likely to rely on recommendations when they are able to understand how they work (Yeomans et al., 2019).

Humans have similar relationships with algorithmic decision aids as with other humans (Nass, Fogg & Moon, 1996). Therefore, algorithms are often developed to act like humans, for example, algorithms can imitate human language (Madhavan & Wiegmann, 2007b). Additionally, individuals apply polite standards and stereotypes like gender, when they interact with a computer and feel „attracted" to it when their personalities go in line with the "personalities" of the computer (Nass & Lee, 2001). Nevertheless, people still, in many cases, distrust the advice of algorithms, which might also depend on the response time of algorithms (Efendić, Van de Calseyde & Evans, 2020). According to Efendić et al. (2020), people find slow performed, algorithm-based forecasts less accurate and consequently of poorer quality. Therefore, they are less likely to rely on them. The opposite applies to human forecasts. Individuals perceive slow performed human forecasts as more accurate and consequently of higher quality and are therefore willing to use them more often. People assume that a longer response time indicates the effort invested, for both algorithmic- and human-based predictions. However, individuals judge these two forecast methods differently, concerning effort and quality. Human-based forecasts are perceived as complex and difficult to make. Therefore, response time (effort) correlates positively with quality. In contrast, humans perceive algorithmic forecasts as easy and therefore, the length of the response time (effort) does not correlate with quality (Efendić et al., 2020).

To sum up, people seek a social relationship with the medium of judgment (Alexander et al., 2018; Prahl & Van Swol, 2017). They believe that they have more in common with human-based recommendations (Prahl & Van Swol, 2017) because it is easier to understand why a human suggests such a recommendation in comparison to algorithms (Yeomans et al., 2019). Therefore, algorithms are more and more programmed to act like humans (Madhavan & Wiegmann, 2007b).

4.1.4 Disuse of Algorithms

Finally, the last approach to mention regarding this subchapter is the erroneous disuse (underutilization) of algorithms. Disuse of algorithms is described as the resulting failures which take place when people mistakenly do not rely on algorithms (Parasuraman & Riley, 1997). People tend to disuse algorithms more than human decision aids (Dzindolet et al., 2002). To explain this approach, it is important to include the role of underutilization of decision aids and the reasons, like prior expectation and experience with algorithms, the experts fear towards algorithms, and the lack of training in using algorithms, which affect it. Scholarly sources describing this cause are illustrated in table 8.

Cause	Sources	
Disuse of Algorithms	19	Arkes et al. (1986); Burton et al. (2020); Commerford et al. (2019); Corey & Merenstein (1987); Dietvorst et al. (2015); Dzindolet et al. (2001); Dzindolet et al. (2002); Green & Hughes (1986); Kaplan (2000); Lee & Moray (1992); Lee & See (2004); Logg et al. (2019); Luong et al. (2020); Luo et al. (2019); Montazemi (1991); Parasuraman & Riley (1997); Promberger & Baron (2006); Whitecotton (1996); Workman (2005);

Table 8: Disuse of Algorithms

People often reject the possibilities of algorithms in decision making and this leads to the erroneous underutilization of algorithmic models which are perceived as unnecessary (Arkes et al., 1986). For example, Corey & Merenstein (1987) tested an algorithmic prediction aid for heart disease diagnosis. The algorithmic model was able to decrease the false-positive prediction rate from 71% to 0%. Despite this positive effect, this result was not really accepted by doctors. Doctors underutilized the decision aid because of the low recognized usefulness of it, only 2.8% of them utilized the prognostic aid (Corey & Merenstein, 1987).

The underutilization of decision aids has different reasons. Firstly, trust plays a crucial role in the disuse of algorithms, especially when people's trust does not match with the algorithm's real capabilities. If people's trust lags behind the algorithm's real capabilities, distrust emerges and leads to underutilization of the algorithmic advice (Lee & See, 2004). Additionally, people weight up the perceived reliability of human and algorithm-based predictions to determine on which advice they should rely (Dzindolet, Beck, Pierce, & Dawe, 2001). Consequently, people's disuse towards decision aids arises, when the perceived reliability of the algorithmic decision aid is low and therefore, the perceived capabilities of the algorithm are underestimated (Dzindolet et al., 2001; Dzindolet et al., 2002). This behavior arises because of people's urge for self-reliance and control (Dzindolet et al., 2002).

Secondly, the decision-makers' prior expectations with regards to algorithms influence this behavior. Most people do not face a decision aid with a blank state. Decision-makers have prior expectations when it comes to the capabilities of an algorithm and its interaction with a decision aid. Beforehand, they are wondering about how the algorithm might perform, how it should perform, and how it works. These expectations might result from experiences gained from previous interactions with algorithms or simply from absorbed knowledge these individuals acquired through the interaction with close people such as friends or family, or even from different types of media (Burton et al., 2020). For example, the expectations and opinions of work colleagues or managers affect the viewpoint of other employees towards decision aids (Workman, 2005). These pre-generated expectations might cause people to react differently to human and algorithmic predictions, although the advice of both predictions is identical (Burton et al., 2020). Not uncommonly, individuals expect algorithms to be perfect (Dzindolet et al., 2002). Therefore, disuse emerges when individuals notice that the algorithm is imperfect and capable of making errors (Dzindolet et al., 2002). In addition, faults with environmental situations and algorithms lead to poor algorithm performance, resulting in a decrease in trust and to disuse of decision aids (Lee & Moray, 1992; Lee & See 2004). Consequently, the previously generated expectations might influence the way in which people use algorithms (Burton et al., 2020).

Thirdly, people's previous experience with algorithmic decision aids has an impact on their utilization (Dietvorst et al., 2015). Experience is positively related and domain expertise is negatively related to the use of decision aids (Montazemi, 1991; Whitecotton, 1996). For example, two people with different backgrounds are given the task to predict the performance of a specified market. One of them is an experienced forecaster who has a broad knowledge on how to use algorithm decision aids at his/her command. The other person is an experienced economist who has extensive knowledge on the subject at his/her disposal but is not familiar with algorithms at all. The forecaster probably feels insecure about interpreting the market intuitively and would use the algorithm as decision support. For the economist, it might exactly be the other way around. S/he has a lot of knowledge about the market and therefore feels more confident to make the forecast intuitively and without the help of an algorithm. Here, the algorithmic decision aid would be perceived as unnecessary by the economist (Burton et al., 2020). Research indicates that people increasingly rely on algorithmic-based decision aids if they gain more experience with this technology (Commerford, Dennis, Joe & Wang, 2019; Luo, Tong, Fang & Qu, 2019). However, academic literature on this matter also shows the opposite. People are more likely to use a decision aid when they have no prior experience with algorithms (Dietvorst et al., 2015; Logg et al., 2019; Luong, Kumar & Lang, 2020). As a result, according to Dietvorst et al. (2015) people are willing to disuse decision aids to a larger extent if they already have prior experience with them, because they might already notice them making an error.

Fourthly, the reason for experts' aversion towards and thus underutilization of data-based decision aids could be the fear that the use of decision aids could reduce their professional attitude in the perception of individuals (Kaplan, 2000). The fear of experts is quite justified (Promberger & Baron, 2006). Patients perceive doctors who use an algorithmic decision tool as less competent than doctors who make decisions without such a tool (Arkes et al., 2007; Promberger & Baron, 2006).

Finally, training managers in the correct use of decision aids influences the effectiveness and the use of algorithms. Consequently, managers who are not provided with a well-suited training are more likely to disuse the algorithmic decision aid and to rely on human advice (Green & Hughes, 1986).

In conclusion, the disuse and therefore underutilization of algorithms has many reasons. People's trust in the capabilities of algorithms, prior expectations and experiences have a great impact on people's use of decision aids. Managers could have the fear that the decision aid decreases their professionalism (Kaplan, 2000) or are not well-trained to use decision aids in the right way (Green & Hughes, 1986).

All in all one can say that after reviewing the main causes of algorithm aversion which are algorithm error, divergent rationalities, the domain of judgment, and the disuse of algorithms, the causes lie in various approaches. As individual differences also play a role in how people react to an algorithm, the following subchapter reviews the existing scholarly sources about this topic to analyze the differences in individual characteristics. Due to lack of academic literature covering the topic of individual differences, they are not divided into algorithm aversion and algorithm evaluation in the following subchapter.

4.2 Individual Differences

One area that influences people's trust in automation are individual differences. Research has shown that there are significant differences in individual characteristics of how people trust algorithm-based decision aids (e.g. Hoff & Bashir, 2015; Thurman et al., 2019). Despite the effect of individual differences on the human-algorithm relationship is still unclear, in this subchapter, the variables of culture, age, gender, and personality are reviewed. The individual characteristics such as culture, personality, culture, unlike gender, develop over time. Nevertheless, these variables stay stable when it comes to a specific interaction (Hoff & Bashir, 2015). As illustrated in table 9, excluding duplicates, 27 papers are consulted to review the influence of individual differences regarding trust in the human-algorithm relationship. The variables culture, age, and personality do not differ that much regarding the number of papers used. While for the variable gender with only 5 sources, the fewest papers were found.

Results of Search	Number of Articles
Culture	5
Age	9
Gender	11
Personality	9
Sum	**34**
Excluding Duplicates	7
Total Articles	**27**

Table 9: Individual Differences

4.2.1 Culture

The first individual characteristic that might influence the relationship between humans and algorithms is culture. It is important to include this variable as almost everyone identifies him- or herself with a certain type of culture (Hoff & Bashir, 2015). In this context, humans' trust differs across generations, religious affiliation, places (e.g. countries, cities), as well as races (e.g. Naef, Fehr, Fischbacher, Schupp & Wagner, 2008). Research papers used to review this individual difference are illustrated in table 10.

Individual Difference	Sources	
Culture	5	Hoff & Bashir (2015); Huerta et al. (2012); Li et al. (2010); Naef et al. (2008); Rau et al. (2009);

Table 10: Culture

Although the assumption that culture has an impact on the relationship between human and algorithm exists, there is only a little amount of scholarly research that proves this. According to Huerta, Glando & Petrides (2012), the impact algorithm-based systems have on humans is different across countries. The reason for this might lay in the people's perception of algorithm-based decision aids. For example, in contrast to Americans, Mexicans are willing to rely on an algorithmic-based decision aid to a greater extent and do not want to rely on a manual decision aid. Americans, however, tend to rely less on algorithmic-decision aids and tend to rely more heavily on manual decision systems (Huerta et al., 2012). Additionally, taking the area of human-robot interaction into consideration, one can say that individuals from different cultures might perceive social robots differently (Li, Rau, & Li, 2010). For example, there might be differences in how people from different countries react to the communication of robots. According to Rau, Li & Li (2009), Germans perceive robots as less likable and less trustworthy compared to Chinese. Therefore, Germans are willing to rely on implied pieces of advice from robots to a smaller extent than Chinese. Chinese, as a result, feel more attracted to an implicit communication method than Germans (Rau et al., 2009).

To conclude one can claim that the two mentioned examples suggest the impact of culture on trust in the human-algorithm relationship. In order to explain the individual differences in this context in more detail, more research needs to be consulted (Hoff & Bashir, 2015).

4.2.2 Age

The second individual difference which is going to be explained as an important factor is the variable age. Hoff & Bashir (2015) suggest that diverse age groups use different approaches when it comes to their judgment of the trustworthiness of an algorithmic decision aid. Nevertheless, people's behavior is not that clear, because their way of judging, and therefore the impact of the variable age, depends on the context (Hoff & Bashir, 2015). Scholarly sources investigating the variable age in the context of algorithms is illustrated in table 11.

Individual Difference	Sources	
Age	9	Araujo et al. (2020); Ho et al. (2005); Hoff & Bashir (2015); Logg et al. (2019); Lourenço et al. (2020); Pak et al. (2012); Sanchez et al. (2004); Thurman et al. (2019); Thurman & Fletcher (2019);

Table 11: Age

Scholars carried out several investigations to analyze the variable age and came to different results. On the one hand, Logg et al. (2019) did not discover any connections between the variable age and the tendency to rely on an algorithmic decision aid. On the other hand, however, research found differences between age groups as described in the following in more detail. As mentioned above, the effect of the variable age depends on the context (Hoff & Bashir, 2015). One stream of research suggests that people at a higher age are more likely to trust and use an algorithm than people at a lower age. People at higher age are superior in calibrating their level of trust to the inconsistent reliability of an algorithm than people at lower age (Sanchez, Fisk & Rogers, 2004). Interestingly, there are no differences in how individuals calibrate their level of trust in decision aids when the algorithm makes an error (Ho, Wheatley & Scialfa, 2005). As a contrast, the other stream of research suggests that older people are less likely to rely on an algorithmic decision aid than younger people. According to Araujo, Helberger, Kruikemeier & De Vreese (2020), the individual factor age is negatively associated with the perceived usefulness of automated decision-making. For example, in the domain of online financial support systems, older people are less satisfied and have less trust in the algorithmic interaction than younger people (Lourenço, Dellaert & Donkers, 2020). Moreover, in the domain of choosing the source of news, people at a higher age want to receive news from an editor rather than from an algorithm-based personalization (Thurman et al., 2019). The examples described in this stream might have different reasons. According to the study of Lourenco et al. (2020), the expertise with online services might play a role. For older people it is more challenging to use an online service tool because they have less expertise with technology (Lourenço et al., 2020). Additionally, older people's rejection of algorithmic news personalization could be because this age category is the main group of consuming traditional types of media (Thurman & Fletcher, 2019). In addition to these two different streams, younger people's trust in the algorithmic decision aid increases when a photo of an expert adorns the interface of a decision aid, compared to older people (Pak, Fink, Price, Bass & Sturre, 2012).

In conclusion, the existing academic literature examining the variable age in the context of trust in the human-algorithm relationship is still conflicting. More research needs to be consulted to ensure a better understanding of this variable (Hoff & Bashir, 2015).

4.2.3 Gender

An additional variable that might influence the relationship between humans and algorithms could be gender. The variable gender might have an impact on human interaction with technology (Hoff & Bashir, 2015). Research papers used to review the individual characteristic gender are illustrated in table 12.

Individual Difference	Sources	
Gender	11	Araujo et al. (2020); Bhattacharya et al. (2012); Hoff & Bashir (2015); Lee (2008); Logg et al. (2019); Lourenço et al. (2020); Lundeberg et al. (1994); Nomura et al. (2008); Prince (1993); Thurman et al. (2019); Tung (2011);

Table 12: Gender

Despite the suggestion that gender could have an impact on trust in the human-algorithm relationship (Hoff & Bashir, 2015), a part of research has shown that that the variable gender does not influence people's reliance on algorithmic decision aids (e.g. Logg et al., 2019; Thurman et al., 2019). However, some investigations point out that there are differences in how males and females interact and respond to different sorts of technology. For example, in financial matters, the individual characteristic gender might play a role in advice taking (Bhattacharya, Hackethal, Kaesler, Loos & Meyer, 2012). Research has shown that females are less confident about their skills when it comes to making appropriate financial decisions in comparison to males (e.g. Lundeberg, Fox & Punccohar, 1994; Prince, 1993). Therefore, females might be more likely to consider advice (Lourenço et al., 2020). In the area of people's reactions towards computers, individuals react differently to flattery used by computers. Women are inclined to react positively to it while it has a negative effect on men (Lee, 2008). Additionally, gender plays a role in the perceived usefulness of automated decision making. Females perceive automated decision making as significantly less useful in comparison to males (Araujo et al., 2020). These examples and further investigations in the field of human-robot relationships (e.g. Nomura, Kanda, Suzuki & Kato, 2008; Tung, 2011) indicate that there may be differences regarding the variable gender with regard to how individuals respond to algorithmic decision aids. Differences especially emerge in two areas: the appearance of algorithms and their interaction with individuals (Hoff & Bashir, 2015).

Summing up one can state that the way in which gender influences human-algorithm interaction is still disputed. It is suggested that although significant gender-specific differences in human-algorithm interaction have not yet been discovered, they should be taken into account when developing certain algorithmic systems (Hoff & Bashir, 2015).

4.2.4 Personality

Finally, the last individual characteristic found in scholarly sources regarding trust in human-algorithm interactions is personality. Research has shown, based on the similarity-attraction hypothesis, that individuals feel attracted to each other when they are characterized by similar personalities (e.g. Blankenship, Hnat, Hess & Brown, 1984; Byrne & Griffitt, 1969; Duck, 1973). The effect of matching does not only work for human-human relationships, but might also work when it comes to human-machine relationships. Individuals are more prone to rely on algorithms when the algorithm displays similar personality characteristics to those of the user (Nass & Lee, 2001; Nass, Moon, Fogg, Reeves & Dryer, 1995). Dominant users feel more attracted to dominant language and submissive users to submissive language when interacting with a computer (Nass & Lee, 2001). Phrases like "You should definitely do this" (p.172) can be used to attract dominant users and phrases like "Perhaps you should do this" (p.172) tend to appeal to submissive users (Nass & Lee, 2001). Scholarly sources used to review this variable are illustrated in table 13.

Individual Difference	Sources	
Personality	9	Blankenship et al. (1984); Byrne & Griffitt (1969); Duck (1973); Hoff & Bashir (2015); McBride et al. (2012); Merritt & Ilgen (2008); Nass & Lee (2001); Nass et al. (1995); Szalma & Taylor (2011);

Table 13: Personality

The individual characteristic personality influences people's willingness to use algorithmic decision aids in different ways. For example, in the area of medical prognoses, nurses characterized by a more intuitive personality are inclined to rely more heavily on algorithmic-based diagnosis aids than nurses characterized by a more sensing personality (McBride, Carter & Ntuen, 2012). In the context of personality, it is also important to include more specific personality traits (Hoff & Bashir, 2015). Research suggests that the five personality traits openness, conscientiousness, extraversion, agreeableness, and neuroticism might have an impact on the reaction towards algorithms as shown in the following. For example, the domain of automation agreement is normally not related to personality. But neuroticism is the exception and shows a negative correlation to it (Szalma & Taylor, 2011). Also the personality trait extraversion plays a role in people's trust in algorithms. Individuals with a more extroverted personality are more likely to trust machines than people with a more introverted personality. Moreover, people with a rather extraverted personality tend to have high initial trust when interacting with machines (Merritt & Ilgen, 2008).

In conclusion, these mentioned examples suggest that individuals tend to rely more heavily on algorithmic-based decision aids when they have a more intuitive, emotionally stable, and extraverted characterized personality (Hoff & Bashir, 2015).

All in all it can be stated that even through one still notices a lack of findings regarding individual differences, this subchapter shows that there exist some significant differences in individual characteristics which influence the human-algorithm relationship. However, a more extensive research would be necessary to get a better understanding of this relationship. As shown in Table 9 at the beginning of this subchapter, the variable gender is the most investigated individual characteristic compared to the other three variables but is still conflicting and not clear. After reviewing the causes of algorithm aversion and the individual differences influencing the human-algorithm interactions, the next subchapter shows the different areas in which people do not rely on algorithms.

4.3 Areas in which Algorithms are rejected

After reviewing all the causes and variables influencing people's reactions towards algorithmic decision-aids, this subchapter shows when people do not rely on algorithms. As previously mentioned, the issue of algorithm aversion is that people are inclined to rely more heavily on human than on algorithmic advice, even though algorithms are more accurate than humans (Dietvorst et al., 2015). Therefore, it is important to include the areas in which individuals react negatively towards algorithm-based decision aids. Beforehand, the context of perceived subjectivity and objectivity should be considered. In most cases, people tend to rely on human judgments to a greater extent than on algorithm judgments (Dietvorst et al., 2015). But according to Castelo et al. (2019), individuals have the tendency to rely on advice from algorithms more heavily when the task is perceived as objective and more in human judgment when the task is perceived as subjective.

To ensure a better understanding of algorithm aversion, this subchapter reviews the areas of medical, economic and business, legal, military, and driving decision-making as well as the area of subjective recommendations, where algorithms are rejected and, in contrast to that, human judgment is relied on. As illustrated in table 14, excluding duplicates, 41 papers are used to describe the areas in which algorithms are rejected. The amount of papers available for the various areas differs quite a bit. Most papers which are taken into account for this review describe the areas of medical, economic and business decision-making, whereas, in comparison, only a few academic sources describe legal, military, diving decision-making, and the area of subjective recommendations.

Results of Search	Number of Articles
Medical decision-making	18
Economic & Business decision-making	18
Legal, Military, Driving decision-making	3
Subjective Recommendations	6
Sum	**45**
Excluding Duplicates	4
Total Articles	**41**

Table 14: Areas in which Algorithms are rejected

4.3.1 Medical decision-making

The first area in which algorithm forecasts are often rejected is in the context of medical decisions. This was the first field of research where aversion towards algorithm was detected (Meehl, 1954). In the following paragraph the aversion of physicians and patients towards algorithms is explained. Research papers investigating medical decision-making regarding algorithm aversion are illustrated in table 15.

Rejected Area	Sources	
Medical decision-making	18	Arkes et al. (2007); Bennett & Hauser (2013); Bigman & Gray (2018); Dawes (1979); Dawes et al. (1989); Eastwood et al. (2012); Gough (1962); Grove & Meehl (1996); Grove et al. (2000); Kleinmuntz (1990); Komaroff (1982); Longoni et al. (2019); Marchese (1992); Meehl (1954); Patel et al. (2009); Promberger & Baron (2006); Sawyer (1966); Shaffer et al. (2013);

Table 15: Medical decision-making

The first pioneer research on algorithm aversion was conducted, as previously mentioned, by Meehl (1954). The investigation was about the topic of clinical (human) versus actuarial (algorithm) forecasts. The main finding was that a statistical model outperforms skilled people relying on their intuition in prediction-making (Meehl, 1954). Substantial research about clinical versus statistical prognoses was able to endorse this suggestion (e.g. Dawes et al., 1989; Gough, 1962; Grove & Meehl, 1996; Grove et al., 2000; Marchese, 1992; Sawyer, 1966). In the conceptual work of Dawes et al. (1989), almost 100 papers were reviewed according to the dilemma of clinical versus actuarial decision-making. This investigation concluded that in each of the reviewed studies the statistical prognosis was equal or superior to the human prognosis (Dawes et al., 1989). Since the technology has developed in the last decades, AI systems can reduce errors and improve efficiency in the hospital (Bennett & Hauser, 2013; Patel et al., 2009). Despite the findings which suggest that algorithmic forecasts equal or outperform human forecasts in the context of medical prognosis, people still prefer to rely on a prognosis made by a human than on one made by an algorithmic decision aid (e.g. Eastwood, Snook & Luther, 2012; Longoni et al., 2019; Promberger & Baron, 2006). On the one hand, doctors reject the use of algorithmic decision aids. They rely on clinical methods, although actuarial decision aids would be available for them to use (Kleinmuntz, 1990) because of the belief that actuarial methods are dehumanizing, unfair in nature, and the fear that with the use of algorithms the "art" of human judgment will be lost (Dawes et al., 1989; Dawes, 1979; Komaroff, 1982). On the other hand, this rejecting behavior can also be found with patients. Patients rather rely on doctors' prognosis than on algorithmic prognosis because it decreases the patients feeling of responsibility (Promberger & Baron, 2006) and patients suspect that algorithmic decision aids will not consider their unique individual characteristics in the same way as doctors (Longoni et al., 2019). Patients feel more confident trusting physicians when they do not include algorithmic decision aids in their prognosis (Eastwood et al., 2012; Shaffer et al., 2013). They perceive doctors using an algorithmic decision aid as less professional, less thorough, and consider them having a lower level of ability when it comes to making a diagnosis compared to doctors who make an aid free prediction (Arkes et al., 2007). Additionally, people have the tendency to show aversion towards algorithms in moral decisions. For example, when deciding whether a surgery with a small probability of dying should be performed or not. Individuals have the tendency to rate the algorithmic-based system as less permissible and less acceptable compared to the human decision if they find themselves in a situation in which they can choose between a doctor or an algorithmic-based system (Bigman & Gray, 2018).

In conclusion, algorithm aversion in the domain of medical decisions has been researched for decades and until now not much has changed. People are still averse towards algorithmic decision aids.

4.3.2 Economic and Business decision-making

The second area in which algorithmic decision aids are often rejected is in economic and business decision-making. In the following paragraphs aversion towards algorithms for economic and business decision-making is explained, including the areas of marketing and sales, finance, and personal selection. Scholarly sources investigating aversion towards algorithms in this context are illustrated in table 16.

Rejected Area	Sources	
Economic & Business decision-making	18	Buckley et al. (2000); Bucklin et al. (1998); Cortina et al. (2000); Dawes (1979); Diab et al. (2011); Dietvorst et al. (2015); Fildes & Goodwin (2007); Highhouse (2008); Kuncel et al. (2013); Lee (2018); Lievens et al. (2005); Lodato et al. (2011); Luo et al. (2019); Önkal et al. (2009); Rynes et al. (2002); Sanders & Manrodt (2003a); Sanders & Manrodt (2003b); Schmidt & Hunter (1998);

Table 16: Economic & Business decision-making

In the field of managerial decision-making, people assume that some tasks require either mechanic skills or human skills. When it comes to mechanical perceived tasks, individuals perceive human and algorithmic-based decisions as equally acceptable in terms of trustworthiness and fairness. Regarding tasks requiring human skills, people perceive both decision types differently. Algorithms are perceived as less fair and less trustworthy. People feel more doubtful towards algorithmic decisions than towards human decisions (Lee, 2018). Regarding forecasts in organizations, decision-makers often rely too excessively on unstructured forecasting methods and tend to reject erroneously statistical methods even though statistical forecast models can outperform human judgment (Fildes & Goodwin, 2007; Sanders & Manrodt, 2003b). Managers often dilute predictions with their decisions (Fildes & Goodwin, 2007).

In the area of marketing, algorithms could help to support various processes up to complete automation (Bucklin et al., 1998). In marketing and sales, according to Sanders & Manrodt (2003a), the major part of decision-makers uses spreadsheets e.g. Microsoft Excel or Lotus, followed by intern developed prediction systems, commercial offered systems, and the non-use of prediction methods for forecasting tasks. Only a small percentage of decision-makers use prediction systems, developed by external vendors. Decision-makers stated that they are often dissatisfied with their forecast system. This was mainly the case with the use of spreadsheets and less the case with the use of commercial prediction methods. Therefore, decision-makers in marketing and sales reported that they often do not necessarily rely on algorithmic prediction systems and do not resort to adding subjective adjustments to the prediction. Even though decision-makers using commercial forecast software made more accurate forecasts, the major part still prefers to rely on other forms of forecast methods, such as spreadsheets or human judgment (Sanders & Manrodt, 2003a). In addition, the reaction of people towards chatbots should be mentioned in this context, as chatbots can be used in marketing and sales for various purposes, such as for advertising or product sales. According to Luo et al. (2019), unrevealed chatbots (individuals do not notice that it is an AI-based chatbot) are equally successful as experienced employees and four times more successful than inexperienced employees in generating product sales through calls. However, when potential customers interact with chatbots and the true "identity" of the chatbots is revealed and the customer realizes that they are AI-based and not real humans, the purchasing rate of the potential customer decreases. They even tend to end the interaction early because chatbots are perceived as less empathetic and knowledgeable (Luo et al., 2019).

In the field of financial decision-making, algorithm aversion can also be detected. When individuals are offered with identical advice in stock price forecasts, either from a human or from an algorithm, they respond differently to it. Individuals are inclined to dismiss the algorithmic prediction more often than the human prediction, even though both forecasts were beneficial (Önkal et al., 2009).

In the field of employee selection, although there exist cost-efficiency algorithmic-based methods, people still prefer to rely on the traditional way of conducting interviews (Buckley, Norris & Wiese, 2000; Connelly & Ones, 2013; Diab et al., 2011; Kuncel, Klieger, Rynes, Colbert & Brown, 2002). The issue of this behavior is that more standardized methods are perceived as being superior as opposed to less standardized methods in selection procedures (Schmidt & Hunter, 1998). Less standardized methods, such as interviews, give little insight into the future performance of the potential employee (Cortina, Goldstein, Payne, Davison & Gilliland, 2000). The rejection of algorithmic-based decision aids can be found on both sides: employers and potential employees. The existing research indicates that employers erroneously prefer to rely on intuition-based decision-making instead of including decision aids in their selection process (Highhouse, 2008; Kuncel et al., 2013; Lievens, Highhouse & DeCorte, 2005; Lodato, Highhouse & Brooks, 2011). The reason for this behavior might be the overconfidence bias, which is previously explained in more detail, in the cause of algorithm aversion "Divergent Rationalities". For example, retail managers pay much more attention to the abilities of potential employees found from unstructured interviews than from the results of tests conducted (Lievens et al., 2005) because they have more trust in their own intuition (Highhouse, 2008).

Potential employees react quite similarly in this domain and feel more doubtful towards algorithmic decision aids than towards human judgment. They perceive standardized decision aids as less trustworthy and less fair (Dawes, 1979; Lee, 2018) and perceive traditional methods such as interviews as more professional, flexible, personal, sufficient, and precise (Diab et al., 2011). Potential employees find that important decisions like the selection of an employee should be made on the basis of a personal face to face interview, as all other methods are evaluated as being dehumanizing (Dawes, 1979). This phenomenon, however, is described in more detail above, in the subchapter "Causes of Algorithm Aversion - Divergent Rationalities". The same effect of employee selection can be found in student selection. In the study of Dietvorst et al. (2015) participants were assessed to rate the performance of MBA applicants through a human or an algorithmic method. Before the selection of the method, they got to see a human and an algorithm prediction. Participants' tendency to rely on algorithmic forecast decreased after noticing that it made an error, but humans' tendency to rely on people forecasts did not decrease if a human made a mistake. People punish algorithm errors more than human errors (Dietvorst et al., 2015). Also, the algorithmic error is described in more detail above, in the subchapter "Causes of Algorithm Aversion - Algorithm Error".

To sum up, one can state that people often reject the use of algorithms in the fields of marketing, sales, and finance. Additionally, employers and potential employees show this behavior in personal selection. Individuals tend to rely on their intuition more and are often biased in their decision making.

4.3.3 Legal, Military, and Driving decision-making

The next area in which algorithmic decision aids are often rejected is in legal, military and driving (self-driving vehicles) decisions. In the following paragraphs, the aversion towards algorithms of these fields is reviewed. Research papers used to describe these are illustrated in table 17.

Rejected Area	Sources	
Legal, Military, Driving	3	Bigman & Gray (2018); Eastwood et al. (2012); Liu et al. (2019);

Table 17: Legal, Military, and Driving decision-making

In legal decision making, individuals react differently to decision-making strategies including a human decision-maker or an algorithm decision aid (Bigman & Gray, 2018; Eastwood et al., 2012). For instance, when it comes to deciding whether an offender will be granted bail or not, individuals feel more skeptical and less comfortable towards a decision from an algorithmic-based system, compared to a human decision (Eastwood et al., 2012). Furthermore, the question of whether to grant a lawbreaker parole or not can be made by a human being or even an algorithm. But people have the tendency to show aversion towards algorithms for moral decisions. Therefore, for this case, individuals perceive it as less permissible to rely on an algorithmic-based system and prefer to leave the decision to a human committee (Bigman & Gray, 2018).

In military decision-making people's aversion towards algorithm can also be detected. For example, in the case of a drone attack towards a terrorist, where the drone could kill the offender but also harm civilians. Individuals can either choose if the decision for the drone's attack is made by an algorithm or by a human officer. They react differently to both scenarios. Individuals are less permissible toward the algorithm-based decision than to the human decision and are apt to reject algorithms in decision-making for moral topics (Bigman & Gray, 2018).

In the area of self-driving vehicles, individual's perception towards human-driven and self-driving cars differ (e.g. Bigman & Gray, 2018; Liu et al., 2019). Driving cars are characterized as risky and prone to causing accidents. People perceive traffic accidents involving autonomous driving vehicles as more dramatic than traffic accidents involving human-driven vehicles, even if the self-driving car does not cause the accident (Liu et al., 2019). During accidents, people in the car and pedestrians are often affected by the risk of dying. Individuals react differently if the algorithm of the autonomous driving vehicle or the human driver of the car is responsible for life or death in accidents. For this moral decision, people show aversion towards the algorithm and evaluate the decision of an algorithm as less permissible as opposed to human decisions (Bigman & Gray, 2018).

To conclude, people show aversion in legal, military and driving decisions. This is especially the case because people show more aversion towards algorithms in moral decisions.

4.3.4 Subjective Recommendations

The last area in which people do not want to rely on algorithms are subjectively perceived recommendations. In the following paragraphs, the aversion towards algorithmic-based recommendations is described, which includes recommendations of jokes, movies, dating partners, and books. Scholarly sources used to review this area are illustrated in table 18.

Rejected Area	Sources	
Subjective Recommendations	6	Castelo et al. (2019); Dietvorst et al. (2015); Fitzsimons & Lehmann (2004); Jakesch et al. (2019); Sinha & Swearingen (2001); Yeomans et al. (2019);

Table 18: Subjective Recommendations

Aversion towards algorithms occurs in many different contexts. Especially tasks that involve subjective judgment, e.g. recommendations of jokes, are presumably a large factor (Castelo et al., 2019; Yeomans et al., 2019). This behavior is caused by the people's conviction that algorithms are not capable of performing subjective tasks (Castelo et al., 2019), even though algorithmic recommendations can outperform human recommendations in this context (Yeomans et al., 2019). In addition, individuals are sometimes confronted with product recommendations that contradict their first impression of choice. In this case, they tend to show reactance towards the algorithm-based recommender system and start to avoid consulting further recommendations (Fitzsimons & Lehmann, 2004). This can lead to algorithm aversion (Dietvorst et al., 2015). According to Castelo et al. (2019), individuals perceive algorithmic advice for subjective tasks as useless and are less comfortable relying on them in comparison to human advice. The study of Sinha & Swearingen (2001) shows a contradiction: even though participants relied on human recommendation for movies and books more than on recommender systems, they were still satisfied with the recommender system and found it useful (Sinha & Swearingen, 2001).

Algorithmic recommendation systems are able to outperform human recommendations in predicting jokes that people find funny, even though recommendations such as jokes are perceived as subjective and as a uniquely human domain. Nevertheless, individuals are inclined to reject the algorithm system and prefer to rely on human advice, from family, friends, or strangers for recommending a joke (Yeomans et al., 2019). Recommendations regarding movies, books, or about finding a romantic partner (dating) are also perceived as subjective and show similar effects as joke recommendations. Regarding these domains, individuals trust in the human recommendations more than in algorithmic recommendations (Castelo et al., 2019; Sinha & Swearingen, 2001). Furthermore, individuals are more likely to interact with an ad for subjective tasks, such as dating, if it shows that it comes from a human rather than from an algorithm (Castelo et al., 2019). In addition, in the area of profile descriptions, people react differently when the descriptions are written by a human or by AI. Individuals tend to reject e.g. Airbnb hosts when they believe that the description was written by an AI-system rather than by a human-being (Jakesch, French, Ma, Hancock & Naaman, 2019).

In conclusion, people are apt to reject subjective recommendations or also profile descriptions generated by algorithmic-based systems. Tasks that are from a subjective nature are presumably large factors that create aversion towards algorithms (Castelo et al., 2019).

Summing up, aversion towards algorithms can be detected in various areas. The most common areas in which a rejection of algorithm can be detected are medical, economic and business, legal, military, and driving decisions as well as subjective recommendations. As mentioned before, the issue of algorithm aversion is that people tend to erroneously reject algorithmic decision aids, even though they often outperform human judgments. This phenomenon is costly for companies (Dietvorst et al., 2015). Therefore, it is important to look at strategies to overcome this issue. The next subchapter deals with this question.

4.4 Overcoming Algorithm Aversion

Finally, the last subchapter to review algorithm aversion deals with strategies on how to overcome this phenomenon. This approach is important for companies, which suffer from a lack of trust towards algorithms. Organizations, such as the government of Finland have already recognized the consequences of this issue and have developed a free online course to learn about the technical and philosophical aspects of AI. The goal of this course is to educate 1% of all EU citizens about the basic characteristics of AI by 2021 ("Elements of AI," n.d.).

In this subchapter, however, strategies found in the academic literature concerning overcoming algorithm aversion are reviewed. This includes the approaches of human in the loop strategy, ecological rationality, human-like algorithm as well as training and motivation. As illustrated in table 19, excluding duplicates, 31 papers are used to describe the strategies to overcome aversion towards algorithms. As becomes apparent in the table 19, in order to review the strategy training and motivation, the largest amount of papers was consulted, namely a sum of 14 papers. In order to give an overview of the human in the loop strategy, however, only four papers were used.

Results of Search	Number of Articles
Human in the Loop Strategy	4
Ecological Rationality	8
Human-like Algorithm	9
Training and Motivation	14
Sum	**35**
Excluding Duplicates	4
Total Articles	**31**

Table 19: Overcoming Algorithm Aversion

4.4.1 Human in the Loop

Decision-makers might need a feeling of confidence when interacting with algorithmic-based decision making (Burton et al., 2020). The lack of confidence is partly influenced by people's perception that errors can be made by algorithms. Individuals are inclined to rely on human judgment more often after seeing how the algorithm performs and notice that the algorithm is imperfect and capable of making errors. This rejection towards imperfect algorithmic-based decision aids can be due to an intolerance for unavoidable errors. Therefore, individuals are more likely to rely on imperfect decision aids when they have the possibility to correct or minimize such errors (Dietvorst et al., 2015). The strategy to implement this suggestion is called human in the loop decision-making, which is described in the following paragraph in more detail. Research papers used to describe the strategy of human in the loop decision making are illustrated in table 20.

Strategy	Sources	
Human in the Loop	4	Burton et al. (2020); Carbone et al. (1983); Dietvorst et al. (2018); Lim & O'Connor (1995);

Table 20: Human in the Loop

Human in the loop decision-making is not a new strategy, but Dietvorst, Simmons & Massey (2018) suggest applying it as a strategy to overcome the aversion towards algorithm. The idea is to increase the use of algorithms by letting individuals make some adjustments in the process of using decision aids. It has a positive impact on the use of algorithmic systems when people are given such a possibility. This strategy leads, on the one hand, to higher satisfaction of individuals with the forecast task and, on the other hand, it leads to higher confidence in, and perception of the algorithmic system in relation to themselves. Consequently, the use of algorithmic decision aids by individuals also increases in the future. Additionally, whether or not people have the possibility to adjust an imperfect algorithm to a higher or lower amount does not affect their level of satisfaction with the decision aid. In this aspect, individuals are relatively insensitive (Dietvorst et al., 2018). This indicates that even a programmed illusion about the possible adjustments of the algorithm could reinforce the tendency to rely on decision aids (Burton et al., 2020). Furthermore, some research has shown that individuals' effort to modify algorithmic-based predictions results often in worse outcomes (e.g. Carbone, Andersen, Corriveau & Corson, 1983; Lim & O'Connor, 1995). According to Dietvorst et al. (2018), however, the limitation of possible adjustments to the algorithmic process prevents individuals from making influential changes to the algorithmic decision model. Therefore, it still enhances forecasting performance.

To conclude, individuals will increase their use of algorithmic decision aids when they get the possibility to slightly modify the algorithm. As a result, they have the feeling to be able to decrease errors resulting from imperfect algorithms (Dietvorst et al., 2018). However, the possibility to adjust the algorithmic aid comes with the issue that more time is required for the entire process. Increased time results in increased costs. Therefore, one could claim that this potential strategy to overcome aversion towards algorithms is limited to areas where decision-makers have sufficient time to deal with such decision aids (Burton et al., 2020).

4.4.2 Ecological Rationality

As explained in more detail in the subchapter "Causes of Algorithm Aversion - Divergent Rationalities", humans are biased in decision-making. People prefer to rely on their own intuition or on that of others rather than on the decision making of algorithms (Arkes et al., 2007). Individuals think that algorithms lack capabilities in decision-making in comparison to humans (Lee, 2018). Additionally, the plurality of individuals' decision making in practice, such as fast-and-frugal heuristics, is often ignored and more focus is lain on the heuristics-and-biases program (Kahneman, 2003). For fast-and-frugal heuristics, aversion towards algorithms might emerge when individuals or algorithms are not able to determine if in a specific scenario a decision under uncertainty or risk should be taken into consideration (Burton et al., 2020). Therefore, the next strategy is to reduce overconfidence bias and to create ecological rationality. The term of ecological rationality is also explained in more detail above in the subchapter "Causes of Algorithm Aversion - Divergent Rationalities". Scholarly sources used to describe these strategies are illustrated in table 21.

Strategy		Sources
Ecological Rationality	8	Arkes et al. (2007); Burton et al. (2020); Hafenbrädl et al. (2016); Kahneman (2003); Lee (2018); Mullins & Rogers (2008); Patterson (2017); Westin et al. (2015);

Table 21: Ecological Rationality

The approach of overcoming overconfidence bias and intuition-based decision making is based on the idea of bridging the relationship between intuition and rationality (Burton et al., 2020). It is difficult to demand from people to learn a new process of making decisions out of nowhere. It is easier to find themselves in their process of decision making and to make improvements to their actual process (Hafenbrädl et al., 2016). In order to achieve this, it is necessary to study the human subconscious processes that affects intuitive decisions to detect the criterion responsible for collecting and evaluating data of individuals (Mullins & Rogers, 2008). Through this procedure, individuals' decision-making process can be subdivided into a number of different steps. The potential for using decision aids increases with each step. This procedure enhances the possibility for a greater extent of interaction, trust, and confidence by adding more transparency on both sides in the human-algorithm relationship (Burton et al., 2020).

This paragraph deals with the approach of how to overcome the aversion towards algorithms when individuals or algorithms are not able to determine if either a decision under uncertainty or risk should be taken into consideration (Burton et al., 2020). Research has mainly focused on the heuristics-and-biases program although other approaches such as the fast-and-frugal heuristics could also be valuable for practice (Burton et al., 2020; Hafenbrädl et al., 2016). When different factors such as cost, time, and access of decision making are considered in practice, an alternative way of decision-making is offered. Algorithmic decision aids could be developed with the goal of focusing on ecological rationality instead of probabilistic rationality. This could be a chance to combine human and algorithmic decision making for problem-solving and thus could lead to improved decisions (Burton et al., 2020). According to Patterson (2017), intuitive cognition is still the dominant force influencing people's decision making. There might be the possibility to develop algorithmic decision aids within the framework of rationality that works in accordance with people and their intuition and not the other way around (Burton et al., 2020; Westin, Borst & Hilburn, 2015). According to Burton et al. (2020), the plurality of decision-making in practice should be accepted. Through alternative decision theories like fast-and-frugal heuristics, new decision-making systems could emerge which may cause less aversion towards algorithms.

In conclusion, to overcome algorithm aversion, bridging the relationship between human and algorithms could help. As a result, higher transparency could be developed which leads to higher interaction with the algorithm. However, higher transparency of algorithms could conflict with performance. Additionally, the acceptance of the plurality of how people make decisions could reduce aversion. Consequently, additional algorithmic decision aids could be developed that are very similar to people's intuitive decision making, which tends to decrease aversion towards algorithms (Burton et al., 2020).

4.4.3 Human-like Algorithms

People seek a social relationship with the medium of judgment which is explained above in more detail in the subchapter "Causes of Algorithm Aversion - The Domain of Judgment" (Alexander et al., 2018; Prahl & Van Swol, 2017). As previously mentioned in the subchapter "Individual Differences - Personality", individuals are more prone to rely on algorithms when the algorithm displays similar personality characteristics to those of the user (Nass & Lee, 2001; Nass et al., 1995). Therefore, this strategy suggests developing algorithms that are more human-like to overcome algorithm aversion. Papers used to describe this strategy are illustrated in table 22.

Strategy	Sources	
Human-like Algorithms	9	Alexander et al. (2018); Castelo et al. (2019); Liu et al. (2019); Martini et al. (2015); Nass & Lee (2001); Nass et al. (1995); Prahl & Van Swol (2017); Wiese et al. (2012); Wiese et al. (2017);

Table 22: Human-like Algorithms

People believe that they have more in common with human- than with algorithm-based recommendations (Prahl & Van Swol, 2017). When individuals recognize their own way of thinking in another human or algorithm, it has a positive effect on their relationship. It leads to an increased level of trust and social connection which consequently improves the performance (Martini, Buzzell & Wiese, 2015; Wiese, Shaw, Lofaro & Baldwin, 2017; Wiese, Wykowska, Zwickel & Müller, 2012). Therefore, when algorithms which show more characteristics of humans are developed, the use of these decision aids could be increased. When individuals are shown real examples of algorithms operating similar to a human, such as the ability to understand emotions or creating art and music, it can increase peoples' perceived effectiveness of the algorithm (Castelo et al., 2019). Algorithms are already increasingly adjusted on human attitudes (e.g. Nass & Lee, 2001; Wiese et al., 2017). For example, self-driving cars are more and more becoming personal companions where the communication style and other characteristics can be adapted according to the drivers' wishes (Liu et al., 2019; Wiese et al., 2017). Self-driving cars are increasingly designed to behave more like a human being to enable humanized driving (Liu et al., 2019; Newcomb, 2014).

Summing up, individuals' use of decision aids could increase through the design of more human-like algorithms (Castelo et al. 2019). This could lead to higher trust and social connection in the human-algorithm relationship (e.g. Wiese et al., 2012).

4.4.4 Training and Motivation

As previously mentioned in the subchapter "Causes of Algorithm Aversion - Disuse of Algorithms", decision-makers often have prior expectations towards the algorithmic decision aid, which have a high impact on how they interact with and perceive algorithmic decision aids. False expectations towards algorithms could lead to aversion (Burton et al., 2020). Additionally, individuals prefer to rely on a human expert rather than on a cold algorithm (Önkal et al., 2009). Algorithmic decision-making is characterized by several calculations. Therefore, this kind of decision-making might require additional motivation for the implementation (Brown, 2015; Burton et al., 2020). To overcome aversion towards algorithms in these contexts, in the following paragraphs, the strategies of training and motivation are reviewed. Scholarly sources used to describe these strategies are illustrated in table 23.

Strategy		Sources
Training and Motivation	14	Alexander et al. (2018); Arkes et al. (1986); Brown (2015); Burton et al. (2020); Diab et al. (2011); Dietvorst et al. (2015); Goodwin et al. (2013); Green & Hughes (1986); Hagmann et al. (2019); Kuncel (2008); Lodato et al. (2011); Önkal et al. (2009); Prahl & Van Swol (2007); Yeomans et al. (2019);

Table 23: Training and Motivation

An approach which can be taken into consideration in order to overcome this cause of algorithm aversion is the advancement of human know-how about algorithm decision aids. To achieve this goal, decision-makers could be trained in various areas (Burton et al., 2020; Diab et al., 2011). They need to learn the importance of such decision aids and how to properly interact with algorithms (Kuncel, 2008; Lodato et al., 2011). Additionally, decision-makers have to be brought as far as to understand statistical concepts and to analyze and interpret statistical results in the right way (Arkes et al., 1986; Burton et al., 2020). It seems that providing individuals with a well-suited training decreases the disuse of algorithms and increases the effectiveness of algorithmic-based decision aids (Green & Hughes, 1986). Furthermore, when individuals get offered an explanation on how an algorithm works, their aversion is likely to be decreased (Yeomans et al., 2019) and their trust to be increased (Goodwin, Gönül & Önkal, 2013). If the decision-maker is able to learn about such approaches, it might help to overcome algorithm aversion (Burton et al., 2020).

The other approach which can be useful to overcome algorithm aversion is increasing people's motivation for using such decision aids. One the one hand, this aimed motivation could be created through economic incentives. A high number of scholarly sources shows that algorithmic decision aids outperform human judgments (e.g. Dietvorst et al., 2015; Yeomans et al., 2019). This creates the expectation that individuals are interested in using decision aids to increase their forecast performance, especially when they earn economic incentives, such as bonuses (Burton et al., 2020). There exists research, however, which is contradictory when it comes to this suggestion. According to Arkes et al. (1986), such incentives cause individuals to decrease their use of algorithmic-based decision aids. However, Prahl & Van Swol (2007) showed that economic incentives do not cause rejection towards algorithms. On the other hand, motivation could be created through social incentives. Individuals' decision-making is might linked to their social environment (Burton et al., 2020). Therefore, information of other people that already used a specific algorithm-based decision aid have a larger positive effect on people's adoption of such decision aids than specific information about the decision aid itself. Information delivered by others is useful to reduce the insecurity of a decision-maker towards a specific algorithm. This helps them to assess the reliability of the decision aid (Alexander et al., 2018). It is still not clear what influence economic and social incentives have on people's behavior towards algorithms. More research would be necessary in order to be capable of evaluating this effect. Nevertheless, it can be suggested that a change in people's behavior is needed to overcome routines and social norms (Burton et al., 2020). To increase people's motivation, similar methods as in behavior economics, e.g. steering people for financial habits, could be taken into account. This suggests developing a program with transparent nudges and boosts to reduce the aversion towards algorithms. In doing so, deficiencies in decision-makers' motivation could be solved without negatively affecting their autonomy (Burton et al., 2020).

In conclusion it can be claimed that, firstly, human training to gain a deeper knowledge of algorithms could reduce the aversion towards algorithms. Secondly, social and economic incentives could help to increase people's motivation for increased use of algorithm aversion. Nevertheless, the effects of incentives are still conflicting and for a better understanding of this strategy more research shall be done. Additionally, a program with transparent nudges and boosts could be introduced. But this might be not sustainable (Burton et al., 2020). Nudges are criticized because they lead to detractions of more sustainable solutions (Hagmann, Ho & Loewenstein, 2019). Therefore, it is important to avoid strategies that detract more costly but more effective strategies that are sustainable over time (Burton et al., 2020).

To sum up, despite the little existing academic literature regarding strategies to overcome algorithm aversion, four different strategies could be identified. This includes the human in the loop strategy, ecological rationality, human-like algorithms as well as training and motivation. These strategies lie in various approaches that could cover some of the main points of the causes of algorithm aversion.

Overall, this chapter reviews the causes of algorithm aversion, the individual differences regarding aversion and appreciation of algorithms, the areas in which algorithms are rejected, and finally, strategies to overcome the aversion towards algorithms. Despite the lack of research, many approaches could be identified and put together to create a comprehensive overview of algorithm aversion. Even though, as previously shown, the major part of research shows the rejection of algorithms, there exists some research that identifies algorithm appreciation. The next chapter deals with this topic.

5. Algorithm Appreciation

The major part of research supports the popular assumption that individuals are averse towards algorithmic decision aids, even though algorithms often outperform human forecasts (e.g. Dietvorst et al., 2015; Yeomans et al., 2019). Consequently, many decision-makers refuse to use algorithm systems in practice. However, recent research has shown that individuals are not always averse to algorithm (e.g. Logg et al., 2019; Thurman et al., 2019). The term algorithm appreciation refers to the phenomenon when people rely on equivalent forecasts made by an algorithm more heavily than on one made by a human (Logg et al., 2019). Research regarding algorithm appreciation is emerging (Araujo et al., 2020) but until today, only a few scholarly sources support this phenomenon (e.g. Dietvorst et al., 2018; Logg et al., 2019; Prahl & Van Swol, 2017; Thurman et al., 2019). Logg et al. (2019) showed that the phenomenon of algorithm appreciation occurs if individuals can choose either between algorithm-only or human-only advice (separately) and also when they can choose between algorithmic or human advice at the same time (jointly). However, appreciation towards algorithms decreases when individuals can choose between their own forecast and the forecast of an algorithm. In certain scenarios, algorithms are even more appreciated compared to a human forecast when individuals are provided with advice from a "black box" algorithm which means that they have no information about how the algorithm works (Logg et al., 2019) In contrast to Logg et al. (2019), Yeomans et al. (2019) propose that individuals' aversion towards algorithm is likely to be decreased when they are confronted with an explanation on how an algorithm works. Furthermore, academic literature showed that individuals are quite willing to rely on an algorithmic decision aid before they notice that the algorithmic is imperfect and capable of making errors (Dietvorst et al., 2015; Prahl & Van Swol, 2017). However, why and when individuals prefer algorithms is an opaque area that is also characterized by contradictory results (Logg et al., 2019).

To provide a comprehensive overview of algorithm appreciation, this chapter reviews, firstly, the causes of algorithm appreciation and, as a second step, it shows the areas in which people rely on algorithms. Also individual differences, such as the variables culture, age, gender, and personality influence algorithm appreciation. These variables regarding this topic, however, have already been described in the subchapter "Individual Differences" of algorithm aversion as they concern both topics, algorithm aversion and algorithm appreciation.

Table 24 gives a broad overview of the distribution of the sources found in academic literature, across the two subchapters. All in all, excluding duplicates, 22 articles are used to review this chapter. As illustrated, most papers found are useful to review the subchapter "Causes of Algorithm Appreciation" with 19 sources. Whereas for the subchapter "Areas in which Algorithms are rejected" with a rather low number of only 5 papers, less scholarly sources were found. After a short introduction which aims at providing a better understanding of this topic, a more detailed explanation is going to follow in the next subchapters. The following subchapter deals with the question of what causes influence appreciation towards algorithms.

Topic	Sources	
Causes of Algorithm Appreciation	19	Alexander et al. (2018); Diab et al. (2011); Dietvorst et al. (2015); Dietvorst et al. (2018); Dijkstra et al. (1998); Dijkstra (1999); Dzindolet et al. (2001); Garg et al. (2005); Kerr & Bruun (1983); Layton et al. (1994); Lee & See (2004); Mosier & Skitka (1996); Mosier et al. (1998); Parasuraman & Manzey (2010); Parasuraman & Riley (1997); Prahl & Van Swol (2017); Robinette et al. (2016); (2017); Yeomans et al. (2019);
Areas in which Algorithms are rejected	5	Castelo et al. (2019); Logg et al. (2019); Thurman et al. (2019); Robinette et al. (2016), (2017);
Sum	**24**	
Excluding Duplicates	2	
Total Articles	**22**	

Table 24: Sources of Algorithm Appreciation

5.1 Causes of Algorithm Appreciation

In this subchapter, the causes of algorithm appreciation found in the academic literature are reviewed. When looking at scholarly sources on algorithm appreciation, different causes can be identified: objectivity, rationality, environmental influences, transparency, additional information, the possibility of modifying the algorithmic process as well as the misuse of algorithms.

As illustrated in table 25, 19 papers are used to describe the causes of algorithm appreciation. The amount of papers available for the various areas differs quite a bit. In order to review the misuse of algorithms, the largest amount of papers was consulted, namely a sum of 12 papers whereas for the other causes less papers were used.

Results of Search	Number of Articles
Objectivity, Rationality, and Environmental Influences	4
Transparency, additional Information, and the Possibility of Modification	3
Misuse of Algorithms	12
Sum	**19**
Excluding Duplicates	0
Total Articles	**19**

Table 25: Causes of Algorithm Appreciation

5.1.1 Objectivity, Rationality, and Environmental Influences

Algorithm Appreciation is caused by different factors. A factor that impacts algorithm appreciation is that individuals think that an algorithmic system is characterized by more objectivity and rationality than a human-being (Dijkstra et al., 1998; Dijkstra, 1999). Furthermore, environmental influences affect whether people rely on human or algorithmic advice to a greater extent. Individuals who find themselves in time-critical situations tend to rely more heavily on the advice of a robot than on that of a human (Robinette, Howard &

Wagner, 2017; Robinette, Li, Allen, Howard & Wagner, 2016). Papers used to describe these causes are illustrated in table 26.

Causes		Sources
Objectivity, Rationality, Environmental Influences	4	Dijkstra et al. (1998); Dijkstra (1999); Robinette et al. (2016); (2017);

Table 26: Objectivity, Rationality, and Environmental Influences

5.1.2 Transparency, additional Information, and the Possibility of Modification

Other causes of algorithm appreciation stand in connection with transparency of the algorithm, additional information about the algorithm from other people, and the possibility of individuals to modify the algorithmic process. Individuals are more likely to rely on an algorithmic decision aid when the algorithm is transparent and they are able to understand how it works (Yeomans et al., 2019). Additionally, information of other individuals that already used a specific algorithm-based decision aid has a positive effect on people's adoption of algorithms. This helps them to reduce their insecurity towards algorithms and to assess the reliability of the decision aid (Alexander et al., 2018). Furthermore, individuals will increase their use of algorithmic decision aids when they get the possibility to slightly modify the algorithm. Consequently, they have the feeling to decrease errors resulting from imperfect algorithms (Dietvorst et al., 2018). This approach is previously explained in more detail in the "Human in the Loop Strategy" in the subchapter "Overcoming Algorithm Aversion". Scholarly sources used to review these causes are illustrated in table 27.

Causes		Sources
Transparency, additional Information, Possibility of Modification	3	Alexander et al. (2018); Dietvorst et al. (2018); Yeomans et al. (2019);

Table 27: Transparency, additional Information, and the Possibility of Modification

5.1.3 Misuse of Algorithms

Finally, the last approach to mention in this context is the misuse of algorithms. Misuse of algorithms is described as the resulting failures which take place when individuals erroneously rely on algorithms (Parasuraman & Riley, 1997). If people's trust surpasses the algorithm's real capabilities, overtrust emerges and leads to the overdependence on the algorithmic advice (Lee & See, 2004). Individuals sometimes tend to rely on decision aids too heavily because they are biased towards algorithms (Mosier & Skitka, 1996). To review the misuse of algorithms it is important to include the role of automation bias. To understand the causes of algorithm appreciation, the factors influencing automation bias are especially important. Scholarly sources describing this approach are illustrated in table 28.

Cause	Sources	
Misuse of Algorithms	12	Diab et al. (2011); Dietvorst et al. (2015); Dzindolet et al. (2001); Garg et al. (2005); Kerr & Bruun (1983); Layton et al. (1994); Lee & See (2004); Mosier & Skitka (1996); Mosier et al. (1998); Parasuraman & Manzey (2010); Parasuraman & Riley (1997); Prahl & Van Swol (2017);

Table 28: Misuse of Algorithms

Automation is, as previously mentioned, used to assist in various tasks. When an algorithmic decision aid works, it helps to increase the performance of a forecast task (Garg et al., 2005) and, in addition, is able to outperform human advice (e.g. Diab et al., 2011; Dietvorst et al., 2015). However, next to advantages that come with automation, also the issues which emerge need to be mentioned. One of these issues is that individuals become overreliant on the algorithmic-decision aid which, in academic literature, is referred to as automation bias (Mosier & Skitka, 1996). The effect of the automation bias emerges when individuals rely on advice from automation-based decision aids as a heuristic replacement for searching and proceeding various kinds of information. Consequently, people are inclined to rely on automation to a greater extent than on human advice (Mosier & Skitka, 1996). Automation bias can result in positive and negative outcomes. When the automation-based decision aid makes a correct forecast, it leads to a beneficial outcome (Parasuraman & Manzey, 2010). However, automation bias also has negative consequences which are resulting in omission and commission errors. Omission errors, on the one hand, occur when decision-makers fail to react to upcoming events because the automation-based decision aid erroneously did not provide certain information. Commission errors, on the other hand, occur when the automation-based decision aids provide wrong information about an upcoming event and the decision-maker erroneously relies on it (Mosier & Skitka, 1996; Mosier, Skitka, Heers & Burdick, 1998). After reviewing the consequences of automation bias, the next paragraphs show factors that influence automation bias. These factors help to get an additional understanding of causes regarding algorithm appreciation in certain scenarios.

In academic literature, three factors are mentioned which influence automation bias: authority, cognitive miser as well as diffusion of responsibility (Dzindolet et al., 2001; Mosier & Skitka, 1996). The first factor is authority, which describes that people perceive automation-based decision aids as superior experts when they compare their own abilities with the capabilities of the decision aid (Dzindolet et al., 2001). Individuals are more prone to using automation-based decision aids because they perceive the capabilities of such systems as superior to human advice and therefore as more reliable and trustworthy (Mosier & Skitka, 1996). For example, individuals are quite willing to rely on an automation-based decision aid, but only until they notice that the capabilities of the decision aid are not that good as expected and capable of making errors. After noticing the decision aid making an error and therefore being imperfect, confidence towards it decreases (Dietvorst et al., 2015; Prahl & Van Swol, 2017).

Cognitive miser, the second factor influencing automation bias, describes people's tendency to choose the easiest way. Decision aids provide decision-makers with advice. This advice can lead to heuristic behavior from the decision-maker. This means that individuals prefer to rely on the advice of the decision aid to save effort and time, instead of absorbing and analyzing the provided information by themselves (Mosier & Skitka, 1996). This behavior takes place in different degrees. In the extreme case, decision-makers accept the advice without further hesitation, whereas in less extreme cases the advice from the decision aid has a large impact on the decision (Dzindolet et al., 2001). For example, pilots show different behavior depending on whether they are provided with an automation advice or not. Pilots who are provided with a route plan generated by an automation-based decision aid spend less time evaluating time-efficient route alternatives than pilots who do not receive advice (Layton, Smith & McCoy, 1994).

The last of the three factors influencing automation bias is the diffusion of responsibility. This factor explains the perceived responsibility of individuals in group tasks. Human beings are inclined to show less effort in group projects than in situations in which they work alone. The reason for this behavior is that the responsibility for the projects' outcome is divided among the individual project members (Mosier & Skitka, 1996). This behavior comes from the area of social psychology and is also known as "free-riding" (Kerr & Bruun, 1983). When this behavior is applied to the relationship between humans and decision aids, individuals who have the possibility to get advice from automation often rely on it because they put less effort into the task as when they would work alone. Individuals feel less responsible for the outcome when they get advice from a decision aid and tend to rely on it (Dzindolet et al., 2001).

Summing up, individuals show the behavior of overreliance (misuse) on algorithmic decision aids which can be named as automation bias (Mosier & Skitka, 1996). This behavior emerges if people's trust surpasses the algorithm's real capabilities (Lee & See, 2004). On the one hand, automation bias can result in positive outcomes when the decision aid provides the right advice (Parasuraman & Manzey, 2010). On the other hand, automation bias can result in negative outcomes when omission or commission errors occur (Mosier & Skitka, 1996). Three main factors which influence the automation bias and therefore show when algorithm appreciation occurs, are found in scholarly sources: authority, cognitive miser as well as diffusion of responsibility (Dzindolet et al., 2001; Mosier & Skitka, 1996). After reviewing the causes of algorithm appreciation, the next subchapter shows the different areas in which people rely on algorithms.

5.2 Areas in which Algorithms are appreciated

After reviewing the causes influencing an individual's appreciation towards algorithms, this subchapter shows the areas in which people tend to rely on algorithmic advice. Before doing this, however, individuals' perceived subjectivity and objectivity should be considered. In most cases, people tend to rely on human advice to a greater extent rather than on algorithm advice (e.g. Dietvorst et al., 2015; Yeomans et al., 2019). However, individuals have the tendency to rely more heavily on advice from algorithms when the task is perceived as objective. If the task is perceived as subjective, however, they tend to trust human judgment to a greater extent (Castelo et al., 2019). Under which circumstances individuals prefer algorithms is still debated (Logg et al., 2019). In academic literature several examples are shown in which people rely on algorithmic decision aids. Because it is still opaque when this behavior is shown, the following mentioned areas refer to the recent research regarding the topic of algorithm appreciation.

This subchapter reviews the areas of visual estimation, song foresting, and person perception tasks, as well as the area of news selection where human advice is discounted and, in contrast to that, algorithm advice is relied on. As illustrated in table 29 and 30, excluding duplicates, 5 papers are used to describe the areas in which algorithms are appreciated, whereas 4 papers are used to describe the certain areas.

Results of Search	Number of Articles
Visual estimation Task	1
Song forecasting task	1
Person-perception Task	1
News Selection	1
Human-Robot Interaction	2
Sum	**6**
Excluding Duplicates	2
Total Articles	**4**

Table 29: Areas in which Algorithms are appreciated

	Sources	
All Areas	5	Castelo et al. (2019); Logg et al. (2019); Thurman et al. (2019); Robinette et al. (2016), (2017);

Table 30: Sources of Areas in which Algorithms are appreciated

As Castelo et al. (2019) point out, individuals tend to rely more heavily on advice from algorithms when the task is perceived as objective. However, the phenomenon of algorithm appreciation is shown in different tasks, also in more subjective ones. Especially, if a closer look at the study of Logg et al. (2019) is taken. The first area in which this phenomenon is shown are in visual estimation tasks. When people have to estimate the weight of a person on a picture and receive equal advice either from an algorithm or from a person, they react differently to it. In this scenario, individuals show algorithm appreciation and therefore rely more heavily on algorithmic than on human advice, even though only few information is provided about how the algorithm works (Logg et al., 2019).

The second scenario in which algorithm appreciation occurs is in a more subjective task, namely a song forecasting task. Individuals react differently to human and algorithmic advice when they have to forecast the popularity of music songs for a top list of this genre which will soon be published. Regarding the same advice provided either by an algorithm or a human-being, individuals are inclined to rely on algorithmic advice more heavily than on human advice (Logg et al., 2019).

The third task where this phenomenon is shown is in a highly subjective task, namely in person-perception. When individuals read a description of a person, are shown a picture of another person afterwards and have to evaluate if these two people match together, they prefer to rely on the provided algorithmic than on human advice (Logg et al., 2019).

In the area of news selection, Thurman et al. (2019) found support for algorithm appreciation. Individuals prefer personalized news recommendations, which are connected to their previous news behavior, more from an algorithmic system than from a human editor. It seems that individuals who have a lower level of trust in journalism are more likely to rely on an algorithmic aid because they are suspicious of human editors. They might think that an algorithmic recommendation aid is kind of immune from contaminated or untrustworthy media (Thurman et al., 2019).

In the area of robot-algorithm interaction, algorithm appreciation is shown under certain environmental influences. For example, in fire evacuation scenarios individuals rely on the advice of robot assistance to show themselves the way out of the building, even if they know that the robot performed worse in previous events. In this scenario, however, it should be noted that individuals acted under specific time-critical conditions (Robinette et al., 2016; 2017).

To conclude, despite the lack of research concerning appreciation towards algorithms, some areas could be detected. However, for a better and more comprehensive understanding of this effect regarding different areas, more research should be undertaken.

Overall, algorithm appreciation is a new phenomenon that needs more attention to get a better understanding of this topic. Despite the lack of existing academic literature, after reviewing the causes and the areas in which this phenomenon occurs and not to forget the individual differences, which are described in the topic "Algorithm Aversion" but refer to both topics, this chapter offers an insightful overview of the causes of this phenomena and in which areas appreciation towards algorithm occurs.

6. General Discussion

The aim of this systematic literature review was to identify the existing state of research that deals with humans' reactions towards algorithmic decision aids (statistical models, automation, AI, machines). The literature which emerged from the literature search process was analyzed based on larger research streams of algorithmic aversion and algorithmic appreciation. A total of 128 peer-reviewed research articles were taken into consideration. The algorithm aversion research stream indicates that people and algorithmic decision making are still difficult to merge, although this technology is growing rapidly, and shows the tendency of improved decision-making (e.g. Dietvorst et al., 2015; Yeomans et al., 2019). Through the increased development and implementation of such technologies it is likely that algorithmic decision aids become highly relevant in the future. Nonetheless, recent literature on algorithm appreciation has also shown that people are not always reluctant in relying on algorithmic decision aids and that the positive response towards algorithms is increasing (Araujo et al., 2020). By consulting academic literature dealing with the two major research streams of algorithm aversion and algorithm appreciation, different minor research streams related to these phenomena could be identified through a close analysis. This includes causes, individual differences, different areas in which algorithms are rejected or appreciated, as well as approaches to reduce algorithm aversion. However, many findings detected are contradictory and therefore a meaningful connection is difficult to render. It is important to note that identified approaches often overlap and it is difficult to distinguish between different points. In the following paragraphs the findings of this literature review are connected, compared, and discussed. Each of the reviewed topics identified is taken into consideration to highlight conflicting and overlapping factors. Furthermore, some findings are linked to some relevant theories that have not been addressed in the review. This section starts with the discussion of the causes of algorithm aversion and algorithm appreciation and what strategies could be taken into account to overcome aversion towards algorithms. More specifically, individual differences, causes of aversion and appreciation as well as potential strategies to overcome algorithm aversion are connected and discussed. Secondly, the areas in which algorithms are rejected or appreciated are discussed. Afterward, a section regarding theoretical and management implications is provided. Finally, limitations of this review are reported as well as implications for future research are suggested.

As mentioned, this section starts in the following paragraphs with the discussion of the causes of algorithm aversion and algorithm aversion as well the strategies which could be taken into account to overcome the aversion towards algorithms. First of all, individual differences such as culture, age, gender, personality can be considered for every cause of algorithm aversion and algorithm appreciation. But for a connection of the findings, they fit most in the paragraph below where the cause of algorithm aversion "The Domain of Judgment" as well as the strategy of "Human-like Algorithms" to overcome algorithm aversion is combined and discussed.

The first cause mentioned in this review which influences people's aversion towards algorithms is the algorithm error. Individuals react negatively towards algorithms after they notice that a decision aid does not operate as perfect as expected. When they notice an algorithm making an error and therefore being imperfect, it decreases their use and their level of trust towards algorithmic decision aids (Dietvorst et al., 2015; Dzindolet et al., 2002). However, the tendency to rely on human advice does not decrease if a human makes a mistake (Dietvorst et al., 2015). People are more sensitive to algorithm errors compared to mistakes made by a human being (Dzindolet et al., 2002; Madhavan & Wiegmann, 2007a). The reason for this might be people's prior experiences and expectations towards algorithms which also influences the disuse of algorithms. Furthermore, the cause of algorithm error is influenced by different factors, such as peoples' desire for perfect predictions, the error rate of algorithms, the error timing, the difficulty of the task, the role of confidence, as well as peoples' belief that algorithms are dehumanizing. A cause of algorithm appreciation could be the provided possibility offered to humans to modify the algorithmic process. Individuals are more likely to rely on algorithmic decision aids when they get the possibility to modify the algorithmic process. As a result, they have the feeling to decrease the imperfection of algorithms and thus, the potential errors (Dietvorst et al., 2018). A strategy to overcome peoples' fear of algorithmic errors, which goes in line with the mentioned cause of algorithm appreciation is the human in the loop strategy. Applied in the human-algorithm interaction, Dietvorst et al. (2018) showed in his study that humans will increase their use of algorithms as decision aid when they get the opportunity to modify the algorithm process. There also exist other types of decision-making regarding the distribution of autonomy. Early research on algorithm aversion shows support for alternative models regarding the distribution of autonomy in the human-algorithmic relationship (e.g. Einhorn, 1972; Meehl, 1954). According to Camerer (1981), people are quite good at collecting data and thus providing input for a model. However, they are rather weak at combining them effectively. For algorithms it is the other way around, they are rather bad at collecting data but good at combining data in such a model. In this context, bootstrapping models mobilize this insight. People could collect data intuitively for the model and, after that, an algorithm evaluates it (Burton et al., 2020; Camerer, 1981). Regarding the human in the loop strategy, peoples' tendency to increase their use of algorithms when they can adjust the process could be explained with the theory of peoples' need for control. Leotti, Iyengar & Ochsner (2010) suggest that for humans' well-being it is important to have the ability to control certain factors to achieve the desired outcome. If this theory is applied to the algorithm-human interaction, it could mean that humans who are skeptical about the performance of an algorithm have the desire to control the algorithmic process in order to avoid potential errors. However, scholarly sources have also demonstrated that humans' effort to modify an algorithmic process often results in weaker outcomes (e.g. Carbone et al., 1983; Lim & O'Connor, 1995). Nevertheless, Dietvorst et al. (2018) showed that people increase their use when they can even slightly adjust the algorithmic process. Therefore, limiting the possible modification of individuals to less impactful parts of the process prevents users from making influential changes to the outcome.

The second factor that influences algorithm aversion are divergent rationalities. In this relation the heuristic and bias program should be taken into consideration. Regarding the heuristic and bias program, people are often biased in decision-making. When people are biased by overconfidence judgment, it influences the rationality of decision-making and often results in irrational decisions (Croskerry & Norman, 2008). This makes decision-makers think that that they do not need any algorithmic advice at all (Arkes et al., 1986). However, in contrast to the overconfidence bias, the automation bias shows a contrasting view. Humans sometimes tend to rely on algorithms too heavily because they are biased towards the real capabilities of decision aids (Mosier & Skitka, 1996). Furthermore, research shows that people consider experts who do not rely on algorithmic decision aids to be more professional. Consequently, they tend to rely on experts more heavily when they realize that the decision was made based on intuition rather than on a decision aid (Arkes et al., 2007; Önkal et al., 2009). However, factors that influence automation bias show a contradictory result. Individuals often perceive the judgement of decision aids as superior to the one made by humans when they compare their abilities with the capabilities of an algorithm (Dzindolet et al., 2001). Consequently, they often perceive the capabilities of such systems as superior to human abilities, and thus, as more reliable and trustworthy (Mosier & Skitka, 1996). Moreover, people also judge algorithmic decision aids as dehumanizing because they think that they do not consider their unique individual characteristics as a human expert would do (Longoni et al., 2019). However, research regarding algorithm appreciation has also shown that individuals rely on algorithmic advice to a larger extent because they perceive an algorithmic decision aid as more objective and rational than a human-being (Dijkstra et al., 1998; Dijkstra, 1999). In academic literature, by focusing more heavily on heuristics-and-biases research, the research about the plurality of making decisions in practice, such as fast-and-frugal heuristics, is neglected. For this type, beneficial decisions are described as ecological rational (Arkes et al., 2016). Ecological rationality relates to the practice and states that the rationality of decision-making depends on the environment (Todd & Gigerenzer, 2007). This includes simple heuristic, such as decisions under uncertainty, where probabilities and alternatives are unknown. As opposed to that, when it comes to rational-choice theory, algorithms operate in more risky scenarios where probabilities are known (Hafenbrädl et al., 2016; Todd & Gigerenzer, 2007). The cause of algorithm appreciation "Environmental Influences" states that when people find themselves in time-critical scenarios, they are inclined to rely more heavily on the advice of an algorithm than on that of a human, even if the algorithm performed worse in previous scenarios (Robinette et al., 2016; 2017). Nevertheless, if an individual or an algorithm is not able to determine whether a decision under risk or uncertainty is better, algorithm aversion could emerge (Burton et al., 2020). In response, to overcome the overconfidence bias and intuition-based decision making, a strategy could be bridging the relationship between intuition and rationality. This procedure offers the opportunity for a more intensive interaction by adding more transparency on both sides in the human-algorithm relationship (Burton et al., 2020). The cause of algorithm appreciation "Transparency" supports this approach. Individuals are more likely to rely on an algorithm when more transparency is provided and they are able to understand how the decision aid works (Yeomans et al., 2019). Additionally, decision aids could be developed to be more ecological rational instead of probabilistic rational. There might be the possibility to develop decision aids within the framework of rationality that operate in accordance with peoples' intuition (Burton et al., 2020; Westin et al., 2015). This could lead to alternative decision methods which may cause less aversion towards algorithms.

The domain of judgment is the next cause of algorithm aversion mentioned in this review. Individuals seek a social relationship with the medium which provides advice (Alexander et al., 2018; Prahl & Van Swol, 2017). They believe to have more in common with human- than with algorithm advice (Prahl & Van Swol, 2017). The reason for this behavior could be that it is easier for individuals to understand why a human provides such advice, while advice from an algorithm is perceived as opaque (Yeomans et al., 2019). To overcome this cause of algorithm aversion, more human-like algorithms could be developed. When humans perceive a mind in another medium, it shows a positive effect on their relationship which leads to a higher level of trust and social connection (Wiese et al., 2017). In this context the individual differences found in academic literature regarding algorithm aversion and algorithm appreciation could be discussed. The Individual difference "Personality" could be taken into consideration to support this strategy. Academic literature has shown, based on the similarity-attraction hypothesis, that humans feel attracted to each other when they show similar personality traits (e.g. Blankenship et al., 1984; Byrne & Griffitt, 1969; Duck, 1973). The effect of similar personalities could, beside in the human-human relationship, also be applied in the human-algorithm relationship. Humans are more likely to rely on decision aids when the algorithm displays personality traits which are similar to their own (Nass & Lee, 2001; Nass et al., 1995). For example, according to Nass & Lee (2001), individuals with a more dominant personality feel more attracted to dominant language whereas individuals with a more submissive personality to submissive language when interacting with an algorithm. Here, also the person-positivity bias might support this assumption. This bias suggests that attitude objects are assessed as more beneficial when they show similarities with humans (Sears, 1983). Consequently, when algorithmic decision aids would show more characteristics of humans, their use might be increased. In addition, also the variables of age, gender, and culture may impact the human-algorithm relationship. Even though that there are conflicting and often confusing findings, research suggests that there might be an influence. The influence of these variables may lie on the context. Regarding the variable age, more conflicting results were found compared to the variable personality. On the one hand, Logg et al. (2019) did not discover any connections between the variable age and the tendency to rely on an algorithmic decision aid. On the other hand, however, research found some differences between age groups, where the main part supports the assumption that older people are less likely to rely on an algorithmic decision aid than younger people (e.g. Araujo et al., 2020; Thurman et al., 2019). A reason for this behavior could be that for older people it is more challenging to work with a decision aid because they have less expertise with technology (Lourenço et al., 2020). With regard to the variable gender, research findings are also contradictory and still unclear. A part of research shows that there is no influence of gender in the human-algorithm relationship (e.g. Logg et al., 2019; Thurman et al., 2019), while other sources show the opposite. For example, women perceive decision aids as significantly less useful in comparison to men (Araujo et al., 2020). Females are inclined to react positively towards flattery used by an algorithm while it has a negative effect on men

(Lee, 2008). For the influence of the variable culture in the human-algorithm relationship, only a little amount of scholarly research that supports this assumption could be found. According to Huerta et al. (2012), the impact of algorithms on humans differs across countries. Additionally, individuals from different cultures perceive social robots differently (Li et al., 2010). The suggestions of the individual differences might play a role in developing human-like algorithms. If all of these variables are considered, it would be possible to create algorithms which are quite similar to humans. There might be a possibility to provide algorithms that are adapted to the target group. Also Hoff & Bashir (2015) suggest that although gender-specific differences in human-algorithm interaction are still unclear, they should be taken into account when developing certain algorithmic systems.

The last approach mentioned concerning the causes of algorithm aversion is the disuse, or, in other words, underutilization of decision aids. The reaction towards decision aids might be influenced by prior expectations and experiences with algorithms (Burton et al., 2020). The cause of algorithm appreciation “additional Information” supports this assumption. According to Alexander et al. (2018), information provided by individuals who have already interacted with a certain decision aid has a positive effect on individuals’ adoption of algorithms. This additional information helps people to reduce their insecurity and to determine the reliability of the algorithmic decision aid (Alexander et al., 2018). Also, prior experience with algorithms could be a factor. But in this point research shows contradicting results. On the one hand, academic literature indicates that people rely more heavily on algorithms if they have prior experience with this technology (Commerford et al., 2019; Luo et al., 2019). On the other hand, research shows the opposite (Dietvorst et al., 2015; Logg et al., 2019; Luong et al., 2020). For example, the study of Dietvorst et al. (2015) shows that people are more likely to reject a decision aid if they have prior experience at their disposal which they can refer back to. This might be because people initially think that an algorithm is perfect and after experiencing it perform, they notice that it is capable of making errors, which leads to disuse. However, some factors show contradicting findings regarding the disuse of algorithms, mentioned in the subchapter “Causes of Algorithm Appreciation – Misuse of algorithms”. Cognitive miser would be such a factor, which shows that people often choose the easiest way. Instead of investing time and effort in absorbing and analyzing information by themselves, they might tend to rely on algorithmic advice (Mosier & Skitka, 1996). Furthermore, the diffusion of responsibility should be mentioned, which states that people put less effort into a project when they work in a group compared in scenarios when they work alone (Mosier & Skitka, 1996). This suggests that individuals who can get algorithm advice are inclined to rely on it because they commonly invest less effort in the task (Dzindolet et al., 2001). Regarding algorithm aversion, experts have the fear that they are perceived as less professional when using decision aids (Kaplan, 2000), which might be justified in some cases. Arkes et al., (2007) showed that individuals perceive decision-makers who take an algorithmic decision aid in consideration as less competent than decision-makers who make decisions without the aid of an algorithm. However, in this case the factor “authority” which has an impact on automation bias mentioned in the subchapter “Causes of Algorithm Appreciation – Misuse of algorithms”, shows a contradictory finding. Individuals often perceive the capabilities of algorithms as better than their abilities and, consequently, as more reliable and trustworthy (Dzindolet et al., 2001; Mosier & Skitka, 1996). Additionally, also lack of training regarding the use of algorithms could lead to aversion towards algorithms. In response to these causes a strategy regarding training and motivation could help to decrease algorithm aversion. It seems that if decision-makers are provided with well-suited training to increase their knowledge about algorithms, it could reduce aversion towards algorithms and increase the effectiveness of decision aids (Green & Hughes, 1986). Regarding the approach of motivation, offering decision-makers economic or social incentives could increase their motivation to use algorithmic decision aids. But the effects of such incentives on decision-makers and on the usage of algorithms are not clear (e.g. Arkes et al., 1986; Prahl & Van Swol, 2007). Additionally, a program with transparent nudges and boosts could be applied to increase people’s motivation to use decision aids. However, nudges are criticized for detracting more sustainable solutions (Hagmann et al., 2019). Consequently, when implementing such a method, it is important not to detract more effective strategies that are more sustainable over time (Burton et al., 2020).

After connecting and discussing the causes of algorithm aversion and appreciation, individual differences, and strategies to overcome algorithm aversion, the next paragraphs are going to present areas in which the phenomena algorithm aversion and algorithm appreciation occur. However, in which specific situations individuals prefer to rely on or not rely on algorithms is an opaque area with contradictory results. This is why the areas are rather difficult to determine (Logg et al., 2019). The following areas in which these phenomena become apparent are taken out of studies regarding research papers used in this review.

The major part of research which supports the phenomena of algorithm aversion can be found in the area of medicine, which also includes the assumingly first investigation regarding algorithm aversion, where Meehl (1945) investigated clinical vs. statistical methods for forecasts. Regarding this research stream, Dawes et al. (1989) reviewed almost 100 papers and concluded that in all studies the statistical prognosis was equal or superior to the human prognosis. In the area of medicine, rejection of algorithms from patients as well as doctors can be detected (Dawes et al., 1989; Shaffer et al., 2013). In the area of business and management, rejection towards algorithm can be detected in the field of marketing and sales, where workers still prefer to use spreadsheets instead of commercial forecast systems (Sanders & Manrodt, 2003a) as well as towards chatbots, which are rejected when the user gets the information that s/he is interacting with an algorithm rather than with a human (Luo et al., 2019). In employee selection, employers, as well as employees often prefer to rely on unstandardized methods such as interviews instead of decision-aids (e.g. Highhouse, 2008; Dawes, 1979; Lee, 2018). Moreover, according to the experiments conducted by Bigman & Gray (2018), individuals are inclined to reject algorithms in moral decisions. This includes scenarios in the areas of legal, medical, military as well as driving decision making. In contrast to this, algorithm appreciation is shown according to a scenario in the human-robot interaction characterized by time-critical conditions (Robinette et al., 2016; 2017) as well as in news selection, where individuals prefer personalized news recommended from an algorithm than from a human editor (Thurman et al., 2019). According to Castelo et al. (2019), humans tend to rely more heavily on advice from algorithms when the task is perceived as objective (e.g. financial advice) and more on human advice when the task is perceived as subjective (e.g. joke recommendation) because they believe that algorithms are not capable of performing subjective tasks. Regarding subjectively perceived recommendations, people are apt to reject algorithms and prefer to rely on human recommendations. This includes recommendations for jokes, books, movies, or about finding a romantic partner (dating) (Castelo et al., 2019; Sinha & Swearingen, 2001; Yeomans et al., 2019). Furthermore, regarding profile descriptions, individuals are inclined to reject e.g. Airbnb hosts when they believe that the description was created by AI rather than by a human (Jakesch et al., 2019). However, contracting results are found by Logg et al. (2019). In more subjective tasks such as visual estimation tasks where people have to estimate the weight of a person, song forecasting task where individuals have to forecast the popularity of music songs, as well as person-perception where people have to evaluate whether people match together, algorithm appreciation is detected. In the more objective field of financial decision-making, people prefer to rely on human advice regarding stock price forecasts. It is difficult to determine the areas in which these phenomena occur because it is still opaque and characterized by conflicting results. Additionally, peoples' reactions to algorithms might not lie in a specific area, but more on the context and environmental influences. The findings suggest that decision-makers as well as users are often apt to reject algorithms. However according to recent findings in algorithm appreciation, the positive response toward algorithms is increasing.

After discussing the different findings of this systematic literature review regarding algorithm aversion and algorithm appreciation, the next two subchapters will discuss theoretical as well as management implications. Finally, limitations of this review as well as further research will be provided.

6.1 Theoretical Implications

This systematic literature review contributes to the human vs. nonhuman research stream by reviewing people's reactions towards algorithms. However, the findings of algorithm aversion and algorithm appreciation from different contexts are often conflicting and leave many questions unanswered. After discussing the findings of these phenomena, several research gaps can be identified. Consequently, in the following paragraphs conflicting findings are highlighted to provide theoretical implications. Overall, for all areas regarding algorithm aversion and appreciation further research is needed to enhance a more accurate understanding. In the following paragraphs the more relevant research gaps are discussed.

Research has neglected the plurality of decision-making methods. A more detailed focus should be laid on alternative methods to make decisions. Consequently, it is suggested to investigate the influence of algorithm aversion and algorithm appreciation in other decision methods, such as in bootstrapping models (Burton et al., 2020). Furthermore, according to Dietvorst et al. (2018), people increase their use of decision aids if they get the opportunity to modify the algorithm process. The reason for this behavior could lie on people's desire for control (Leotti et al., 2010) and people's expectations regarding the way the algorithm performs (Dietvorst et al., 2018). Therefore, the effects of such a human in the loop strategy to reduce algorithm aversion could be further investigated. The role of the people's desire for control should be investigated for this strategy. Additionally, it would be worth investigating whether it is applicable for the average users to reduce their often negative prior expectations towards algorithm (Burton et al., 2020).

Research suggests that prior experiences influence algorithm aversion and algorithm appreciation. However, contrasting results were found regarding the influence of prior experiences on the use of algorithms (e.g. Commerford et al., 2019; Dietvorst et al., 2015). Additionally, the motivating effect of economic or social incentives on the usage of algorithms is unclear (Arkes et al., 1986; Prahl & Van Swol, 2007). Therefore, it is suggested to investigate the effect of prior experiences with algorithms in the human-algorithm interaction as well as the effect of social and economic incentives on the motivation for using decision aids. Furthermore, regarding the misuse and disuse of algorithms, the overconfidence and automation bias were mentioned. It is not clear what impacts these behaviors in the human-algorithm relationship. Further research should be conducted to gain insights when people tend to be overconfident or overreliant towards algorithms.

Moreover, individual differences could be taken into account. Research suggests that the variables culture, age, gender, and personality influence the human-algorithm interaction (e.g. Hoff & Bashir, 2015; Thurman et al., 2019). However, due to lack of empirical findings, these effects cannot be shown appropriately. It might be crucial to understand the influences of people's characteristics on the interaction with and reaction towards algorithms. This could be especially important when considering the human-like algorithm strategy which suggests providing algorithmic-based decision aids that are more similar to the characteristics of the user. This might increase their attraction towards algorithms and therefore, also their utilization. Consequently, it is suggested to investigate the influence of these variables in the human-algorithm interaction to enhance a better understanding of factors impacting this relationship.

This review provides an overview of findings showing in which areas people reject or appreciate algorithms. However, it is difficult to identify specific areas in which these phenomena occur. Additionally, peoples' reactions towards decision aids might not only occur in a specific area. It is rather dependent on the context and environmental characteristics. For example, according to Robinette et al., (2016; 2017), people appreciate algorithms when they find themselves in time-critical scenarios. Consequently, it is suggested to investigate environmental factors, such as time-critical situations, influencing the human-algorithm interaction. Additionally, the assumption that individuals rely on algorithms to a greater extent for objective tasks than when it comes to subjective tasks, should be considered (Castelo et al., 2019). Research has shown that individuals rely on human advice for subjective recommendations such as for jokes, books, movies, or about finding a romantic partner (dating) (Castelo et al., 2019; Sinha & Swearingen, 2001; Yeomans et al., 2019). But recent findings regarding algorithm appreciation revealed that also in more subjective tasks algorithm appreciation is detected (Logg et al., 2019). Furthermore, aversion towards algorithm aversion was detected in the study of Bigman & Gray (2018) for moral decisions in the medical, legal, military, and driving decision-making. Consequently, it is suggested to investigate if there are differences in peoples' reactions towards objective or subjective perceived tasks as well as in people's reactions towards moral scenarios.

6.2 Managerial Implications

Companies are often worried that employees or customers do not rely on algorithms (Haak, 2017), even though algorithmic-based decision aids are capable of outperforming humans in various domains (e.g. Einhorn, 1986; Grove & Meehl, 1996; Grove et al., 2000; Yeomans et al., 2019). Aversion towards algorithms is costly and consequently crucial for companies to understand (Dietvorst et al., 2015). Therefore, the findings of the strategies on how to overcome algorithm aversion offer insightful implications, especially for managers, to increase the use of algorithms for employees as well as for customers. When algorithm aversion impacts a company's performance, market research could be conducted to find out which of the mentioned causes impacts such a behavior. In response to this, they could implement a strategy to overcome algorithm aversion.

It might be difficult to demand from people to rely on a new way of advice, such as algorithms, when they are not used to such decision aids. Forcing employees or customers to use and rely on algorithms might lead to dissatisfaction and a more decreased use. Therefore, when managers notice that employees lack knowledge regarding algorithms, they could develop a motivation and training program to reduce the skepticism towards algorithms. Research suggests that when customers and employees are shown the importance and how to correctly interact with algorithms, it has a positive effect on their use (Kuncel, 2008; Lodato et al., 2011). It could be beneficial for employees and customers to bring more transparency in the algorithmic forecast process so that users are able to understand how an algorithm works and to see their advantages (Yeomans et al., 2019). For employees it might be important to increase their knowledge of statistics regarding analyzing data (Arkes et al., 1986).

Especially in the field of marketing human like algorithms could increase the use of algorithms. Research has shown that people feel attracted to each other when they show similar personality characteristics (Nass & Lee, 2001; Nass et al., 1995). Applying this suggestion in the human-algorithm relationship, marketers could develop algorithms that match more heavily to the characteristics of the target group. They could include individual differences, such as culture, age, gender, and personality, which are suggested to influence the human-algorithm relationship. These personal characteristics could be used to develop a target-group-like algorithm, which is personalized and adapted to the customer's characteristics. For example, according to Nass & Lee (2001), individuals with a more dominant personality feel more attracted to dominant language when interacting with algorithms.

Moreover, to only provide employees or customers with the choice to rely on an algorithm or human judgment seems counterproductive. Therefore, when individuals are skeptical about the imperfection of algorithms, the offered possibility to be part of the algorithmic process increases their use of it (Dietvorst et al., 2018). This could be applied to employees and customers. When individuals are offered to even slightly adjust the algorithm in the forecast procedure, they tend to rely on algorithm advice to a greater extent. Managers could offer the possibility to only modify small but not relevant factors of the algorithm forecast which do not impact the outcomes and therefore do not influence the forecast performance. As a result, the forecast performance in companies can increase because it is closer to the algorithmic-based forecast (Dietvorst et al., 2018).

Furthermore, it could be difficult to demand from employees or customers to learn a new process of decision-making. It might be easier to find themselves in their process of decision-making and to make improvements in their actual process (Hafenbrädl et al., 2016). There might be the possibility to develop decision aids within the framework of rationality that works in accordance with people and their intuition (Burton et al., 2020; Westin et al., 2015). Consequently, by considering alternative decision theories, new decision-making systems could emerge which may cause less aversion towards algorithms.

Summing up, companies could apply different strategies in order to overcome aversion towards algorithms. Strategies such as motivation and training could be easier to implement, whereas creating new types of decision aids that are in accordance with people's level of intuition could be more challenging to be implemented. For the field of marketing, the human-like algorithms might be the best strategy because individual characteristics of customers could be taken into consideration to develop a target-group-like algorithm.

6.3 Limitations and Future Research

This systematic literature review provides a comprehensive overview of how people react to algorithms. Therefore, valuable insights are reviewed and discussed which contribute to and serve as a basis for further research in the field of human vs. non-human research. Nevertheless, this review has limitations that must be considered, which offer directions for further investigations regarding this topic.

The literature search process was conducted using five different databases. For this process the keywords "algorithm aversion" and "algorithm appreciation" were taken into consideration because they specify these phenomena most accurately. The additional extensive forward and backward search, and the query of recommended articles from databases resulted in a satisfying number of articles. Despite the combination of search in databases and forward and backward searches, it might be possible that not all relevant articles addressing individuals' reactions towards algorithms have been detected. Dissertations, thesis, and working papers were excluded. From the resulting articles, the findings were categorized into different themes. However, other researchers might have categorized them differently.

As already mentioned, in this systematic literature analysis the search in databases was conducted restricted to two relevant keywords. This might have led to the fact that several research streams relevant to this topic have only partially been included in this review. The keyword trust was not used for the search in databases because it is a broad concept which is described in several non-relevant contexts for this topic. As a result, one important research stream which concerns algorithm aversion and algorithm appreciation, namely the trust and distrust in automation, was probably only partially included in this literature review. This also applies to other research streams, such as robot-human interactions, computer-generated content, as well as the research stream about ethics in algorithm decision-making. These mentioned research streams might have added some additional insights for reviewing these phenomena. Therefore, further literature reviews could also aim to include these research streams in the literature search process to give a broader and more accurate review of people's reactions towards algorithms.

A further limitation of this review is that the terms of "algorithm" or "decision aid" were used as umbrella terms for different types of technologies. Therefore, this literature analysis did not explicitly differentiate between automation, artificial intelligence, etc. Future research could overcome this limitation and could potentially show if there are differences or similarities of human reactions towards automation-based or AI-based decision aids.

As this analysis of literature has shown, the attention for this topic is increasing. Due to the rapid growth of technologies, the application possibilities of algorithms will grow. Together with this development, the reactions of people against algorithms will also develop. The literature covering algorithm appreciation shows that there is a tendency that people increasingly react positively towards algorithmic advice. Since this technology is developing rapidly, studies and literature analyses will be of great importance in the future to obtain and discuss important results concerning different areas.

7. Conclusion

Research regarding reactions towards algorithms is still scarce, characterized by overlapping but also conflicting and often confusing findings. Therefore, a meaningful connection is difficult to render. However, the consulted academic literature in this literature review was categorized into four themes: causes of algorithm aversion and appreciation, individual differences, areas in which algorithms are rejected or appreciated, and strategies to overcome algorithm aversion. Regarding causes of these phenomena, one the one hand, algorithm error, divergent rationalities, the domain of judgment, and the approach of disuse were detected. These stand in connection to algorithm aversion. On the other hand, the causes of objectivity, rationality, environmental influences, transparency, additional information, the possibility to modify the algorithm, and the approach of misuse of algorithms were detected which were connected to algorithm appreciation. Also individual differences, such as culture, age, gender, personality are suggested to have an impact on both research streams, algorithm aversion and algorithm appreciation. But, only little and to some extent conflicting academic literature supports the influence of individual differences on people's reactions towards algorithms. In order to overcome the aversion towards algorithm, the strategies of human in the loop, ecological rationality, human-like algorithms as well as training and motivation, which address some of the main points of the causes of algorithm aversion, are provided. These strategies, however, rely on findings but also suggestions from literature. Therefore, a little amount of research supports the claims made about the effects of these strategies on people's reactions towards algorithms. Furthermore, both phenomena were shown to appear in different areas. Aversion towards algorithms was found in the medical, economic, and business decision-making, as well as for moral decisions in legal, military, and driving tasks. Subjective recommendations have also shown the effect of algorithm aversion, whereas, in other subjective tasks, such as in visual estimation, song forecasting, and person-perception, algorithms appreciation was found. Algorithm appreciation was also shown for news selection and in a time-critical scenario in human-robot interaction. However, it is difficult to determine in which areas these phenomena occur, because these phenomena might not depend on the area, but more on the context of the scenario.

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Appendix

	Reference	Title	Method[a]	Topic[b]	Key Findings
1	Alexander et al. (2018)	Why trust an algorithm?	E	Av & Ap	This article points out that social proof has a positive influence on the utilization of algorithmic models.
2	Araujo et al. (2020)	In AI we trust? Perceptions about automated decision-making by artificial intelligence	E	Av & Ap	This article shows that the variable gender plays a role in the individuals' perceived usefulness of automated decision making. Females perceive automated decision making as significantly less useful in comparison to males.
3	Arkes et al. (1986)	Factors influencing the use of a decision rule in a probabilistic task	E	Av	Individuals with higher knowledge of the subject are inclined to use decision aids less than knowledgeable ones. This behavior leads to the erroneous underutilization of algorithmic models
4	Arkes et al. (2007)	Patients derogate physicians who use a computer-assisted diagnostic aid	E	Av	Patients perceive physicians who use an algorithmic decision tool as less competent than doctors who make decisions without such a tool.
5	Arkes et al. (2016)	How bad is incoherence?	C	An	Coherence is not a standard for rationality. Beneficial decisions are specified as ecological rational.
6	Armstrong (1980)	The seer-sucker theory: The value of experts in forecasting	C	Av	This article describes the role of experts in forecasting. Hiring experts is really expensive but there are indications that it is not worth spending a lot of money for the search process.
7	Banker & Khetani (2019)	Algorithm overdependence: how the use of algorithmic recommendation systems can increase risks to consumer well-being	E	Av & Ap	This article shows both aspects. Firstly, people often rely on their judgment instead of the judgment of algorithm. Secondly, people tend to overrely on algorithmic decision aids.
8	Baron (2000)	Thinking and Deciding	C	Av	This paper includes topics such as human cognition and rationality and, therefore, also overconfidence bias. Overconfidence Bias appears when people show extreme confidence.
9	Bennett & Hauser (2013)	Artificial intelligence framework for simulating clinical decision-making: A Markov decision process approach	S	Av	This article shows the effects of AI in hospitals. Since the technology has developed in the last decades, AI systems are able to reduce errors and improve efficiency in the hospital.
10	Bhattacharya et al. (2012)	Is unbiased financial advice to retail investors sufficient? Answers from a large field study	S	Av & Ap	In financial decisions, the individual characteristic gender might play a role in advice taking.

11	Bigman & Gray (2018)	People are averse to machines making moral decisions	E	Av	People are averse towards algorithmic-based moral decisions in various areas, such as medicine, military, and law.
12	Blankenship et al. (1984)	Reciprocal Interaction and Similarity of Personality Attributes	S	Av & Ap	Individuals feel attracted to each other when their personalities match (similarity-attraction hypothesis).
13	Brown (2015)	Decision science as a by-product of decision-aiding: A practitioner's perspective	C	Av	Algorithmic-based decision making is characterized by calculations. Consequently, this type of decision making requires additional motivation for the implementation.
14	Buckley et al. (2000)	A brief history of the selection interview: May the next 100 years be more fruitful	C	Av	This paper, based on a review, shows that employers prefer to use the traditional way of making interviews as a selection method.
15	Bucklin et al. (1998)	From decision support to decision automation	C	Av	This article discusses the potential future role of marking regarding automation. They state that a lot of tasks in marketing can not only be supported by algorithms but may also be automated.
16	Burton et al. (2020)	A systematic review of algorithm aversion in augmented decision making	C	Av	This article provides a review of the topic algorithm aversion. It includes causes and strategies to overcome this phenomenon.
17	Byrne & Griffitt (1969)	Similarity and awareness of similarity of personality characteristics as determinants of attraction	E	Av & Ap	This article investigates the approach of personality-similarities. Humans feel attracted to each other when their personalities match.
18	Camerer & Johnson (1991)	The process-performance paradox in expert judgment: How can experts know so much and predict so badly?	C	Av	This article deals with experts. It shows that regression models are capable of outperforming experts.
19	Carbone et al. (1983)	Comparing for different time series methods the value of technical expertise individualized analysis, and judgmental adjustment	E	Av	This research paper shows that individuals' efforts to modify algorithmic-based predictions often results in worse outcomes.
20	Castelo et al. (2019)	Task-Dependent Algorithm Aversion	E	Av & Ap	This article shows that humans do not really rely on algorithms for tasks that seem subjective. If people perceive an algorithm to be more objective, it increases the use of it

21	Commerford et al. (2019)	Complex estimates and auditor reliance on artificial intelligence	E	Av	This article indicates that algorithm aversion is costly. Individuals could increasingly rely on algorithmic based decision aids when they increase their experience with this technology.
22	Corey & Merenstein (1987)	Applying the acute ischemic heart disease predictive instrument	S	Av	This research paper shows that doctors erroneously underutilize algorithmic models.
23	Cortina et al. (2000)	The incremental validity of interview scores over and above cognitive ability and conscientiousness scores	C	Av	This article indicates that less standardized methods such as interviews provide little insight into the future performance of an employee.
24	Croskerry & Norman (2008)	Overconfidence in clinical decision making	C	Av	Individuals characterized with overconfidence are inclined to make illogical and irrational decisions.
25	Dane & Pratt (2007)	Exploring intuition and its role in managerial decision making	C	Av	This article provides a definition of intuition. It is defined "as affectively charged judgments that arise through rapid, nonconscious, and holistic associations" (p.40).
26	Dane et al. (2012)	When should I trust my gut? Linking domain expertise to intuitive decision-making effectiveness	E	Av	A large part of decisions is not based on the collection and analysis of information, but rather on the subconscious level of intuition. This paper describes the crucial part of domain expertise in intuition-based decision-making.
27	Dawes (1979)	The robust beauty of improper linear models in decision making	C	Av	This article is a review regarding clinical versus statistical prediction. Statistical models are superior to clinical models.
28	Dawes et al. (1989)	Clinical versus actuarial judgment	C	Av	Individuals can consult either the clinical or the actuarial method. Research shows that the actuarial method outperforms the clinical method.
29	Diab et al. (2011)	Lay perceptions of selection decision aids in US and non-US samples	E	Av	This article shows that algorithms make better forecasts than humans. But, participants prefer to rely on human-made interviews, because they perceive it as more professional and fairer.
30	Dietvorst et al. (2015)	Algorithm aversion: People erroneously avoid algorithms after seeing them err	E	Av & Ap	This article points out that individuals are less inclined to rely on an algorithm after noticing it making an error. They punish an algorithm more than a human regarding making mistakes.
31	Dietvorst et al. (2018)	Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them	E	Av & Ap	This research paper shows that if people get the possibility to modify the algorithmic forecast process, it increases their confidence and the likelihood of using it.

32	Dijkstra (1999)	User agreement with incorrect expert system advice	E	Ap	People think that an algorithmic advice is characterized with objectivity and rationality to a greater extent than a human advice.
33	Dijkstra et al. (1998)	Persuasiveness of expert systems	E	Ap	This article indicates that people think that an algorithmic system is characterized with more objectivity and rationality than a human-being.
34	Duck (1973)	Personality similarity and friendship choice: Similarity of what, when?	E	Av & Ap	This research paper shows that people feel attracted to each other when their personalities match.
35	Dzindolet et al. (2001)	A framework of automation use	C	Av & Ap	This article shows that people weight up the perceived reliability of human and algorithm-based predictions to determine on which advice they should rely. Additionally, factors influencing automation bias are described: authority, cognitive miser as well as diffusion of responsibility.
36	Dzindolet et al. (2002)	The perceived utility of human and automated aids in a visual detection task	E	Av	Individuals are more sensitive towards algorithm errors. Consequently, their level of trust decreases after noticing that the algorithm is capable of making errors.
37	Eastwood et al. (2012)	What people want from their professionals: Attitudes toward decision-making strategies	E	Av	Individuals rate the clinical method as being better than the actuarial method. Patients feel more positively towards physicians when they do not include algorithmic decision aids in their prognosis.
38	Efendić et al. (2020)	Slow response times undermine trust in algorithmic (but not human) predictions	E	Av	This research paper shows that individuals' tendency to rely on an algorithm depends on the response time.
39	Einhorn (1986)	Accepting error to make less error	C	Av	Aversion towards algorithms arises because humans think that algorithms will make an error and humans have the ability of perfection.
40	Fildes & Goodwin (2007)	Against your better judgment? How organizations can improve their use of management judgment in forecasting	S	Av	Decision-makers often rely too excessively on unstructured forecasting methods and tend to erroneously reject statistical methods. Managers often dilute the predictions with their decisions.
41	Fitzsimons & Lehmann (2004)	Reactance to recommendations: When unsolicited advice yields contrary responses	E	Av	Individuals are confronted with product recommendations that contradict their first impression of choice. In this case, they tend to show reactance towards the algorithm-based recommender system and start to avoid and to contradict further recommendations.

42	Garg et al. (2005)	Effects of computerized clinical decision support systems on practitioner performance and patient outcomes: a systematic review	C	Ap	This research paper shows that automation-based decision aids help to increase the performance of the forecast task.
43	Goodwin et al. (2013)	Antecedents and effects of trust in forecasting advice	E	Av	This article shows that when individuals get offered with an explanation on how an algorithm works, it increases their stated trust in it.
44	Gough (1962)	Clinical versus statistical prediction in psychology	S	Av	This research paper shows that the statistical method is capable of outperforming the clinical method.
45	Green & Hughes (1986)	Effects of decision support systems training and cognitive style on decision process attributes	E	Av	It seems that providing individuals with a well-suited training decreases disuse of algorithms and increases the effectiveness of algorithmic based decision aids.
46	Grove & Meehl (1996)	Comparative efficiency of informal (subjective, impressionistic) and formal (mechanical, algorithmic) prediction procedures: The clinical–statistical controversy	C	Av	This article shows that the mechanical method of diagnosis is more accurate than the clinical method.
47	Grove et al. (2000)	Clinical versus mechanical prediction: A meta-analysis	C	Av	Statistical predictions are equal or superior to clinical prediction.
48	Hafenbrädl et al. (2016)	Applied decision making with fast-and-frugal heuristics	C	Av	This research article states that it is difficult to demand from individuals to learn a new process of making decisions from nowhere. It is easier to find out where they find themselves in their decision-making process and how to make improvements to their actual process.
49	Hagmann et al. (2019)	Nudging out support for a carbon tax	E	Av	Nudges often lead to detractions from more sustainable solutions.
50	Highhouse (2008)	Stubborn Reliance on Intuition and Subjectivity in Employee Selection	C	Av	This article shows that humans have a resistance on statistical models because they have more trust in their own intuition.

51	Ho et al. (2005)	Age differences in trust and reliance of a medication management system	E	Av & Ap	This article shows that individuals at a higher age are more likely to trust and use an algorithm than people at a lower age.
52	Hoff & Bashir (2015)	Trust in automation: Integrating empirical evidence on factors that influence trust	C	Av	Review about factors which influence trust in automation. The study found three levels of variability: Situational, dispositional and learned trust.
53	Jakesch et al. (2019)	AI-Mediated Communication: How the Perception that Profile Text was Written by AI Affects Trustworthiness	E	Av	Individuals are apt to reject Airbnb hosts when they believe that the description was written by an AI-system rather than by a human-being.
54	Kahneman (2003)	A perspective on judgment and choice: mapping bounded rationality	E	Av	This research paper indicates that intuition-based decision-making is correct in occasional situations.
55	Kaplan (2000)	Culture counts: how institutional values affect computer use	S	Av	This article is about aversion towards computers in hospitals. A cause of aversion towards algorithmic models could be the doctors fear, that the use of decision aids could reduce their professional attitude in the perception of individuals.
56	Kerr & Bruun (1983)	Dispensability of member effort and group motivation losses: Free-rider effects	E	Ap	This article tests the free rider effect empirically. Different factors influence people tendency to show a free-riding behavior: characteristics of the group, members as well as tasks (e.g. size of the groups, ability of team members).
57	Kleinmuntz (1990)	Why we still use our heads instead of formulas: Toward an integrative approach	C	Av	Doctors rely on clinical methods to a greater extent, although actuarial decision aids would be available to use.
58	Komaroff (1982)	Algorithms and the "art" of medicine	C	Av	This article shows that individuals believe that algorithm prognosis takes the “art” of human judgment away.
59	Kuncel (2008)	Some new (and old) suggestions for improving personnel selection	C	Av	Decision-makers should learn the importance of decision aids.
60	Kuncel et al. (2013)	Mechanical versus clinical data combination in selection and admissions decisions: A meta-analysis	C	Av	This article shows that in the area of employee selection, employers erroneously prefer to rely on intuition-based decision-making instead of including decision aids in their selection process.

61	Layton et al. (1994)	Design of a cooperative problem-solving system for en-route flight planning: An empirical evaluation	E	Ap	This article shows an example of automation bias. Pilots who are provided with a route plan generated by an automation-based decision aid spend less time in evaluating time-efficient route alternatives than pilots who do not receive advice.
62	Lee (2008)	Flattery may get computers somewhere, sometimes: The moderating role of output modality, computer gender, and user gender	E	Av & Ap	This research paper shows that women and men react differently to flattery used by computers. Females are inclined to react positively to it, while it has a negative effect on males.
63	Lee (2018)	Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management	E	Av	Humans perceive algorithmic-based decision aids as less trustworthy, less fair, and feel more negatively towards them than on human advice.
64	Lee & Moray (1992)	Trust, control strategies and allocation of function in human-machine systems	E	Av	This article shows that faults with environmental situations and algorithms lead to poor algorithm performance, resulting in a decrease in trust and to disuse of decision aids
65	Lee & See (2004)	Trust in automation: Designing for appropriate reliance	C	Av & Ap	Individuals do not rely on algorithmic-decision aids appropriately.
66	Li et al. (2010)	A cross-cultural study: Effect of robot appearance and task	E	Av & Ap	This article shows that individuals from different cultures perceive social robots differently.
67	Lievens et al. (2005)	The importance of traits and abilities in supervisors' hirability decisions as a function of method of assessment	S	Av	This research paper indicates that employers prefer using more intuitive approaches for assessment and selection of potential employees.
68	Lim & O'Connor (1995)	Judgemental adjustment of initial forecasts: Its effectiveness and biases	E	Av	This article shows that peoples' effort to modify algorithmic-based predictions often results in worse outcomes.
69	Liu et al. (2019)	Machines versus humans: People's biased responses to traffic accidents involving self-driving vehicles	E	Av	Traffic accidents involving autonomous driving vehicles are perceived more negatively than traffic accidents involving human-driven vehicles.

70	Lodato et al. (2011)	Predicting professional preferences for intuition-based hiring	S	Av	Employers prefer to rely on intuition-based decision-making instead of including decision aids in their selection process.
71	Logg et al. (2019)	Algorithm appreciation: People prefer algorithmic to human judgment	E	Av & Ap	This paper challenges the view that people are averse towards algorithms. Six experiments show that people rely more heavily on algorithmic rather than on human judgment.
72	Longoni et al. (2019)	Resistance to Medical Artificial Intelligence	E	Av	This article shows that individuals believe that algorithmic tools will not consider their unique individual characteristics.
73	Lourenço et al. (2020)	Whose Algorithm Says So: The Relationships Between Type of Firm, Perceptions of Trust and Expertise, and the Acceptance of Financial Robo-Advice	E	Av & Ap	In the domain of online financial support systems, older people are less satisfied and have less trust in the algorithmic interaction than younger people.
74	Lundeberg et al. (1994)	Highly confident but wrong: Gender differences and similarities in confidence judgments	S	Av & Ap	Females are less confident about their knowledge to make appropriate financial decisions in comparison to males.
75	Luo et al. (2019)	Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases	E	Av	Unrevealed chatbots are equally successful as experienced workers, and four times more successful than inexperienced workers in generating product sales. When people interact with chatbots and then the true "identity" of the chatbots are revealed, the purchasing rate of the potential customer decreases. When people have prior AI experience leads to more purchases. It leads to higher purchases when the reveal of the chatbots identity is placed at the end of the interaction.
76	Luong et al. (2020)	Algorithmic decision-making: examining the interplay of people, technology, and organizational practices through an economic experiment	E	Av	This article shows that humans are more likely to use a decision aid when they have no prior experience with algorithms.
77	Madhavan & Wiegmann (2007a)	Effects of information source, pedigree, and reliability on operator interaction with decision support systems	E	Av	This research paper shows that individuals are more sensitive towards machine errors than human errors.

78	Madhavan & Wiegmann (2007b)	Similarities and differences between human-human and human-automation trust: An integrative review	C	Av	This paper shows that human mistakes are not perceived as being negative by the user. The reason for that is people believing that humans are imperfect and therefore allowed to make mistakes.
79	Madhavan et al. (2006)	Automation failures on tasks easily performed by operators undermine trust in automated aids	E	Av	This research paper indicates that when an algorithm fails to perform an easy task, the individuals' level of trust decreases because they believe that the algorithmic model is not capable of solving more challenging tasks.
80	Manzey et al. (2012)	Human performance consequences of automated decision aids: The impact of degree of automation and system experience	E	Av	This article shows that algorithmic errors have a more negative effect on trust if they occur at the beginning of the usage than errors occurring later in the usage.
81	Marchese (1992)	Clinical versus actuarial prediction: A review of the literature	C	Av	This paper indicates that the statistical method outperforms the clinical method.
82	Martini et al. (2015)	Agent appearance modulates mind attribution and social attention in human-robot interaction	E	Av	Algorithms are capable to follow gazes.
83	McBride et al. (2012)	The impact of personality on nurses' bias towards automated decision aid acceptance	E	Av & Ap	In the area of medical prognoses, nurses characterized by a more intuitive personality tend to rely more heavily on algorithmic based diagnosis aids than nurses characterized by a more sensing personality.
84	Meehl (1954)	Clinical versus statistical prediction: A theoretical analysis and a review of the evidence	C	Av	This article shows that statistic formulas are able to outperform qualitative judgments, but doctors prefer to rely on their judgment.
85	Meehl (1986)	Causes and effects of my disturbing little book	C	Av	Review of his published article in 1954. The major part of insights provided in 1954 was still relevant 30 years later.
86	Merritt & Ilgen (2008)	Not all trust is created equal: Dispositional and history-based trust in human-automation interactions	E	Av & Ap	People with a more extroverted personality are more likely to trust machines than people with a more introverted personality.
87	Montazemi (1991)	The impact of experience on the design of user interface	E	Av	This article shows that experience is positively related to the use of decision aids. Domain expertise, however, is negatively related.

88	Moore & Healy (2008)	The trouble with overconfidence	E	Av	The overconfidence bias can be distinguished in three different types: Overestimation, overplacement and overprecision.
89	Mosier & Skitka (1996)	Human decision makers and automated decision aids: Made for each other?	C	Ap	Three main factors influence the automation bias: authority, cognitive miser as well as diffusion of responsibility.
90	Mosier et al. (1998)	Automation bias: Decision making and performance in high-tech cockpits	E	Ap	Automation bias results in negative consequences: omission and commission errors.
91	Mullins & Rogers (2008)	Reliance on intuition and faculty hiring	C	Av	This article shows that it is necessary to study the human subconscious processes that affect intuitive decisions. This allows to detect the factors responsible for collecting and evaluating data of individuals.
92	Naef et al. (2008)	Decomposing trust: Explaining national trust differences	S	Av & Ap	Trust differs in various cultures, generations, places (e.g. countries, cities) as well as races.
93	Nass & Lee (2001)	Does computer-synthesized speech manifest personality? Experimental tests of recognition, similarity-attraction, and consistency-attraction	E	Av & Ap	Individuals apply polite standards and stereotypes when they interact with a computer. They feel attracted to the computer when their personalities fit together.
94	Nass et al. (1996)	Can computers be teammates?	E	Av	Humans enter in a kind of relationship with algorithmic decision aids in a way similar to other humans.
95	Nass et al. (1995)	Can computer personalities be human personalities?	E	Av & Ap	This article shows that people are willing to rely on algorithms when the algorithm displays similar personality characteristics to those of the user.
96	Nomura et al. (2008)	Prediction of human behavior in human–robot interaction using psychological scales for anxiety and negative attitudes toward robots	E	Av & Ap	Attitude, emotions and communication have an impact in interacting with robots. Additionally, this paper indicates that there may be differences regarding the variable gender in how individuals respond to robots.

97	Önkal et al. (2009)	The relative influence of advice from human experts and statistical methods on forecast adjustments	E	Av	This paper shows that individuals apt to rely more on human than on algorithmic advice in stock price forecasting.
98	Pak et al. (2012)	Decision support aids with anthropomorphic characteristics influence trust and performance in younger and older adults	E	Av & Ap	This research article indicates that younger people's trust in the algorithmic decision aid increases when a photo of an expert is on the interface of a decision aid. This stands in contrast to the behavior of older people.
99	Parasuraman & Manzey (2010)	Complacency and bias in human use of automation: An attentional integration	C	Ap	This paper shows that automation bias can also result in positive outcomes. This is the case when the decision aid gives the right advice.
100	Parasuraman & Riley (1997)	Humans and automation: Use, misuse, disuse, abuse	C	Av & Ap	This article describes disuse and misuse of algorithms. Misuse of algorithms is described as the resulting failures which take place when individuals erroneously rely on algorithms. Disuse of algorithms is described as the resulting failures which take place when people mistakenly do not rely on algorithms.
101	Patel et al. (2009)	The coming of age of artificial intelligence in medicine	C	Av	This paper indicates that AI systems are capable of decreasing errors and improve efficiency in the hospital.
102	Patterson (2017)	Intuitive cognition and models of human–automation interaction	C	Av	Intuitive cognition is the dominant force influencing people's decision making.
103	Prahl & Van Swol (2017)	Understanding algorithm aversion: When is advice from automation discounted?	E	Av & Ap	Review of interpersonal advice and human-automation trust. People rely on algorithms significantly less than on human recommendations after receiving bad advice. Decision makers think that they are more similar to humans than to algorithms.
104	Prince (1993)	Women, Men, and Money Styles	S	Av	This article shows that women are less confident about their knowledge to make appropriate financial decisions in comparison to men.
105	Promberger & Baron (2006)	Do patients trust computers?	E	Av	This article indicates that people rather prefer to rely on a recommendation from a physician than on a recommendation provided by an algorithm.

106	Rau et al. (2009)	Effects of communication style and culture on ability to accept recommendations from robots	E	Av & Ap	This article gives insights about individual differences. Germans perceive robots as less likable and less trustworthy compared to Chinese
107	Robinette et al. (2016)	Overtrust of robots in emergency evacuation scenarios	E	Ap	People show overtrust in certain scenarios when they are in emergency, time-pressure scenarios.
108	Robinette et al. (2017)	Effect of robot performance on human–robot trust in time-critical situations	E	Ap	This article shows that peoples' trust in robots decreases after seeing the robot making an error.
109	Rynes et al. (2002)	HR professionals' beliefs about effective human resource practices: Correspondence between research and practice	E	Av	This paper indicates that employers prefer to use the traditional way of making interviews as a selection method.
110	Sanchez et al. (2004)	Understanding reliance on automation: Effects of error type, error distribution, age and experience	E	Av & Ap	This article shows that people at higher age are superior in calibrating their level of trust to the inconsistent reliability of an algorithm than people at lower age.
111	Sanders & Manrodt (2003a)	Forecasting software in practice: Use, satisfaction, and performance	S	Av	Decision-makers in marketing and sales often avoid using commercial offered prediction systems which would improve their forecast performance.
112	Sanders & Manrodt (2003b)	The efficacy of using judgmental versus quantitative forecasting methods in practice	S	Av	This research papers shows that statistical forecast models can outperform human judgment.
113	Sawyer (1966)	Measurement and prediction, clinical and statistical	C	Av	This article indicates that the statistical method outperforms the clinical method.
114	Shaffer et al. (2013)	Why Do Patients Derogate Physicians Who Use a Computer-Based Diagnostic Support System?	E	Av	This article shows that people see experts using decision-support-systems as less professional with a lower level of ability than experts who make an aid free prediction.
115	Sieck & Arkes (2005)	The recalcitrance of overconfidence and its contribution to decision aid neglect	E	Av	Individuals perceive algorithmic decision aids as “dehumanizing” and decision-makers which rely on their intuition and experience as more caring.

116	Sinha & Swearingen (2001)	Comparing recommendations made by online systems and friends	E	Av	Individuals rely more heavily on human recommendations than on recommendation systems for movies and book.
117	Schmidt & Hunter (1998)	The validity and utility of selection methods in personnel psychology: Practical and theoretical implications of 85 years of research findings	C	Av	This article shows that more standardized methods are superior to less standardized methods in selection procedures.
118	Szalma & Taylor (2011)	Individual differences in response to automation: The five factor model of personality	E	Av & Ap	This article shows that neuroticism shows a negative correlation to the individual difference: personality.
119	Thurman & Fletcher (2019)	Has digital distribution rejuvenated readership? Revisiting the age demographics of newspaper consumption	S	Av & Ap	This research paper indicates that the reason for older individuals' rejection of algorithmic news personalization might be that this age group consumes traditional types of media the most.
120	Thurman et al. (2019)	My friends, editors, algorithms, and I: Examining audience attitudes to news selection	S	Av & Ap	This article indicates that in the domain of choosing the source of news, people at higher age are willing to receive news from an editor rather than from an algorithm-based personalization.
121	Todd & Gigerenzer (2007)	Environments that make us smart: Ecological rationality	C	Av	Ecological rationality is an approach that refers to the real world. It states that the level of rationality regarding a decision depends on the environment in which the decision is made.
122	Tung (2011)	Influence of gender and age on the attitudes of children towards humanoid robots	E	Av & Ap	This article shows that there is a difference regarding the variable gender on how children feel attracted to robots.
123	Westin et al. (2015)	Strategic conformance: Overcoming acceptance issues of decision aiding automation?	C	Av	This article is about strategic conformance. This refers to match peoples' and algorithmic decision-making.
124	Whitecotton (1996)	The effects of experience and confidence on decision aid reliance: A causal model	E	Av	This article shows that experience is positively related to the use of decision aids. Domain expertise, however, is negatively related with the use of decision aids.

125	Wiese et al. (2012)	I see what you mean: how attentional selection is shaped by ascribing intentions to others	E	Av	The perception that a certain agent could be a human being leads to intentional stance compared to the perception that a certain agent could be an algorithm.
126	Wiese et al. (2017)	Designing artificial agents as social companions	C	Av	When individuals see the mind in another party (e.g. human or algorithm) it shows a positive effect on the relationship. It leads to an increased level of trust and social connection.
127	Workman (2005)	Expert decision support system use, disuse, and misuse: a study using the theory of planned behavior	S	Av	This article is about the disuse and misuse of decision aids. The expectations and opinions of work colleagues or managers affect the viewpoint of other employees towards decision aids.
128	Yeomans et al. (2019)	Making sense of recommendations	E	Av & Ap	Recommender systems are superior to human advice, no matter if the advice comes from family, friends or strangers. But humans do not rely on algorithms. They rely on human advice to a larger extent.

[a]Method: E = experimental design; C = conceptual/review: S = study (non-experimental design)
[b]Topic: Av = Algorithm Aversion; Ap = Algorithm Appreciation; Av & Ap = Algorithm Aversion and Algorithm Appreciation

Table 31: Reference list with Author, published Year, Method, Topic, and Key Findings

Affidavit

I hereby declare that this Master's thesis has been written only by the undersigned and without any assistance from third parties. I confirm that no sources have been used in the preparation of this thesis other than those indicated in the thesis itself.

This Master's thesis has heretofore not been submitted or published elsewhere, neither in its present form, nor in a similar version.

Innsbruck, 27.05.2020

Place, Date Signature