Journal of Decision Systems

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tjds20

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To cite this article: Alisa Küper, Georg Lodde, Elisabeth Livingstone, Dirk Schadendorf & Nicole Krämer (2024) Mitigating cognitive bias with clinical decision support systems: an experimental study, Journal of Decision Systems, 33:3, 439-458, DOI: 10.1080/12460125.2023.2245215

To link to this article: https://doi.org/10.1080/12460125.2023.2245215

Published online: 08 Aug 2023.

JOURNAL OF DECISION SYSTEMS
2024, VOL. 33, NO. 3, 439–458
https://doi.org/10.1080/12460125.2023.2245215

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Mitigating cognitive bias with clinical decision support systems: an experimental study

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ABSTRACT
Bias in clinical reasoning has been identified as one of the main sources of diagnostic errors. Clinical Decision Support Systems that suggest possible diagnoses and provide information to mitigate cognitive bias could support physicians in finding a less biased diagnosis. We examine the influence of confidence and experience on the probability to adjust the decision after receiving decision aid and whether forming a first opinion beforehand or immediately receiving decision support makes a difference. 103 physicians and medical students participated in an online experiment built on decision tasks formulated to trigger availability and representativeness bias. The analysis showed that the presentation of prevalence data to mitigate availability bias changed the final probability estimate of the diagnosis significantly. Prototypical data to counteract representativeness bias showed no significant change. Medical experience, confidence in the decision, and timing of support had no significant influence on the probability to change the estimate.

ARTICLE HISTORY
Received 14 November 2022
Accepted 1 August 2023

KEYWORDS
Cognitive bias; clinical decision support system; availability bias; representativeness bias; mitigating bias; diagnostic error

1. Introduction

Clinical Decision Support Systems (CDSS) have undergone a rapid evolution since their first use in the 1980s (Sutton et al., 2020). They are now used to help clinicians in their complex decision-making processes, improving medical decisions by providing targeted clinical knowledge, patient information and other relevant health information (Osheroff et al., 2012) and support physicians by processing these large amounts of data (Knop et al., 2022). The adoption of CDSS even showed long-term effects in reducing readmission rates of hospital patients (Park et al., 2022). Some of the most prevalent benefits of the adoption of CDSS are reducing the risk of medication errors, providing the user with reliable information, improving efficiency and patient care, having the possibility to access all information in one place and reducing misdiagnoses (Muhiyaddin et al., 2020; Phillips-Wren, Power, et al., 2019). But what information is specifically needed to reduce misdiagnoses when helping physicians with making well-informed decisions? When

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should this information be presented? What leads to diagnostic errors and how can decision support systems counteract these?

Bias in clinical reasoning has been identified as one of the major sources of diagnostic errors (Croskerry et al., 2013a). Cognitive bias arises in fast, intuitive, heuristic-based decision-making, often necessary to make efficient decisions (Whelehan et al., 2020). There have been various studies investigating the effectiveness of different, mostly cognitive, strategies to counteract or mitigate bias (Mamede et al., 2010, 2020; Van Den Berge & Mamede, 2013). Several suggestions of using technological support systems were presented to make the decision process more objective and thus reduce negative effects such as cognitive bias (Ludolph & Schulz, 2018; Phillips-Wren, Jefferson, et al., 2019; Philp et al., 2021; Power et al., 2019; H. G. Schmidt & Mamede, 2022), especially in situations of high uncertainty or time constraints (Johnson-Mann et al., 2021). As pointed out by Antoniadi et al., (2021), however, there is still research needed to investigate this option of successfully counteracting biases by utilising new possibilities provided by technology. Some of these technologies include new opportunities presented by artificial intelligence and machine learning (Wang et al., 2019). Xiong et al. (2022) address the possibility of the machine assisting humans in adjusting for cognitive biases by supplementing missing knowledge through an explainable decision-making process, however, they emphasise that current studies mostly focus on the general assistance of decision-making and less on the specific possibilities of machines correcting for human and cognitive limitations. Phillips-Wren, Power, et al., (2019) further investigated the interplay of cognitive bias, risk attitude and decision support systems and call for more research focusing on the limitations of human decision makers, concentrating on cognitive bias and decision aids to generate useful insight for system development and usage.

A decision support system that suggests possible diagnoses and additionally provides information to mitigate cognitive bias could support physicians in finding the correct diagnosis. A study by Crowley et al. (2013) developed an automated, computer-based method of recognising cognitive heuristics and biases, showing that the detection of biases by technology can be possible. This was further investigated within a recent study detecting anchoring and recency bias through machine learning systems (Sinha et al., 2022).

With the detection of bias, decision support systems might be able to mitigate said bias by presenting appropriate information. Wang et al. (2019) presented a framework in which they qualitatively tested whether presenting specific information mitigating various biases could support physicians in making better informed decisions. In their study, physicians provided qualitative insights on what information they would be interested in to potentially make better informed decisions. Theoretical frameworks were suggested, but more research testing technology-based mitigating strategies in controlled settings is needed. Investigating different ways of improving diagnoses would be beneficial to identify the effectiveness of interventions and see which merit further developments and final implementation have (Ranji & Thomas, 2022). In an extensive literature review, Kliegr et al. (2021) demonstrated the role of cognitive bias in the interpretation of machine learning applications and call for more psychological studies investigating the potential of debiasing techniques presented by machine learning systems. Thus, in this study, we want to test potential debiasing information in purposefully biased situations in a quantitative manner to specifically see if the mitigation of bias would be fruitful when presented by a decision support system. Additionally, potential influencing factors shall be investigated.

Factors such as confidence in the decision and medical experience will be regarded, building upon research from Dreiseitl & Binder (2005) concluding that physicians were significantly more likely to follow the suggestions of a decision support system when they were less confident in their initial diagnosis. Additionally, physicians that were less experienced were more likely to accept the advice of the CDSS and change their diagnosis (Dreiseitl & Binder, 2005). We want to test these factors in regard to situations in which cognitive bias is specifically triggered and the support system is providing not only the conclusive diagnosis but additional information to mitigate bias.

Lastly, there are varying opinions on whether physicians should form a first uninfluenced opinion before receiving support from a CDSS. While Kostopoulou et al. (2015) say that reminding general practitioners early of possible diagnoses leads to higher accuracy, physicians in the study of Wang et al. (2019) mentioned that they rather receive decision support by a system after first checking the case themselves. Thus, the difference in the decision between immediately receiving decision support and receiving it after forming a first uninfluenced opinion in situations specifically influenced by cognitive bias will be tested in this study. While physicians have been asked for their preference, to our knowledge there is no quantitative evidence comparing both options directly.

The corresponding research question of this study is: What information is needed to mitigate cognitive bias through decision support systems and to what extend is this influenced by medical experience, confidence and the time of support?

In summary, the detailed goals of this study are: 1) to test debiasing methods and to find out whether they can succeed in mitigating biases, 2) to investigate influencing factors like confidence and experience on the probability to adjust the decision after receiving decision aid and 3) to investigate whether forming a first opinion beforehand or immediately receiving decision support makes a difference.

By investigating this, we contribute to research concerning CDSS and their potential merit in mitigating bias. Insights acquired through this study can be relevant for future decision support system studies and potentially be used in the development of support systems.

The paper is structured in the following way. First, we provide a general overview of the different concepts relevant to this study and present the corresponding research background from which we derive our hypotheses. After explaining our methodology, we present our results. Finally, these results are discussed and the theoretical and practical implications of the study for future research and system development are mentioned.

2. Research background

2.1 Clinical decision support systems

CDSS are information systems developed to help clinicians make better clinical decisions (Garg et al., 2005). They assist with the retrieval of relevant information and communicate information that is important in the particular context. The systems do not make their own decisions but support the physician in the form of knowledge and analyses, often providing additional information at the point of care so that the physician can combine their own knowledge with it. The software is designed to aid decision-making by matching individual patient characteristics with computerised clinical knowledge based on assessments and recommendations specific to this patient (Sim et al., 2001). By now there is a multitude of machine learning and artificial intelligence systems integrated into support systems (Antoniadi et al., 2021).

The range of ways CDSS can support physicians is vast: including but not limited to support in form of alarm systems, disease management, prescription, drug control, and diagnostics (Sutton et al., 2020). One possible clinical support system is a differential diagnosis decision support system that assists physicians in the diagnostic process by generating differential diagnoses from information previously fed into the system (McParland et al., 2019; Müller et al., 2019). Entering clinical findings, patient history and demographic data offers a list of potential diagnoses. By providing a second diagnostic opinion, the system offers the opportunity to the physician to adjust a first diagnostic decision based on additional data (Jussupow et al., 2021). Shared decision-making assisted by a decision support system is suggested to be a useful tool in mitigating negative effects of bias and heuristics, without putting more strain on additional physicians as decision-makers (Thomas et al., 2021).

Using checklists for differential diagnoses has previously shown to increase accuracy of medical students (Kämmer et al., 2021; Shimizu et al., 2013), suggesting that an implementation as a decision support system could improve the process of diagnosis. Diagnostic decision support systems itself have high accuracy (Ramnarayan et al., 2007; Riches et al., 2016) and have shown to succeed in improving the accuracy of physicians and medical students (Martinez-Franco et al., 2018; Riches et al., 2016; Staal et al., 2022). The benefit of this heightened accuracy was also shown in a real-life setting, where the adoption of a system generating differential diagnosis lists for patients in the outpatient department resulted in less incidences of diagnostic errors and therefore higher patient safety (Kawamura et al., 2022). Decision support systems can thus be used to ensure the quality and safety of care even in crisis situations (Reuter-Oppermann et al., 2022). CDSS are expected to not only reinforce physicians' knowledge but also help reduce cognitive bias (Harada et al., 2021a).

2.2 Cognitive bias in medicine

When physicians make clinical decisions, for example, when finding the most probable diagnosis for a patient, they make use of two different systems of decision-making. This is based on the dual-process theory established by Kahneman (Kahneman, 2011). This theory differentiates between an intuitive and an analytical system of decision-making. The first and intuitive system is subconscious and operates faster, using less cognitive resources. In contrast, the second system, the analytical mode, is conscious, slow going and needs deliberate and more cognitive effort.

Humans mostly rely on the intuitive mode, since it offers fast solutions, which in the clinical context can even be lifesaving, such as in life-threatening situations with high uncertainty (Croskerry et al., 2013a). While cognitive bias can occur in both types of systems, the intuitive system is more prone to bias because it is based on heuristics, rules of thumb derived from prior experiences, to save resources and time.

Bias can negatively affect decision-making and lead to diagnostic errors. Thus, according to Croskerry (2009) optimal diagnostic decision-making would be a blend of both systems. Therein, the intuitive mode would provide fast decisions, but should bias arise, the second system needs to activate to counteract said bias.

There are more than a hundred failed heuristics or cognitive biases in the medical context, as thoroughly listed by Croskerry (2002). In this study, we will focus on two of the most commonly described biases, availability bias and representativeness bias (Erel et al., 2021; Lucchiari & Pravettoni, 2012), building on previous research.

Availability bias is 'the tendency for things to be judged more frequently if they come readily to mind' (Croskerry, 2002). This includes emotionally salient, traumatic, more recent (Richie & Josephson, 2018), unusual or adverse events that are more memorable (Wang et al., 2019), and therefore come easily to mind and thus are leading to availability bias (Erel et al., 2021). Croskerry (2002) offers the following clinical example: 'Thus, if an emergency physician saw a patient with headache that proved to be a sub-arachnoid haemorrhage (SAH), there will be a greater tendency to bring SAH to mind when the next headache come along'.

The suggested mitigation strategy is gathering of objective information and making an estimation on the true base rate of a diagnosis. According to Wang et al., (2019) support systems might achieve this by showing prior probability of a diagnosis to help seek the base rate. Physicians argue that they would like to see prevalence data, to help them rule out unfit diagnosis (Wang et al., 2019). Therefore, we want to investigate whether presenting several differential diagnoses with additional information about their base rate probability can help mitigate a previously triggered availability bias, to see if the integration of such information in a support system would be helpful in supporting less biased decision-making.

H1: Debiasing measures in form of prevalence data presented by a decision support system will lower the impact of availability bias on the diagnostic decisions made by users.

Representativeness heuristics and the subsequent bias entails judging the likelihood of an event belonging to a particular class due to similarities and thereby disregarding whether it belongs to a similar but different class of diagnoses (Wang et al., 2019). One example presented by Richie and Josephson (Richie & Josephson, 2018) for representativeness bias is that 'a physician may overestimate the likelihood of Kawasaki disease in an Asian child with fever, rash, and conjunctival injection in whom virus would actually be more common'.

Wang et al., (2019) suggest mitigating this by comparing the disease with prototypes of possible diagnoses and identifying similarity distances as well as contrasting differences. The presentation of prototypical data of possible diagnoses will be tested in this study in a situation in which representativeness bias is previously elicited, to see if the presentation of this information is enough to possibly trigger reflective reasoning and thus counteract said bias (Mamede et al., 2021).

H2: Debiasing measures in form of prototypical information presented by a decision support system will lower the impact of representativeness bias on the diagnostic decisions made by users.

2.3 Additional influencing factors

Confidence. Dreiseitl and Binder (Dreiseitl & Binder, 2005) showed that physicians are more willing to accept the recommendation of a support system when they are less confident in their diagnosis. Consequently, the question arises whether higher confidence in the initial diagnosis leads to physicians being less likely to adapt their diagnosis when receiving support from a decision support system. Should this be the case, additional actions need to be taken and integrated in support systems to assure the aid is considered and accepted by the user, even when their confidence is high. On the other hand, users that have low confidence in their own diagnosis might also be more likely to fall for incorrect decision support system advice (Jussupow et al., 2021). Therefore, in this study, we want to investigate whether confidence in the decision has a significant influence on the probability to change the decision when different biases are involved in the decision-making situation.

H3: High confidence has a negative influence on the probability to change the diagnosis when receiving support from a decision support system.

Medical experience. Medical experience has been shown to be an important factor influencing the adoption of CDSS and their decision aid. Khairat et al. (2018) mention clinical experience as one of several influencing factors for effective adoption of decision support. This is also in line with research by Phillips-Wren, Jefferson, et al., (2019) showing that nurses did not use the CDSS, because they believed to be competent and trained to decide without the aid of technology. This resulted in them relying more on their own judgement than the suggestions of the CDSS. This was also the case for the adoption of a CDSS for antibiotic management in the study by Laka et al. (2021), where more experienced physicians did not want to use the system for fear of compromising their own work. In general, higher clinical experience has been shown to influence collaborative performance, possibly due to overconfidence, or believing the system to be less accurate than an experienced physician (Knop et al., 2022). A small but significant negative correlation between higher experience of the physicians and the likelihood of changing the diagnosis was found (Dreiseitl & Binder, 2005). Especially, less experienced physicians have been shown to benefit more from the support of CDSS in comparison to more experienced physicians (Chang et al., 1999; Friedman et al., 1999). This might also be due to more experienced physicians being more likely to disregard decision support advice, even if it is correct (Jussupow et al., 2021) and inexperienced physicians, on the other hand, being more likely to accept incorrect system advice (Harada et al., 2021b). How does medical experience influence the decision when receiving additional information from a CDSS targeted at providing information to specifically mitigate bias? Erel et al. (2021) specifically mention the need for additional studies investigating differences concerning medical experience and cognitive bias. In our study, we did not test subjective experience, but experience based on years either spend in medical study or employed as physicians and its influence on the willingness to adapt one's decision.

H4: A high level of experience has a negative influence on the probability to change the diagnosis when receiving support from a decision support system.

Time of support. Additionally, Wang et al. (Wang et al., 2019) mentioned that physicians explained that they preferred to form a first uninfluenced opinion before receiving support from a decision support system. However, they conclude in their study that showing feature values before class attribution can help avoid biases like confirmation bias that triggers backward reasoning and therein disregarding of alternative hypotheses (Wang et al., 2019). Kostopoulou et al. (2015) agree that reminding general practitioners early of possible diagnoses leads to higher accuracy. Jussupow et al. (2021) mention that early AI advice might influence the early decision-making process of physicians. Hence, we want to investigate whether there is a difference between the group immediately receiving decision aid and the group giving a first uninfluenced estimation. Therefore, we posit the following research question:

Table 1. Factor definition and operationalisation.

Factor	Definition	Operationalization	References
Availability Bias	[. . .] the tendency for things to be judged more frequently if they come readily to mind	Clinical vignettes by Richie & Josephson (Richie & Josephson, 2018)	(Croskerry, 2002; Richie & Josephson, 2018)
Representativeness Bias	[. . .] judging the likelihood of an event belonging to a particular class due to similarities and thereby disregarding whether it belongs to a similar but different class of diagnoses	Clinical vignettes by Richie & Josephson (Richie & Josephson, 2018)	(Richie & Josephson, 2018; Wang et al., 2019)
Medical Experience	Years spend in medical training or practice	For medical practitioner: "How many years of professional medical experience do you have?" For medical student: "What is your current year of medical study?"	(Laka et al., 2021; Phillips-Wren, Jefferson, et al., 2019)
Confidence	Confidence in the given estimates	"How confident are you in your decision?" [7 point Likert-scale from "very unconfident" to "very confident"]	(Dreiseitl & Binder, 2005; Jussupow et al., 2021)
Time of Support	Decision support before forming a first opinion and after forming a first opinion	Comparison of estimates and confidence before and after receiving decision support	(Kostopoulou et al., 2015; Wang et al., 2019)

RQ1: Does forming a first opinion beforehand or immediately receiving decision support make a difference for the final decision?

All relevant factors are summarised in Table 1, which additionally provides information about operationalisation and relevant references. Constraints of space and context are restricted to a western environment, specifically physicians and medical students.

3. Method

This study employed a three-group between-subjects design with additional insights provided through a within-subjects design of the third group. An online survey hosted on the platform SoSci Survey was administered from January 2022 to April 2022 to German-speaking medical personnel and students. Medical students received 5 euros as compensation for their participation. Recruitment efforts were assisted by physicians of the university hospital in Essen, Germany. This study was previously approved by the ethics committee of the University of Duisburg-Essen.

In total, 116 participants were recruited. On average, participants needed 7 min and 18 s (437.85 s) to finish the questionnaire. Therefore, upon viewing the complete dataset participants that finished the survey in a too fast or too slow time frame based on the relative speed index (Leiner, 2019) provided by SoSci Survey or had faulty or missing data were excluded. The relative speed index measures how much faster than the typical participants, the median of time taken, the participants finished the survey. The time taken across conditions varied between an average of 383.03 s for the control group, 435.83 for group 2 and 501.28 for group 3. The final sample consisted of 103 participants.

The survey consisted of the collection of demographic data and an experimental setup.

Demographic data included age, gender, whether they are physicians or medical students and their medical experience in years for medical personnel or years of study for students. The average age of the full dataset was 28.63 years, 31 out of 103 participants were male. Participants that indicated being a student were asked for their current year of study. The minimum medical school period for students was 1 year, and the maximum was 7 years with an average of 4.57 years. Participants that answered to be a physician were asked for their years of professional medical experience. The sample of 28 physicians ranged below 1 year to 35 years of experience, with an average of 9.86 years. Table 2 lists detailed demographic data for the complete sample, additionally divided by occupation.

In the experimental-setting, participants were randomly assigned into three groups using the random number generator provided by SoSci Survey. Every group was presented with six different clinical scenarios and a corresponding decision-making task under the influence of availability or representativeness bias. The clinical scenarios, or

Table 2. Demographic data of the sample ($N = 103$).

	Total	Physician	Student
Gender	72 female (69.9 %)	20 female (71.4 %)	52 female (69.3 %)
Occupation		28 (27.2 %)	75 (72.8 %)
Age – average	28.63 (SD = 7.77)	36.93 (SD = 7.80)	25.53 (SD = 5.02)
Age – median	26 (range = 19–61)	34.50 (range = 27–61)	25 (range = 19–52)
Experience		9.86 (SD = 7.87)	4.57 (SD = 1.20)

'vignettes' in the following, were adapted from the study of Richie and Josephson (Richie & Josephson, 2018) and translated into German language. Each vignette consisted of a description of a clinical scenario in less than a hundred words, which used text manipulation to encourage the use of heuristics and therein triggering availability or representativeness bias for one of the possible differential diagnoses. In their study, Richie and Josephson (Richie & Josephson, 2018) demonstrated that phrasing the scenario in a way that the participant is asked to imagine themselves in a hypothetical scenario increases the chance of availability bias. For representativeness bias, redundant information presented in the clinical scenarios made the case seem more prototypical for the targeted diagnosis. Based on these prior empirical results, the text manipulation was deemed capable of making diagnosis seem more available and representative for the targeted diagnosis. After reading these manipulated vignettes, participants were asked to estimate the probabilities of three to four different possible diagnoses, including the above mentioned, potentially biased, diagnose option on a scale from 1 to 16. In this experiment, additional information was provided to some groups to potentially mitigate said bias.

Group one ($n = 32$) served as a control group and did not receive any additional information as a decision aid. They had to read the vignettes and underneath give an estimate on a 16-point scale from 'impossible' to 'definite' on how likely they thought the three to four different diagnoses were. Additionally, they were asked to rate their confidence on a 7-point Likert scale from 'very unconfident' to 'very confident'.

Group two ($n = 42$) also read the clinical vignettes and had to give estimates. However, they received additional information next to the three to four possible diagnoses. For vignettes eliciting the availability bias, information about the prevalence of the diagnoses was provided. For vignettes formulated to elicit representativeness bias, prototypical information about the symptoms of the presented diagnoses was shown. Group two was also asked to rate their confidence.

The third group ($n = 29$) received the unaided decision task from group one at first. They had to give their unaided estimates and indicate their confidence. Then, they were presented with the same vignettes again but received the decision aid that group two received previously. They were asked to indicate their probability estimates of the diagnoses again, now with the additional information, and give another assessment of their confidence. Thereby, we had two reference points, one before and one after receiving decision support, and were able to calculate the difference between the two estimates for probability and confidence and use it for further analysis.

At the end, every participant was thanked for their time and was debriefed about the goal of this study. The demographic questionnaire and the experimental introduction can be viewd in Appendix A. The complete data set and material used in this study can be found under the following OSF-link: https://osf.io/nyrtm/?view_only=8d6155573f404f168e7958a9e5948216.

4. Results

All analyses were conducted in IBM SPSS Statistics Version 28. Analyses of hypotheses 1 and 2 were conducted once as a t-test between groups 1 and 2 and additionally within group 3 as a paired t-test. The t-test between groups 1 and 2 indicates that decision support systems that provide information about the base rate probability can significantly help in mitigating the effects of availability bias (t(72) = 2.04, *p* = .022, d = .48). Comparing the mean estimates showed a change from 9.04 to 8.00 on a 16-point scale. This significant change was also the case for the result of the paired t-test within group 3 (t(28) = 6.29, *p* < .001, d = 1.17). The mean estimate dropped from 9.21 to 7.57 for the targeted options. Therefore, hypothesis 1 was confirmed.

For hypothesis 2, however, decision support systems providing prototypical information did not significantly affect representativeness bias between group 1 and 2 (t(72) = 0.10, *p* = .459, d = .02). This is also apparent through the mean value for probability estimation. It only changed from 9.67 to 9.61 on the 16-point scale. Results were similar within group 3 (t(28) = 0.89, *p* = .190, d = .17) with only a mean change from 10.31 to 10.10. Hypothesis 2 was not supported.

Hypotheses 3 and 4 were tested using linear regression analyses. Confidence in the decision did not significantly influence the probability to change the first estimate upon receiving additional information (F(1, 27) = 1.89, *p* = .181, R^2 = .07) in the complete sample of group 3 in regard to availability bias. Furthermore, confidence also did not significantly influence the change of the estimate concerning representativeness bias (F(1, 27) = .04, *p* = .835, R^2 = .00). Additionally, the confidence value itself did not change a lot from the first to the second estimate (*M* = 3.91 to *M* = 4.09 for availability bias and *M* = 4.33 to *M* = 4.49 for representativeness bias). Additional analyses were conducted to check for significance in the different subgroups, physicians and medical students, but no significant results were found. Therefore, hypothesis 3 was not supported.

Furthermore, linear regression analysis showed that experience (F(1, 27) = 2.23, *p* = .147, R^2 = .08) did not influence the probability to change the estimate concerning availability bias in the complete sample of group 3. The linear regression analysis concerning representativeness bias and the whole sample (F(1, 27) = .87, *p* = .359, R^2 = .03) also did not show significant results. Upon looking into the different subgroups, a significant negative influence of experience of physicians on availability bias was found (F(1, 8) = 6.73, *p* = .032, R^2 = .46). Furthermore, 45.7% of the variance whether physicians adjust their estimate concerning availability bias can be explained by experience. The analysis of the effect of experience in medical students on representativeness bias showed no significant influence. Therefore, hypothesis 4 can be accepted for physicians and availability bias. However, it was not supported for the whole sample and medical students concerning availability bias. Furthermore, hypothesis 4 was not supported for the whole sample and the subgroups of physicians and students concerning representativeness bias.

Finally, to investigate research question 1, a t-test comparing differences in probability estimate between the decision of group 2, when receiving immediate support, and the final decision of group 3, after making a first estimate and potentially changing this after receiving support, was conducted. The analysis showed no significant results for availability bias (t(69) = .77, *p* = .444, d = .19) nor for representativeness bias (t(69) = −.82, *p* = .416, d = −.20). Therefore, these results show no difference between receiving support immediately and after forming a first opinion and then receiving the decision support.

All results are summarised in Tables 3 and 4.

Table 3. Mean-values, standard deviation, *T*- and p-values of H1, H2 and RQ1.

	M	SD	T-value	p-value
H1				
within G3	1.632	1.398	6.286	.001
between G1 & G2	1.041	.510	2.041	.022
H2				
within G3	.207	1.252	.890	.190
between G1 & G2	.056	.537	.103	.459
RQ1				
Availability bias	.425	.525	.770	.444
Representativeness bias	−.492	.601	.819	.416

Table 4. F-values, p-values and R^2 of H3 and H4.

	F (1,27)	p-value	R^2
H3			
Availability bias	1.889	.181	.065
Representativeness bias	.044	.835	.002
H4			
Availability bias	2.226	.147	.076
Representativeness bias	.872	.359	.031

5. Discussion

This study investigated the effect of debiasing methods in mitigating cognitive bias when presented via additional information provided by a decision support system, in a situation in which the specific bias was previously triggered.

Previous studies presented general frameworks for counteracting biases, tested in qualitative settings without specifically triggering the bias (Wang et al., 2019). This study focused on two specific biases, availability bias and representativeness bias, to see whether the CDSS can influence the final decision. Additionally, the impact that factors like confidence in the decision and medical experience might have on the probability to change the decision when aided by a support system was tested. Finally, the question of the timing of receiving decision support was considered and whether forming a first opinion made a difference for the final decision.

Analysis for hypothesis 1 testing concerning availability bias showed significant results. By providing additional information consisting of base rate probability percentages, users adjusted their previously biased diagnoses. This is in line with the propositions of Wang et al. (2019), suggesting that support systems might be able to counteract availability bias by showing prior probability of a diagnosis and therein help the user to seek the base rate. This might be due to the base rate triggering reflective reasoning, an effective method against availability bias (Mamede et al., 2021). Deliberate reflection helps physicians to assess their original diagnosis and consider alternatives. This thoughtful contemplation has shown to improve physicians' performance during diagnostic tasks (Mamede & Schmidt, 2022). This possible explanation is supported by group 2 taking longer than group 1 to work on the decision tasks, implying that the additional information might have triggered a more reflective approach. These findings offer an explanation to the various analyses suggesting the usage of decision support systems to make decisions less influenced by cognitive bias

(Antoniadi et al., 2021; Phillips-Wren, Jefferson, et al., 2019; Phillips-Wren, Power, et al., 2019; Power et al., 2019), showing that base rate data can successfully mitigate availability bias.

Hypothesis 2 was not supported. The change in the estimate influenced by representativeness bias was not significantly influenced by the presentation of prototypical data. The study of Wang et al. (2019) suggested that the possibility to compare prototypical information about conditions helps to possibly identify similarity distances and therein counteract bias. This could not be confirmed in this study, possibly due to participants not taking the time identifying similarity distances as well as contrasting differences, which would have presented an additional cognitive effort. According to Kahneman (1982) when reflective reasoning cannot be triggered or even though it is triggered, these processes can still fail to identify errors from the nonanalytic process, resulting in errors still being present. A CDSS that does not only show prototypical information but already presents this information in a way highlighting similarities and differences to demand less cognitive effort from the user might prove to be more successful in mitigating representativeness bias (Wang et al., 2019). Working through prototypical information demands more cognitive effort than considering prevalence data for availability bias mitigation, merely due to the higher amount of information being presented, which might be the reason for no significant results for hypothesis 2.

Furthermore, hypothesis 3 was also not confirmed, showing no significant influence of confidence on whether or how much the estimate was changed. This is contrary to research from Dreiseitl and Binder (2005), which proposed that higher confidence in the initial diagnosis would make it less likely that physicians adapt their diagnosis. Even though the used medical scenarios were previously overseen by physicians to be of different levels of difficulty, this was not investigated further in this study. The clinical vignettes might not be of significant difficulty to trigger a lack of confidence that would be remedied by the aid of a decision support system. Therefore, investigations considering confidence before and after decision support should be controlled for difficulty to get a clearer picture of its influence.

For hypothesis 4, the different subgroups are important. For the overall sample, there was no significant effect on whether experience has an influence on the probability to change the estimate after receiving decision aid. Overall, this does not align with research by Dreiseitl and Binder (2005) who showed experience correlating negatively with the likelihood of changing one's diagnosis. However, specifically a high level of experience of physicians had a negative influence on the degree the diagnosis was adjusted after receiving decision support – but only for availability bias and not representativeness bias. Availability bias is based on prior knowledge of cases that are still present in the mind. It has been shown that availability bias occurs more often in experienced physicians than in less experienced physicians (Garb, 1996; Mamede et al., 2010, 2021), possibly due to a higher amount of available knowledge to use as a basis for judgement. Thus, they especially require raised awareness for cognitive biases such as availability bias and potential mitigation strategies. Experienced physicians have more difficulty to adjust their initial hypothesis when presented with disconfirming information (Eva & Cunnington, 2006). Phillips-Wren et al. (2019) showed that nurses did not use clinical decision support because they trusted their own competence above the technology. This study showed a similar result for physicians receiving aid when availability bias is present.

Finally, our research question concerning whether time of support is important showed evidence that there is no significant difference. This question was proposed because research by Wang et al. (2019) showed that physicians preferred forming a first uninfluenced opinion before receiving any additional support. However, by not using possible support from the start, valuable time might be lost. Furthermore, Kostopoulou et al. (2015) showed that early reminders about possible diagnoses led to higher accuracy in diagnoses overall. The results of this study show that there is no significant difference between estimates prior to and after receiving decision support, this contradicts previous research by Jussupow et al. (2021) saying artificial intelligence might influence the early decision-making process. It instead indicates that it might be beneficial to immediately offer decision support presenting possible diagnoses and supporting data to save time and support physicians in quick and more accurate decisions which are of high value in such a fast-paced environment. Staal et al. (2021) further mention that fast diagnostic reasoning does not necessarily lead to more diagnostic errors. They call for more analyses concerning cognitive bias. Our study suggests that time does not make a significant difference.

5.1 Theoretical contributions and practical implications

This investigation contributes to research concerning decision-making in the clinical environment and, more importantly, how CDSS can support physicians in a more objective decision-making process with reduced negative effects such as cognitive bias. It was shown that prevalence data presented next to differential diagnosis suggestions can mitigate the effects of availability bias, when presented by a decision support system. Prototypical information alone was not sufficient for the mitigation of representativeness bias, thus additional investigations are needed. Confidence in the decision did not have a significant influence. The time of the support did not show a significant difference.

By proving the possibility of CDSS mitigating the negative effects of cognitive bias an alternative mitigation strategy is presented, next to cognitive approaches discussed in other research papers (Croskerry et al., 2013b; Mamede et al., 2010, 2020). Mitigation through technology might be especially helpful in time critical situations with high uncertainty. Exceeding previous insights, our data suggests that there is no significant difference in the diagnostic decision depending on time of support. Therefore, this new-found information can be used to argument for the immediate support of physicians by decision systems. Thereby, vital time can potentially be saved while mitigating the negative effects of cognitive biases.

This paper presents an experimental study that controlled for specific biases to test the effect of previously suggested strategies. This fills the need for more research concerning different ways of improving diagnoses to identify effective interventions that merit further research, development, and final implementation. Thus, the knowledge can be used by developers of support systems for building better systems and learning about valuable information to offer additional differential diagnosis suggestions. With the integration of such information in CDSS, medical practitioners can be supported in more objective decision-making processes. This is especially important, given the influence cognitive bias has on diagnostic errors. A mitigation strategy that does not put more cognitive effort on physicians, but instead helps lighten the cognitive load by presenting critical information, can be a useful tool for reducing diagnostic errors. While this mitigation seems to work regardless of confidence in the decision, this study demonstrated, that the experience of the physician can have an influence on the probability to adopt the aid of the decision support system. This is an important factor to consider in future studies and development of support systems.

5.2 Limitations and future research

The first limitation of this study lies in the small sample size which was restricted to a German sample. This was due to recruitment being aided by physicians of the university hospital in Essen, Germany, and accordingly the questionnaire being translated and conducted in German language. Future studies should recruit internationally and beyond hospital physicians for additional insights. The sample consisted of physicians and medical students. O'Sullivan and Schofield (2019), as well as Surry et al. (2018) showed that medical students and experienced physicians are similarly affected by cognitive bias, therefore testing these two groups is suitable to investigate effects of CDSS in mitigating such bias. The meta-analysis by Ludolph & Schulz (2018) concerning debiasing strategies also showed no differences between student and nonstudent samples related to the effectiveness of bias mitigation strategies. However, some results, as for example the differences in the subgroups of hypothesis 4, showed that there are significant differences regarding the influence of experience between physicians and medical students.

Second, the experimental setting of this study was simulated through medical decision-making tasks that – even though they present realistic clinical scenarios – present limitations in transferring any findings into real-world situations. In real-life, many more factors are present and potentially influence the decisions made by physicians.

Future research needs to investigate more effective ways of presenting counteracting information for representativeness bias, since the prototypical information depicted as bullet points did not show significant results in mitigating the corresponding bias. Thus, the information required to mitigate representativeness bias needs to be researched further in content and presentation to be able to support users the way they need and use it to trigger reflective reasoning for a more informed decision, free of cognitive bias.

Our results suggest that the time of support does not make a significant difference. Further in-depth studies, not only looking at different timings but also the speed of diagnosis, are required, while taking the accuracy of the diagnosis and the influence of bias into consideration. Especially, the time taken for diagnosis should be investigated and controlled for the additional information potentially provided by decision support systems when trying to mitigate cognitive bias. Since physicians work in a high-stress environment, any additional time needed to interact with a decision support system instead of, for example, handling a patient might hinder the final adoption of such a support system (Phillips-Wren, Jefferson, et al., 2019).

Regarding confidence, an in-depth investigation of the role of overconfidence of users in following the suggestions of a support system and adjusting one's diagnosis, especially in conjunction with cognitive bias, may lend valuable insights into the decision-making process. Overconfidence in particular would be measured when system advice is rejected even though it is correct, potentially due to overly high confidence of the user. In contrast to overconfidence, an investigation of overreliance and automation bias should be conducted. Investigating why users reject system advice, even though it is correct, is detrimental to help find the correct balance of appropriate reliance and therein maximising the benefit gained from using decision support systems. Furthermore, to keep the questionnaire section short, experience was measured purely by asking for years of study or professional experience. A more distinctive measurement to account for different studying and professional experiences might offer insights on how cognitive bias and its mitigation connects to personal experience.

Besides medical experience and confidence, trust in the system might prove a valuable influencing factor worth investigating further. This factor grows especially important when considering the integration of artificial intelligence in many CDSS (Harada et al., 2021b; Johnson-Mann et al., 2021; Jussupow et al., 2021; P. Schmidt et al., 2020). Trust in CDSS is further interlinked with the perception and acceptance of the support system.

5.3 Concluding note

In this study, we asked what information is needed to mitigate cognitive bias through decision support systems and to what extend this is influenced by medical experience, confidence, and the time of support. It was shown that a decision support system presenting base rate probability to mitigate availability bias can be helpful and the bias mitigation happens independent of the timing of the support and the medical experience of the users. However, prototypical data to counteract representativeness bias showed no significant change. Neither medical experience nor confidence in the decision had a significant influence on the probability to change the estimate. Timing of support after or before forming a first uninfluenced opinion made no significant difference for the final decision.

By considering these insights in clinical decision support system development, physicians can be further supported in making less error-prone decisions while potentially lightening their cognitive load through technology support.

Acknowledgments

This work was supported by a PhD grant from the DFG Research Training Group 2535 Knowledge- and data-based personalization of medicine at the point of care (WisPerMed), University of Duisburg-Essen, Germany.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

The work was supported by the German Research Foundation (DFG) [RTG 2535 WisPerMed].

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Data availability statement

The data of this study can be accessed via the following OSF-Link: https://osf.io/nyrtm/?view_only=8d6155573f404f168e7958a9e5948216.

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Appendix

Appendix A. Questionnaire and experimental introduction

(1) Demographic data:

1. Wie alt sind Sie? [ ] Jahre

(How old are you? [ ] years old)

2. Mit welcher Geschlechtsidentität identifizieren Sie sich? Männlich, weiblich, diverse, andere: [ ]

(What gender do you identify as? Male, female, diverse, others: [ ])

3. Sind Sie Student*in oder Ärzt*in?

(Are you a student or a physician?)

4. Falls Sie Ärzt*in sind (sonst leer lassen): Wie viele Jahre an medizinischer Berufserfahrung haben Sie? [ ] Jahre

(In case you are a physician (otherwise leave empty): How many years of medical professional experience do you have? [ ] years)

5. Falls Sie Student*in sind (sonst leer lassen): In welchem Studienjahr befinden Sie sich? Jahr [ ]

(In case you are a student (otherwise leave empty): In what year of study are you currently? Year [ ])

(2) Introduction experiment:

"Im Folgenden werden Ihnen verschiedene klinische Szenarien beschrieben. Daraufhin werden Sie gebeten, eine prozentuale Wahrscheinlichkeits-Einschätzung zu drei bis vier verschiedenen Diagnoseoptionen abzugeben. Es sind unterschiedliche Differentialdiagnosen möglich. Wir sind am Entscheidungsprozess interessiert und nicht an der von Ihnen gestellten Diagnose.

Sie durchlaufen zwei Beurteilungs-Zyklen. Zuerst werden Ihnen nur die möglichen Diagnosen präsentiert und Sie sollen Ihr erste Einschätzung abgeben. Dann wird Ihnen in einem zweiten Durchlauf zusätzliche Information wie Prävalenz -Raten und prototypischen Symptomatik der Diagnosen präsentiert. Danach können Sie ihre Wahrscheinlichkeits-Einschätzung anpassen."

English Translation: "In the following experiment various clinical scenarios will be described to you. You will be asked to give a probability estimate of three to four different differential diagnoses. Various differential diagnoses are possible. We are interested in the decision-making process and are not judging the correctness of your diagnosis.

You will face two decision cycles. First you will be shown possible diagnoses and you are asked to make a first estimate. Then you will have a second run with additional information such as prevalence data and prototypical symptoms of the diagnoses. Then you can adjust your estimate if necessary."

Followed by six clinical vignettes targeting availability and representativeness bias by Richie & Josephson [47]

After every vignette: Wie sicher sind Sie sich mit Ihrer Einschätzung? (How confident are you in your decision?)