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Cognitive Biases in Data-Driven Decision-Making - A Literature Review

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Abstract: Today, decision makers face the challenge of making sense of the mass of data generated by digital applications and processes. A sophisticated approach to data analysis, however, can foster a lead time advantage in innovation management and is likely to enhance corporates' competitive strength. Data-driven decision-making and decision-support-systems (DSS) are stated helpful for overcoming the cognitive constraints of decision makers. Nevertheless, critics claim that data-driven decision-making and the underlying algorithms might be prone to biases and likely to introduce deviations from rational judgement in organizations. While this is a crucial issue that needs to be addressed, it seems as if research on this topic remains scarce and scattered. To understand how scientific research has gone about this inquiry so far, we conduct a bibliometric analysis. Based on a dataset of 70 scientific publications we hence aim to outline focus topics of the past and areas for future research.

Keywords: Cognitive bias; data-driven decision-making; decision-support-systems; decision-making; bibliometric analysis

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1 Introduction

Today's business environment is driven by digitalization, with large volumes of data continuously generated. This mass amount of data is providing managerial decision makers (e.g., innovation managers) with the opportunity to make more informed decisions. However, the rapid pace of data obsolescence makes it difficult for decision makers to effectively interpret and use this information (Amankwah-Amoah and Adomako 2019). To overcome the shortages of their data processing capacities as well as their bounded rationality, decision makers are increasingly using data-driven models and related decision-support-systems (DDS) (Zaitsava et al. 2022; Lindebaum et al. 2020). However, the usefulness and effectiveness of data-based models is a topic of controversy as these are also subject to biases. Critics argue that these models may be less accurate than expected due to their reliance on existing, historical, and sometimes unreliable, data (Zaitsava et al. 2022). Thus, research often focuses on technical and ethical aspects of data-based models. At the same time, it can be assumed that data-based models induce cognitive biases as well, as decision makers make sense of suggestions provided by data-based models (Lindebaum et al. 2020) and encounter DSS differently (e.g., Filiz et al. 2021; Dietvorst et al. 2015). Although scholars have already elaborated on this theme, research on the role of biases in the human-DSS-interaction remains fragmented and lacks a clear understanding of the current state of knowledge. It is therefore important to comprehensively analyse and map out, how scientific research has so far gone about this question to outline future research trajectories as well as to leverage the full potential of data-driven decision-making for innovation managers. Thus, this bibliometric analysis contributes to a detailed understanding of the current state of research on whether data-based models promote or mitigate cognitive biases of decision makers.

The remainder of this article is structured as follows. First, we shortly outline the theoretical background of this research stream. Second, we describe the process of data collection as well as the bibliometric methods we apply. Thereafter, we present initial findings of the bibliometric analyses and discuss potential research avenues of the future, before ending with a conclusion.

2 Theoretical Background

Data-Driven Decision-Making

Data-driven decision-making, and DSS in particular, are widely discussed by scholars. DSS are applications that use information technology and software applications to support and improve managerial decision-making (Arnott 2006; Singh 1998), for instance in the context of innovation management. With each technological advancement, DSS has changed (Arnott 2006) and new terms have entered the stage such as 'algorithmic decision-making' (Lindebaum et al. 2020) or 'AI-augmented decision-making' (Keding and Meissner 2021). We stay with the more generic terms 'data-driven decision-making' and DSS, encompassing other expressions and related scientific research.

DSS dispose of greater processing capacities that foster an efficient and timely analysis (Singh 1998) of data that is in continuously produced by digital applications and processes. These systems therefore support human decision makers as the latter face boundary conditions due to limited processing capacity (Simon 1979). This means that decision makers are usually incapable of processing all information in an appropriate time, in particular, as data is outdated quickly.

With the advent of AI gaining more attention and acceptance, organizational decision-making has again changed (Vincent 2021). Related technological advanced DSS provide recommendations and predictions to decision makers, so that they can shift attention from solution seeking to solution evaluation (Keding and Meissner 2021). Therefore, DSS are considered an enabler, allowing decision makers to benefit from the data treasury of today's digitized world. The sophisticated utilization of such DSS is thus a top priority to decision makers and organizations (Zaitsava et al. 2022).

Data-driven decision-making is often considered an add-on that complements human decision-making. Combining the strength of DSS with the unique capabilities of human decision makers synergistically, is suggested to be most promising (Jarrahi 2018). To conclude, it is assumed that an efficient integration of DSS into human decision-making helps corporates in gaining a lead time advantage and in outpacing competitors regarding innovation capacity (Keding and Meissner 2021).

Cognitive Biases

Research on cognition has a long heritage, also in management and business science (Hodgkinson et al. 2023). Much research has discussed the idea of rational decision-making, as the opposite to intuitive decision-making and as the more desirable way of judgement and choice. In one of his seminal papers, Simon (1955) however argues that rational decision-making is rarely possible. Rational decision-making requires full information on the alternatives of choice, on their pay-off, their future developments, as well as on the likely consequences and interdependences of choice alternatives with aspects of the decision environment (Simon 1955). Simon (1990) therefore argues that decision makers are rationally bounded, as they are usually not capable of making fully informed decisions due to limited processing capacities or incomplete information.

Particularly in today's fast paced, dynamic, and complex world, rational decision-making is rarely possible. Decision makers thus heavily rely on heuristics as rules of thumb that facilitate fast and frugal decision-making (Gigerenzer et al. 2022). Heuristics per se do not present a problem. In most of the cases, they are quite helpful instead as they reduce complexity (Hodgkinson et al. 2023) and help decision makers to come to a conclusion, while facing incomplete information (Gigerenzer et al. 2022). They might, however, introduce cognitive biases into decision-making. Cognitive biases display "systematic deviations from rational judgement and thinking" (Hodgkinson et al. 2023, 1034), often show a strong reference to the past, and hence are likely to prevent from making the best decision (Ehrlinger et al. 2016).

Resulting from the intensive studies on cognition, a large magnitude of heuristics and biases has been identified previously (Ehrlinger et al. 2016). Under the most prominent biases are the anchoring bias, availability bias, representativeness bias, framing bias, and overconfidence bias.

Cognitive Biases in Data-Driven Decision-Making

Researchers frequently presume that two opposing poles - intuition and rationality - take effect in decision-making (Hodgkinson et al. 2008). Since DSS show more sophisticated rationality capabilities, it is assumed that they will take over the rational part, while human decision-makers account for the intuitive (Abbasi et al. 2022). Consequently, data-driven decision-making is often viewed as a means of overcoming the bounded rationality of decision makers and facilitating debiasing, resulting in more rational decisions that are less prone to failures (Lindebaum et al. 2020).

At the same time, there is scepticism. What if, rather than eliminating bias, DSS creates it? Research studies show that data-driven decision making is less rational than desired. For example, scholars argue that decision-makers often show a general resistance to data-based (algorithmic) models and refuse suggestions provided by such DSS −a phenomenon called ‘algorithm aversion’ (e.g., Dietvorst et al. 2015). Consequently, they do not accept a DSS proposal but instead rely more in their own judgment and choice. Further, it is assumed that this kind of aversion is eliciting cognitive biases, such as overconfidence (Filiz et al. 2021). The opposite behaviour is also observed, however; by over relying into the suggestions given by DSS and by not questioning the same, an automation bias might be introduced (Keding and Meissner 2021).

3 Bibliometric Analyses

This study is based on a bibliometric analysis. Bibliometric studies use quantitative, statistical methods to analyse data of scientific databases (Jashari et al. 2022; Zupic and Čater 2015). In general, two types of bibliometric analysis can be distinguished: performance mapping and science mapping (Noyons et al. 1999). In a performance mapping analysis, the publication performance of institutions, journals, authors, articles, or geographic regions is assessed (Noyons et al. 1999; Zupic and Čater 2015). For this purpose, citation scores are statistically evaluated. A science mapping analysis, on the contrary, is more interested in the dynamics, structures, and patterns of a scientific research field (Zupic and Čater 2015) as it outlines past developments and future opportunities. A science mapping analysis therefore seems most appropriate for the purposes of this research study.

Details on Data Collection

The data for the bibliometric analysis has been collected in an iterative process. First, an initial search string was developed by a team of interdisciplinary researchers according to McGowan et al. (2018) and refined by iteratively evaluating the titles of the resulting publications in three different databases, namely Scopus, Web of Science and Dimensions. The resulting search string can be found hereafter.

> Query: (("data?driven" OR "data?base*" OR "data?informed" OR "data?support*" OR "artificial intelligence" OR "ai?augmented" OR algorithmic) AND (decision OR judge* OR choice) AND ("cognitive bias" OR "algorithm aversion" OR "anchoring bias" OR "anchoring heuristic" OR "availability heuristic" OR "availability bias" OR "overconfidence bias" OR "confirmation bias" OR "framing bias") NOT (clinical OR medical)) Fields of research (ANZSRC 2020): (“46 Information and Computing Sciences” OR “44 Human Society” OR “4410 Sociology” OR “3801 Applied Economics” OR “38 Economics” OR “3802 Econometrics” OR “52 Psychology” OR “5204 Cognitive and Computational Psychology” OR “35 Commerce, Management, Tourism and Services” OR “3507 Strategy, Management and Organisational Behaviour”)

Secondly, book chapters, reviews and conference proceedings were eliminated and the resulting sets of publications of all databases were compared to avoid duplications. It was concluded that the Dimensions dataset, consisting of 143 publications, is comprehensive and includes the publications from Scopus and the Web of Science. Third, those 143 publications were checked for their accuracy, to do so the titles and abstracts were cross-read to exclude off-topic publications. This resulted in a final dataset comprising 70 publications which can be further used for analysis.

Bibliometric Methods

Science mapping analyses typically combine diverse clustering and mapping techniques to describe the scientific domain more conclusively (Waltman et al. 2010). This study therefore encompasses diverse methods which are shortly described hereafter.

Co-Occurrence Analysis

A co-occurrence analysis is also called co-word or keyword analysis (Zupic and Čater 2015). Subject of interest to the co-occurrence analysis are hence the keywords of publications, included in a dataset. A co-occurrence analysis is the only bibliometric method that is, itself, concerned with the actual content of a publication (Zupic and Čater 2015). It provides a first and rough insight into the themes that seem to be frequently discussed in the scientific domain.

To understand how two terms are related to each other, a co-occurrence analysis defines the link strength between keywords. The link strength between two terms is thereby assessed, based on the number of publications, the two words occur together in. Further, and to generate a satisfactory co-occurrence analysis and to avoid any redundancies, a so-called dictionary must be created beforehand, specifying how to deal with synonyms or differences in notations, as for instance with singular and plural.

Bibliographic Coupling

In addition to keywords, citation data can also be analysed. Two methods are hereby prevalent: co-citation and bibliographic coupling analysis (Jashari et al. 2022). This study includes a bibliographic coupling analysis only, for several reasons. First, and in contrast to a co-citation analysis, bibliographic coupling analyses have less of a historical focus and are therefore more appropriate to map out a rather young research field (Zupic and Čater 2015), as it is the case in this study. Second, bibliographic coupling analyses are often applied to outline future research trajectories (van den Besselaar and Heimeriks 2006) which is one of the objectives of this study. Third, co-citation analyses accentuate publications, considered more important due to their citations, and thereby neglect smaller research clusters that are less cited yet (Zupic and Čater 2015).

To conduct a bibliographic coupling analysis the bibliographies of two publications are contrasted and statistically analysed. Linkages between two publications are hence assessed by means of their shared citations, i.e., references (Jashari et al. 2022). It is thereby assumed that the greater the correspondence between two bibliographies, the stronger the linkage and the more similar the research subjects of two publications (van den Besselaar and Heimeriks 2006). To conduct the bibliographic coupling analysis, we used the opensource software VOSviewer.

Topic Modelling

Only observing the metadata of a set of publications is often not sufficient to get a better understanding of its respective contents. Topic Modelling is a popular machine learning method for analysing text and clustering its content into topics of close thematic proximity. The concept of Topic Modelling is to map the words or phrases in an unstructured text corpus into a low-dimensional (usually 2-dimensional) dataspace to simplify the clustering process (Uys et al. 2008). There are different approaches to Topics Modelling, in this paper we used a combination of GloVe, t-SNE and k-Means clustering. GloVe stand for Global Vectors and is used to map each word to a vector (Pennington et al. 2014). K-Means clustering can be used to cluster a set of datapoints and finally T-SNE (t-distributed Stochastic Neighbour Embedding) is a dimensionality reduction technique for visualizing data in a 2-dimensional dataspace (van der Maaten and Hinton 2008).

4 Bibliometric Results

Topic Modelling

The Topic Modelling of the title and abstract of the 70 publications using GloVe, t-SNE and k-Means clustering yielded a set of seven topics. Those topics are visualized in figure 1 where each topic consists of a set of terms in the same colour. For the sake of visual clarity, only terms which appear in at least 10% of the documents are displayed. The distance between the terms is an approximation for their similarity and their size is respective to the number of documents they appear in.

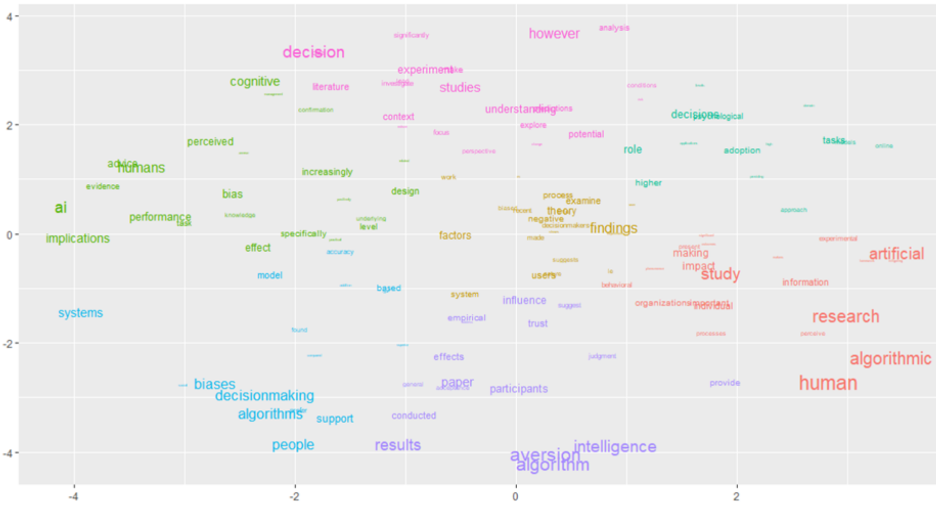

Figure 1 Topic modelling of title and abstract of the 70 publications

The clusters are structured as follows:

- Cluster 1 (top left, green) deals with the human component in AI and cognitive biases.

- Clusters 2 (top, pink) regards experimental studies regarding decisions.
- Cluster 3 (top right, turquoise) focusses the psychological role in decisions.
- Cluster 4 (right, red) deals with the research regarding AI.
- Cluster 5 (bottom, violet) focusses on trust and algorithmic aversion.
- Cluster 6 (bottom left, blue) regards biases in decision-making.
- Cluster 7 (middle, yellow) deals with the theory and negative factors.

While obviously those clusters are close regarding the content, different foci become apparent in the field. Interestingly, there seems to be no focus on a single bias. It is also evident, that there is much explorative research done in the form of studies or experiments. What is missing is a structure of the research field, which fits with the fact that this research topic is new and just emerging, since it became relevant with the fast-paced evolution of data driven decision support methods. In the next step, it might be interesting to regard the trajectory of the topics, for example by computing the average publication year of all publications mapped to each topic. Additionally, the identified topics could be mapped to the respective research fields or journals to discover their main research directions.

5 Future Research Opportunities and Next Steps

Our research findings are still in their infancy and further analyses (i.e., co-occurrence analysis and bibliographic coupling) need to be carried out. Nevertheless, the first findings of our bibliometric analysis, resulting from topic modelling, support our initial assumption that the research field is insufficiently structured. In this regard, researchers should consider elaborating on different biases, relevant for data-driven decision-making. This may become even more important as the introduction of applications such as ChatGPT makes data-driven decision-making more accessible and intuitive to managerial decision makers. Further research studies hence should investigate how the fact that the use of DSS become easier (e.g., via chat) affect decision makers interaction with these. Furthermore, it would be of interest to understand whether these developments and technological advancements lead to a bigger divide between decision makers who trust data and DSS, and decision makers who are sceptical about it - How will managers with different attitudes collaborate in the future?

In order to overcome managers' algorithm aversion and to reduce the negative effects of biased decision-making, researchers should also elaborate on measures that improve data literacy of managerial decision makers, e.g., innovation managers.

6 Conclusion

In this work, we started conducting a structured literature review. To do so, we first identified 70 publications deemed important for the research question. Second, we analysed those publications using topic modelling and identified seven subtopics. The next step will be to conduct further analyses with the goal of structuring the research in the field of cognitive biases in data-driven decision making.

7 Areas for Feedback and Development

Since this work is still research in progress, we are grateful for any feedback regarding our approach. We are especially interested in the following questions:

- Did we miss anything in conducting the search query?
- Did we miss any literature regarding the topic?
- Can you recommend other methods for analysis that the ones described?

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