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Hidden biases in clinical decision-making: potential solutions, challenges, and perspectives

Matteo Vitacca[1], Anna Giardini[2], Lidia Gazzi[1], Michele Vitacca[3]

[1]Psychology Service, ICS Maugeri IRCCS, Institute of Lumezzane (BS); [2]Information Technology, ICS Maugeri IRCCS, Institute of Pavia; [3]Respiratory Rehabilitation Division, ICS Maugeri IRCCS, Institute of Lumezzane (BS), Italy

Abstract

Every day, we must make decisions that range from simple and risk-free to difficult and risky. Our cognitive sources' limitations, as well as the need for speed, can frequently impair the quality and accuracy of our reasoning processes. Indeed, cognitive shortcuts lead us to solutions that are sufficiently satisfying to allow us to make quick decisions. Unfortunately, heuristics frequently misguide us, and we fall victim to biases and systematic distortions of our perceptions and judgments. Because suboptimal diagnostic reasoning processes can have dramatic consequences, the clinical setting is an ideal setting for developing targeted interventions to reduce the rates and magnitude of biases. There are several approaches to bias mitigation, some of which may be impractical. Furthermore, advances in information technology have given us powerful tools for addressing and preventing errors in health care. Recognizing and accepting the role of biases is only the first and unavoidable step toward any effective intervention proposal. As a result, our narrative review aims to present some insights on this contentious topic based on both medical and psychological literature.

Correspondence: Matteo Vitacca, Psychology Service, ICS Maugeri IRCCS, Via G. Mazzini 129, 26065 Lumezzane (BS), Italy.
E-mail: matteovitacca@gmail.com

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Introduction

Every day, we must make numerous decisions. Sometimes our choices and preferences are unremarkable, such as when deciding what to eat for lunch. Sometimes the stakes are higher, and our decisions can have far-reaching consequences. Time and energy are frequently in short supply, and financial constraints are also significant. Furthermore, we must evaluate massive amounts of data in order to make accurate estimates and, as a result, wise decisions. Adaptive information search necessitates the ability to represent the instrumental value of information while focusing on relevant details [1]. Our brain has evolved to maximize process efficiency and achieve a favourable trade-off between cognitive effort and precision [2,3].

As a result, one might wonder where the issue is. Overall, acknowledging that evolution shaped our brains as highly efficient computational organs appears reassuring. When dealing with simple daily issues, it is more convenient to produce quick and adequately satisfying responses, even if they are suboptimal [4]. In contrast, when faced with ambiguous and important challenges, such as making a diagnosis based on a few enigmatic symptoms, precision and intensive information seeking become primary goals.

Furthermore, we have a tendency to take cognitive shortcuts, ignoring details and information that can contradict our assumptions [5]. Besides, the tendency to focus only on prominent and confirmatory cues has been observed across the entire range of mental functioning: from perception and attention to memory, reasoning, and decision-making. To predict the future and minimize changes, we construct a probabilistic picture of the world based on our past experiences [6].

Surprisingly, decision-making appears to be related to, but not entirely dependent on, the overall functioning of executive functions (EFs). EFs are a broad term that refers to a variety of cognitive and behavioural processes. They can be defined as the set of abilities that allow us to successfully implement independent, intentional, and useful behaviours [7]. Among the others, "updating" (the ability to maintain, process, and update information during a task), "shifting" (the ability to rapidly adapt to changing task demands), and "inhibition" (the ability to override automatic and inappropriate responses that may interfere with the completion of a task) are the most comprehensive.

Neuropsychological lesion studies, moreover, led to the identification of two different types of EFs:

The "cool" EFs, required when dealing with abstract and decontextualized tasks and supported at a neurophysiological level by the activation of the DorsoLateral PreFrontal Cortex (DLPFC).

The "hot" EFs, employed in the making of emotionally relevant decisions and powered by the ventromedial PreFrontal Cortex (vmPFC).

The anterior cingulate cortex, which shares many connections with the prefrontal cortex, is another critical area involved in the control of motivation and interfering stimuli [8]. A neuropsychological study comparing ventromedial patients, dorsolateral patients, and normal subjects discovered a significant correlation between the Iowa Gambling Task (IGT) score and other tasks assessing EFs such as flexibility, planning, and inhibition processes for control participants and DLPFC patients. The IGT is a financial-management task in which participants must choose a card from four different decks with varying gains and losses: it is commonly used as a neuropsychological test to assess the ability to make optimal long-run decisions by suppressing the selection of appealing but disadvantageous options. Damage to the vmPFC, on the other hand, has been shown in several studies to impair "reversal learning" (the ability to actively override reward-related responses) and the ability to direct attention to reward-predictive visual cues. Given these factors, the literature supports the hypothesis of EF multidimensionality and suggests that it could be implemented in multiple distributed neural circuits [9].

Based on the theoretical framework discussed above, the following narrative review aims to raise awareness among clinicians of the significant negative impact of biases on the diagnostic process and to present various deployable strategies to prevent cognitive errors and improve clinical decision-making.

Heuristics and biases

Tversky and Kahneman [10] studied and defined the aforementioned cognitive shortcuts as "heuristics" (from the ancient Greek "εὑρίσκω", which means "I find"). Remarkably, the latter was awarded the Nobel Prize in Economic Sciences in 2002 for the significance of his research. According to their studies, heuristics often lead to "biases", which is to say, "misperceptions of reality". Indeed, the term "bias" seems to have been first introduced around the 16th century in France with the meaning of "sloping line". Recently, the psychology literature has used this term to refer to the erroneous judgments and thoughts we routinely commit. Notably, these incorrect cognitive pathways provide us with an insufficient, flawed, and frequently self-serving representation of reality.

Up to date countless biases have been studied and classified [11]. Furthermore, a high degree of internal variability makes it difficult to define a clear and conclusive taxonomy. Figure 1 might be a good example of a sensible preliminary taxonomy, based on the well-established paradigms of dual-process theory [12-15]. Type 1 cognitive processes are autonomous, fast, effortless, stereotyped, and can operate in parallel whereas type 2 processes are slow, computationally expensive, and mostly serial. According to this diagram biases may arise when: i) we rely on type 1 processing and/or serial associative cognitive within a focal bias, without properly activating type 2 processing (*cognitive miserliness*); ii). we fail to sustainedly decouple different simulations of alternative worlds, which is to say that we try to take the type 1 processing offline, thus engaging type 2 processing, but we do not succeed (*override failure*); iii) we succeed in inhibiting type 1 processing, but we lack the mindware (rules, knowledge) to sustain type 2 processing (m*indware gap*); iv) our mindware is contaminated by problematic knowledge and strategies, evaluation-disabling properties, egocentric thinking, maladaptive culturally conditioned beliefs, or even misconceptions about how our minds work (lay psychological theory). All of these rational thinking errors fall under the category "*contaminated mindware"*.

The bias blind spot [16,17] is an example of cognitive error caused by both mindware gaps and contaminated mindware, and it could be considered the ancestor of all other biases. People perceive others to be more biased than themselves because they believe that conscious introspection will help them detect their own biases, whereas the majority of them operate unconsciously. Furthermore, failing to recognize the impact of biases on our judgments while being able to identify them in the judgments and behaviours of others makes us more susceptible to cognitive errors and shortcuts. Biases follow suit and remain strong when self-criticism is absent or too mild.

Even if we think of ourselves as rational and coherent, we all fall victim to biases in everyday life. Several studies [5,18-20] demonstrated that logical fallacies and cognitive errors affect everyone, regardless of expertise, age, gender, or occupation.

Even researchers who have dedicated their lives to studying biases will experience cognitive distortions. Should we simply accept this harsh reality, or should we commit to challenge biases? Both are neither realistic nor recommended [21].

Furthermore, as previously stated, heuristics allow us to save a significant amount of time and effort when dealing with everyday problems.

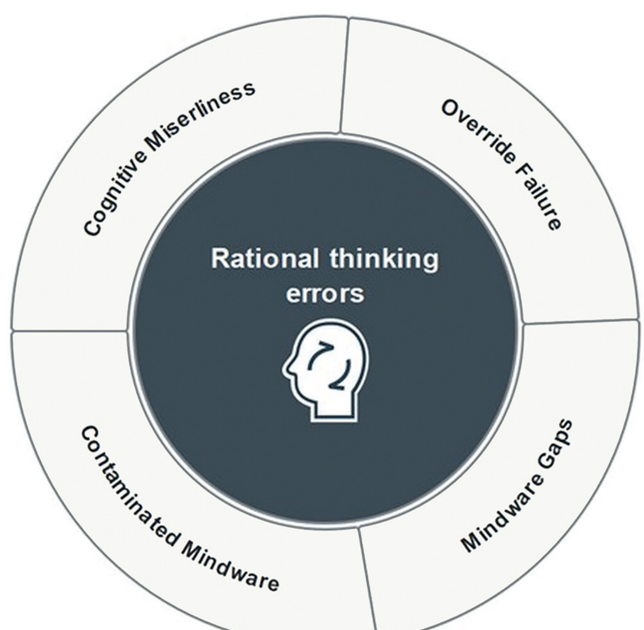

Figure 1. Potential classification of biases.

Biases and clinical decision-making in the medical field

Diagnostic errors in clinical decision-making are not uncommon, and they can have serious, even fatal, consequences [22-24]. Diagnostic error rates are indeed unacceptably high. According to Shimizu *et al*. [25], cognitive errors affect approximately 5% of outpatient medical care visits. Furthermore, diagnostic errors are known to increase the risk of death by nearly 10%. As a result, far from being a minor issue, diagnostic errors place a significant burden on patients and families, necessitating policymakers to implement immediate and concrete solutions. The following are the major factors that contribute to diagnostic errors: i) team factors (blind obedience, premature closure); ii) system factors (no interdisciplinarity, streamlined workflow, poor re-evaluation processes); iii) cognitive factors (time pressure, fatigue, stress, overload, poor clinical education, faulty synthesis, and biases); and iv) no-fault factors (misleading information by the patient, non-specific presentation).

Stress is undoubtedly one of the most significant cognitive factors impairing decision-making processes. Information overload, time constraints, complexity, and uncertainty are all significant decision stressors. There is evidence that stressed people make riskier decisions, do not consider alternative solutions to problems, make more cognitive errors, and rely on oversimplifying strategies. Indeed, coping with stress diverts valuable cognitive resources, lowering the overall quality of information processing and decision making [26]. Furthermore, decision-making competency (DMCy), defined as the proclivity to use metacognitive processes, differs between individuals. Decision environment management (DEM), defined as individual sensitivity to the work environment influencing decision making, also exhibits some variation. Nonetheless, both decisional competencies are related to decision-making performance and are moderated by relevant organizational characteristics such as job performance, job demands, and job resources. Notably, the literature suggests that job resources have a greater impact on the performance of people with higher DEM, implying that stressful work environments can lead to exhaustion and disengagement [27]. The significance of biases among various cognitive factors cannot be overstated, as they are thought to be responsible for approximately one-third of all diagnostic errors [22,24]. Furthermore, while high levels of expertise protect professionals from several biases, they do not protect them from other cognitive errors associated with overestimation of one's own ability and accumulated experience [21,30-31]. Diagnostic flaws, according to the World Health Organization, are a major issue that requires close attention and one of the most interesting/challenging opportunities to improve the overall quality of medical services [28].

The COVID-19 pandemic has created unprecedented and dramatic challenges around the world, forcing us to reconsider many aspects of traditional healthcare systems. The significance of developing modern health information systems (HIS) to collect, analyze, and share data became clear. Unfortunately, most countries continue to struggle to implement such HIS due to myopic governance, inadequate infrastructure and resources, and low community engagement, ignoring their critical role in optimizing decision-making and strengthening preparedness and response capacities. Finally, HIS provide incredible opportunities for reducing fragmentation and costs, fostering community engagement, and combating misinformation [29].

Debiasing methods: strategies to mitigate the impact of biases

Biases hide in every corner of the human decision-making process, and their pervasive presence can have a significant impact on the quality of our decisions. As a result, researchers and policymakers have been looking for an effective way to mitigate the negative impact of biases. Healthcare professionals, like the general population, are subject to biases [30-32]. As a result, designing intervention projects aimed at assisting clinicians and health professionals in properly assessing information and making optimal decisions should be of primary importance. Figure 2 depicts some

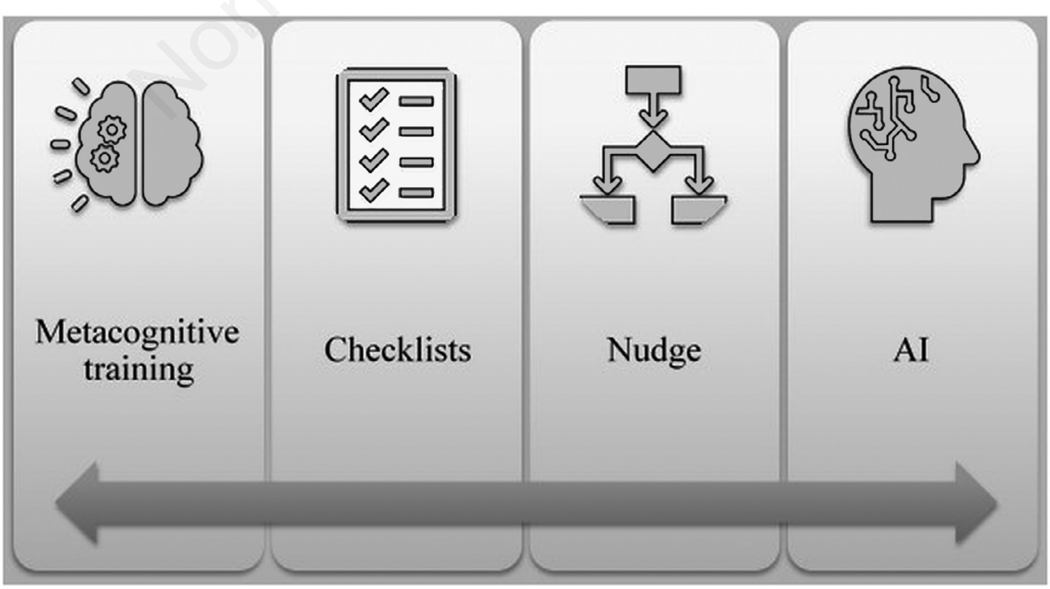

Figure 2. Debiasing methods.

approaches that are widely regarded as effective in reducing the rates and harmfulness of biases.

"*Metacognitive training*" is one of the oldest and most popular debiasing methods, with the goal of making people aware of biases by prompting them to analyse the development of their thoughts and reasoning processes. Indeed, the way we reason is not fixed; on the contrary, it can be improved through self-criticism. As a result, teaching health professionals about the nature and operational mechanisms of biases may aid them in recognizing flaws in the clinical reasoning process in themselves and others [22]. *Checklists* are likely the most easily deployable debiasing method in clinical settings [22,32,36]. They provide a set of medical procedures to be followed in order to obtain a reliable and well-founded diagnosis. Checklists, in particular, assist healthcare professionals in not overlooking relevant details (memory aid) and ensuring rigorous examination of all alternatives (debiasing aid). For example, "rules of thumb" are sets of questions that the clinician should ask themselves to ensure that their diagnostic reasoning is sound. A clinician, for example, may evaluate the validity of their own diagnosis by ruling out the worst-case scenarios, assuming that it is incorrect and thus looking for alternatives, assessing the amount of evidence available, and considering environmental and emotional factors that may influence the diagnosis [37]. Finally, illness scripts combined with self-explanation and structured reflection are an effective anti-"framing bias" tool.

The "*nudge techniques*" represent yet another remarkable path to debiasing. Nudge is a powerful and adaptable approach for inducing positive and long-term changes in decision-making processes. The choice architect creates the choice environment in order to encourage users (clinicians) to make better decisions for themselves and the community. Table 1 depicts an example of how nudge techniques can help health professionals make clinical decisions [38].

It is worth mentioning the model's adaptability. The various clinical tools proposed can be used in a variety of ways. One option is to use digital tools like "Clinical Decision Support Systems (DSSs)" [39]. Indeed, using machine learning's computational power to mitigate cognitive errors could be another option.

Data-driven *artificial intelligence (AI)* has proven to be an excellent tool for processing massive amounts of data and detecting statistical trends. Furthermore, differential diagnosis generators [40], for example, may improve diagnostic accuracy not only by correctly estimating the probabilities involved, but also by assisting the clinician with targeted notifications and questions during the diagnostic process [39].

Opportunities and challenges

Precision medicine is a medical framework that aims to tailor clinical decisions, treatments, and practices to specific patient subsets in order to provide them with optimal therapies based on their medical history and genetic asset. Molecular diagnostics, imaging techniques, and analytics are critical components of precision medicine. The road to precision medicine remains long, but intriguing scenarios have begun to emerge [41]. The arsenal of weapons available to mitigate the rates and harmfulness of biases is extensive and ready for us to use [36].

Metacognitive training appears to be an excellent tool for improving reasoning skills in students and recent graduates. The collaborative use of checklists, rules of thumb, illness scripts, reminder systems, and topic-specific info buttons may best assist clinicians during the diagnostic reasoning process and later in audit and reassessment. Furthermore, activities and intervention projects that raise awareness of the significance of biases and errors are critical to developing a collective culture of healthy self-criticism. To improve the overall quality of clinical decision-making, team meetings, good practices, dialogue, and peer-review between professionals should all be vigorously encouraged [21].

The hope is that diagnostic errors and biases will one day be recognized and accepted without stigma or shame. Furthermore, while all of the preceding action proposals are important, the incorporation of Artificial Intelligence into daily clinical practice appears to be an unavoidable step toward precision medicine [35]. Aside from supporting nudge techniques, AI computing systems can provide extremely accurate predictions and precisely distinguish between different clinical conditions thanks to machine learning techniques. As a result, as precision medicine strives for high levels of accuracy and tailoring of care practices, it will be necessary to automate data collection and analysis of massive amounts of data. Unfortunately, the lack of large, commonly structured datasets has hampered AI approaches in medicine. However, in the future, biomedical datasets will become more ready for analysis. Unlike medical doctors, AI algorithms are not affected or biased by time constraints. Nonetheless, despite the computational power of assistive technology, clinicians should have the final say over patient diagnosis, assessment, and treatment [42-43].

Humans, on the other hand, can see the big picture even when the data is incomplete and scarce, whereas machine learning techniques are extremely data-dependent [42]. Given the inherent differences between human and artificial intelligence, it would be prudent to use AI's strengths to supplement human intelligence's limitations, and *vice versa* [44].

Table 1. Decision-making model. The decision-making model provides for targeted interventions as different biases commonly occur at different points of the diagnostic reasoning process. Modifying the choice architecture should therefore lead clinicians to better judgments and choices. Retrieved from [18].

Workflow	Biases	Clinical tools
Patient presentation	Framing bias	Guided reflective reasoning
Patient history	Base rate bias	Collective intelligence
Identified leading symptom	Availability bias	Debiasing checklists and cognitive forcing strategies
Patient exams	Anchoring bias	Assessing knowledge and instructions at test
Diagnostic tests	Blind obedience and confirmation bias	Educational interventions and digital decision support systems (machine learning)
Diagnosis	Premature closure	Patient engagement

Limitations and risks

The scientific community's interest in biases and their threat to clinical decision-making appears to have grown in the last 20 years, and the rapidly emerging field of debiasing appears to offer exciting opportunities. Nonetheless, feasibility remains a significant issue [45], with numerous risks and limitations: i) *motivational factors*: clinicians require sound and sensible feedback on the benefits of deploying debiasing systems; ii) *a dysfunctional organizational culture;* iii) *poor design*: as Bond *et al.* [40] correctly point out, data-driven approaches frequently lack transparency and explainability; intervention projects should be designed to ensure that clinicians and AI interact as much as possible; the finished product should be aesthetically pleasing, user-friendly, and have significant symbolic value; iv) *lack of technological literacy*: the proper use of debiasing tools is far from obvious, and clinicians should be instructed accordingly; v) *inequalities*: such technological progress necessitates substantial financial investments [41]; social harmonization policies should avoid exacerbating inequalities so that all populations can benefit from debiasing tools; vi) *accountability issues*: as Bostrom [46] warned, AI progress is inextricably linked to ethical and legal concern; prevention policies should clearly define everyone's roles and responsibilities; vii) *doctor-patient relationship*: the words of Zygmunt Bauman [47] should never be underestimated: technological advancement tends to detach individuals from their actions, resulting in fragmentation of one's own accountability; consistent use of technological tools may foster an unsafe sense of alienation in the doctor-patient relationship; viii) *redundancy*: many hospitals have large databases that store medical records, visits, and so on; machine learning systems should work in tandem with these pre-existing datasets; ix) *cost-effectiveness*: costs and benefits of each debiasing method have yet to be properly assessed; more plans and prospects for economic and financial feasibility are required.

More randomized multicentre studies are also required before debiasing methods can be used more widely.

Conclusions

Every day, we must make a variety of decisions ranging from simple and risk-free to difficult and risky. Clinicians' ability to solve problems and make optimal decisions is hampered by cognitive and time constraints. The limitations of our cognitive sources, as well as the need for speed, can frequently degrade the quality and accuracy of our reasoning processes. Indeed, cognitive shortcuts lead us to solutions that are sufficiently satisfying to allow us to make quick decisions. Because suboptimal diagnostic reasoning processes can result in dramatic outcomes, the clinical setting is an especially suitable context for designing targeted interventions to reduce the rates and magnitude of biases. A variety of debiasing methods, including metacognitive training, checklists, nudging, and AI, may benefit medical decision-making. The potential to improve clinical decision-making and reduce cognitive biases is enormous [48].

Recognizing and accepting the role of biases is only the first and unavoidable step toward any effective intervention proposal. Only then will the diagnostician as a medical doctor be able to fully capitalize on its renewed awareness and welcome assistance from debiasing strategies.

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