Applying Insights from Behavioral Economics in Healthcare to Reduce Biased Doctor Recommendations

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Abstract

Behavioral economics has opened many doors in understanding the psychological aspect of decision-making in various fields of study. The focus of this paper is on the rapid expansion of healthcare in the United States and how it presents an increased importance in accurate results with behavioral applications. This paper explores how the availability bias, anchoring effect, and outcome bias affect physicians' decision-making ability when making recommendations to their patients. Previous experiments and observations will be discussed to demonstrate each heuristic's relevance and effect on the patient's health. The solution proposed is a virtual platform to mitigate three biases using a digital algorithm.

1 Introduction

Healthcare productivity in the United States of America has exponentially grown in the past decade from a luxury into a necessity for many Americans because of the drastic implications of COVID-19. The country spends a total of 4.1 trillion dollars annually on health care, equating to 12,530 dollars per person [Dep22]. The increased reliance on health care workers makes it crucial for their patient's diagnosis or advice to be as accurate as possible. However, cognitive biases, which are systematic errors in thinking that occur when processing or interpreting information, occur in physicians' decision-making due to lack of information, rushed thinking, invalid judgment, laziness, and overconfidence. The majority of physicians are unaware of the heuristics that unconsciously manipulate their ability to provide purely impartial advice to their patients. On the one hand, this issue is exceptionally important because more than 250,000 deaths occur as a result of medical errors that include but are not limited to

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missed or delayed diagnosis, medication errors, inadequate follow-ups, and failure to act on test results. On the other hand, some cognitive biases can lead physicians down the wrong path resulting in unnecessary tests, money, and time wasted on data that seemed to point to a (rather) misguided solution.

Behavioral economics is a relatively new field of study that combines psychology, judgment, and economics to generate more accurate interpretations of human behavior. Doctors are in charge of making many complex decisions in their everyday routines, and with every decision comes a probability of accuracy. When patients come in with different symptoms, doctors are tasked with determining the diagnosis, what procedures to recommend, and what medication to prescribe. These decisions require great attention to detail, and while each decision is tailored to produce positive results, behavioral economics have noted over the years how cognitive biases can negatively affect the decision-making process.

Past research results have found at least one cognitive bias that affects an individual physician's ability to make decisions. While over 85 percent of physicians insist that biases don't affect the care they provide, studies across the country have consistently disproved this idea [Sap16]. Cognitive biases are increasingly recognized as a strong candidate for the source of medical error. The concept in clinical practices is not entirely understood, but this increased awareness has resulted in a surge in psychological research in the field.

This paper will use behavioral insights to present recommendations to overcome three different biases in the medical industry. Section 3.1 addresses the availability bias that causes physicians to make judgements based on what comes to mind first under a time constraint. Section 3.2 focuses on how physicians anchor to often misguided information and Section 3.3 emphasizes how they fall short against the outcome bias that makes them disregard the process used to obtain an outcome.

2 Context

Throughout the paper, I will be referring to two different systems that Kahneman emphasizes in his book, Thinking Fast and Slow. To better understand how our brain performs decision-making, he divided our brain into System 1 and System 2. System 1, also known as the automatic system, operates automatically and quickly, with little or no effort or sense of voluntary control [Kah11]. Examples include reading words on a billboard or detecting that one object is more distant than another. System 2, also known as the effortful system, allocates attention to the effortful mental activities that demand it, including complex computations [Kah11]. It requires attention and is disrupted when attention is drawn away; examples include telling someone your phone number or doing mental math.

Looking at Figure 1 below, which line do you think is longer? While it may be tempting to say the line above, both lines are actually the same length. When we rely on System 1 to make a conclusion based on what we first see,

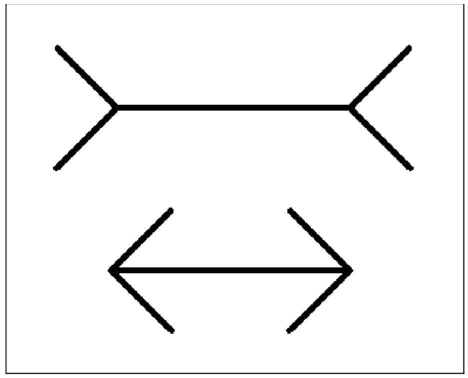

Figure 1: System 1 and System 2 Illusion

the line above appears longer, but when we activate our System 2 thinking, it overrides our initial assumptions because we take the time to compare the lengths in greater detail, allowing us to conclude that both lines are in fact, the same length [Kah11].

From a behavioral economics perspective, algorithms can be designed to counter the unconscious biases that may prevent patients from receiving the most accurate information. This paper will propose a platform and discuss its effectiveness in tackling three different cognitive biases.

One aspect of the algorithm will use insights from the availability bias. The primary objective is to reduce physicians' reliance on the information that comes to their head first by exposing them to other options they may not have come to mind. This can be enacted by presenting the top 3 recommendations based on a patient's symptoms. The recommendations will include potential diagnoses and medical examinations that are more representative than relying on memory.

The second aspect of the platform will address the anchoring effect. When physicians receive new knowledge about their patient, they are unconsciously anchored to the first piece of information they receive, preventing them from making efficient changes. The platform will have two sections that store a patient's past and current information so that the platform will analyze each detail equally without any anchors.

The third and last part will mitigate the outcome bias. Essentially, a confusion matrix can be utilized to compare the predicted versus actual value of each procedure to develop a probability of success not solely based on one outcome. Using a larger data set prevents doctors from only basing the efficiency of a procedure on its outcome.

Sections 3.1, 3.2, and 3.3 will explain each bias in detail and section 4 will conclude the developments advanced in this paper.

3 Heuristics and Biases

3.1 Availability Bias

Our human instinct is to partake in methods that require the least amount of cognitive effort. We try to find shortcuts to solutions that we may perceive as more efficient, when in reality, it may often have the opposite effect. In 1973, Tversky and Kahneman capitalized on this concept and introduced the availability bias: the tendency to judge the frequency of an event based on how many similar instances are brought to mind.

This heuristic was tested in 1993 by Russell Eisenman who examined how media coverage of drug use affected people's perceptions of its impact. 104 undergraduate students were asked, "Is the drug usage in the United States increasing or decreasing over the past several years?" News coverage at the time covered drug related substances much more frequently than our news today. Thus, 70 students said that drug usage was increasing while only 30 students reported that drug usage was decreasing (4 responses were omitted because they wrote "don't know") [Eis93]. However, the National Household Survey on Drug Abuse reported that drug usage, both legal and illegal, was actually decreasing. This is a vivid example of students falling victim to the availability bias because they relied on their memory of the topic to provide a response, and because more dramatic events tend to come to mind more easily, even if it may not coincide with frequency, their media exposure to the topic affected their ability to reach an accurate solution [Eis93].

This heuristic is heavily present in the medical industry where doctors are tasked with routinely giving their patients recommendations by relying on their memory. The availability bias occurs when physicians rely on System 1 to provide representative information based on the results of an examination or what the patient informs them. After examining the illusion in Figure 1, it's clear that depending on System 1 prevents people from providing meaningful, accurate advice. This is a critical issue because more than 250,000 deaths occur as a result of missed or delayed diagnosis, inadequate follow-ups, and failure to act on test results. In addition, the heuristic can lead physicians down the wrong path resulting in unnecessary tests, money, and time wasted on data that seemed to point to a solution that is actually misguided. By recalling only the information that comes to mind more easily, physicians avoid referencing databases that contain an immense amount of knowledge that could lead them towards an alternate diagnosis or recommendation. For example, a physician who has recently missed a diagnosis for a patient will become more aware of it in the future. Vivid yet rare cases come to mind more easily, like an emotionally charged experience of a patient dying [O'S18]. This process results in the physician's brain being 'primed' for the diagnosis, and this priming may lead the physician astray by diagnosing future patients who are at very low risk. While this may not seem unethical but rather a safety precaution, the unnecessary examinations and prescribed medications lead to excessive costs and wasted time [O'S18]]. Especially in the United States, where healthcare is very expensive, each additional examination can cost a patient up to 500 dollars; if the patient needs to stay overnight, an additional 2,150 dollars is added to the bill [Mic22].

In addition, more experienced physicians tend to rely on System 1 more than others because they are more confident in their ability to accurately diagnose patients. Physicians tend to make recommendations from memory almost 80 percent of the time; however, an individual with more experience may be more prone to the availability bias. A between subjects study conducted by Mamede, Gog, and Berge in 2009 aimed to understand how experience could diminish the availability bias in first-year versus second-year internal medicine residents. The procedure included 18 first-year and 18 second-year volunteers, and in phase 1, all 36 volunteers were tasked with evaluating 6 distinct clinical cases by rating how likely a certain diagnosis would be based on the medical information provided: the provided diagnosis was always correct [Mam10]. In phase 2, participants were asked to diagnose 8 new cases through non-analytical reasoning, except 4 cases had findings similar to cases from phase 1 with different diagnoses. The results revealed that second-year residents provided phase 1 diagnoses in phase 2 more frequently than first-year residents, highlighting the idea that second-year residents made more errors consistent with the availability bias. Thus, having more medical experience often unconsciously provokes a sense of overconfidence in physicians, causing them to depend on their biased initial perception [Mam10].

Researchers tackled this heuristic by conducting studies of a similar nature. Sullivan and Schofield conducted a between-subjects treatment where 57 medical students were given a 90 minute lecture that focused on understanding the availability bias and how to recognize and evidently overcome it. Compared to a control group that didn't participate in the lecture, however, the results proved disappointing as 40 of the 57 students failed to retain and implement the content; hence, there was no improvement in their decision making [O8]. While the concept of focused informative sessions may seem like an appealing solution, it yields a low success rate.

Fortunately, a more productive method exists. Our brain's instinct to rely on System 1 is heavily prone to bias, so the solution would be to trigger System 2. By proactively provoking more reflection and slowing down, the availability bias can be muted. Thus, I propose a medical search engine, hypothetically named DocYoda. It will serve as a browser extension that will be added to the physician's existing online platform. The extension will prompt physicians during patient interactions to enter anywhere from 3 to 15 symptoms their patient is experiencing—whereby entering more symptoms produces more accurate results. Within seconds, the website will list the top 3 potential diagnoses and medical examinations for the patient. This prompt and efficient platform provides physicians with insights they can reference instead of solely relying on their memory.

The rapid acceleration of artificial intelligence in healthcare systems encourages doctors to broaden their perspective based on machine learning algorithms. DocYoda is the beginning of an automated future that will stimulate recommendations less prone to bias.

3.2 Anchoring Effect

Humans tend to remember the first piece of information presented to them better than things learned later on [Mye22]. The first piece of information is referred to as the "anchor" that is unconsciously referenced when making subsequent judgements. In 1974, Tversky and Kahneman labeled this phenomenon as the anchoring effect, a cognitive bias that causes people to rely too heavily on the first piece of information they receive as a point of reference.

The heuristic often results in insufficient adjustments that can lead to drastic overestimates or underestimates depending on the reference point. Tversky and Kahneman (1974) conducted a between subjects treatment wherein two groups of high school students estimated a numerical expression within 5 seconds. The first group had to compute 8 x 7 x 6 x 5 x 4 x 3 x 2 x 1, while the second group was asked to compute 1 x 2 x 3 x 4 x 5 x 6 x 7 x 8. Both expressions are equivalent in product except the first one is presented in descending order while the second one is in ascending order. Since both expressions are analogous, one would expect the median estimate to be similar for both groups, but the median for the descending sequence was 2,250 while the median for the ascending sequence was 512; to put these numbers in perspective, the actual answer is 40,320. In both groups, students unconsciously used the first number they saw as an anchor and adjusted their answer accordingly since 5 seconds wasn't enough time to solve the expression [Tve74]. Since 8 is much larger than 1, students in group 1 guessed a much larger number based on the first number they saw and vice versa.

The anchoring effect in physicians' decisions making consists of prioritizing the first piece of information presented, causing them to perceive additional insights inaccurately because of their inability to adjust their anchor to what they first heard. The extensive casualties of the heuristic can be seen in a real world example presented by Edward Etchells where a 61 year old man was repeatedly diagnosed with the same disease even when his conditions grew worse with the provided treatment [Etc15]. The man, with a history of smoking, complained of a burning pain in his left foot. When an exam was performed, the primary care physician referred him to podiatry and attributed his numbness to peripheral neuropathy, which is the result of damage to the nerves located outside of the brain and spinal cord. The patient returned again six more times over the span of two months with worsening symptoms, but each time, no additional exams were performed as his complaints were repeatedly attributed to his prior diagnosis of peripheral neuropathy. Unfortunately, the patient's lower leg became severely dark in color, and when sent to the emergency room, he had developed multiple infections and required an above-the-knee amputation. The surgeons in care believed that his pain was due to progressive peripheral arterial disease and not peripheral neuropathy.

The physicians in care didn't consider alternate diagnoses even when additional information was presented because they underestimated the risk of failure.

This example of disjunctive anchoring occurs in risk assessment when people anchor to the initial low risk probability of failure even if the number of critical components increases. For example, when considering if you should take your car to the repair shop before a long road trip, only one of multiple scenarios has to occur for your car to break down: flat tire, dead battery, electrical issue, etc. Individuals tend to underestimate the probability of each car failure to occur independently, so when looking at the larger picture, they underestimate the true likelihood of the car failing at all [Med16]. Likewise, the physicians in the example above underestimated the severity of the case. They didn't adjust their anchor sufficiently to perform additional tests, causing them to prioritize data that supports their initial impression, even if it's incorrect. In this case, it led to an unnecessary amputation. Evidently, a physician's inability to interpret new information accurately can have dangerous implications on a patient's health.

To overcome the anchoring bias, a popular strategy is to actively seek information that contradicts an individual's opinion and give more thought to new information [Sar19]. The issue with this concept pertains to physicians' lack of time to analyze alternate options and reference relevant resources. A larger factor would be the lack of sleep many physicians endure, placing them at a higher risk of relying on their System 1 thinking. Many physicians work under tight time constraints and are under high pressure in an environment full of distractions [Sar19]. These difficult working conditions make it hard for physicians to employ System 2 analytical thinking. Thus, to ensure physicians aren't unnecessarily cognitively loaded, I propose the expansion of the hypothetical extension, DocYoda. The expansion will include a background section for physicians to create profiles for each patient to enter developing medical information, such as a recent heart attack or a history of smoking, that may skew the results. The background section will be split into two sections: historical data and modern data.

This historical section will include past medical examinations, diagnoses, or medications that the patient previously had but not anymore. This type of information will provide insights about past details for the algorithm to take into consideration. This aspect is crucial because physicians may inaccurately interpret historical data as less relevant based on their initial exposure to the patients' health concerns. Furthermore, the modern data section will include all of the patient's ongoing symptoms and medications that affect their health at a given point in time. As new information comes in, like an updated test result of diabetes or an increasing severity of throat pain, recommendations made by the platform will be able to evaluate all pertinent information equally, which prevents biased anchoring to the initial impression by physicians. It's critical that all information, both historical and modern, is interpreted with no bias to prevent misdiagnosis or lack of required action.

For the algorithm to efficiently decipher data from both sections, it will look for specific target words to correlate the data in the patient's profile to the information in a larger data set. The larger data set will serve as the document with detailed descriptions of each diagnosis and examination that the algorithm will constantly refer to. For example, suppose the modern section under patient X says "patient experiences a sore throat for the past 3 weeks, a high temperature, and red and swollen tonsils." In that case, the algorithm will look for target words— "sore throat", "temperature", "tonsils" —to accurately correlate the symptoms to a diagnosis. Similar to the Control F command on our computers, the algorithm will search for the key words in the larger data set, and based on which diagnosis contains the most words listed as symptoms, it will list it as 1 of 3 potential diagnoses. In this case, the symptoms have a stronger positive correlation to strep throat.

A potential drawback to this solution would be keeping a patient's outdated information instead of updating their profile when new information, such as a new test result, comes in. If a physician forgets to update the information, the recommended diagnoses and examinations won't be as accurate as it would be otherwise. This issue is something physicians have to proactively address by making it a priority for the health of their own patients. Nonetheless, DocYoda will serve to conquer both the availability bias and anchoring effect in an efficient, user-friendly platform accessible to healthcare workers across the globe.

3.3 Outcome Bias

We make decisions intuitively every day of our lives, from deciding when to get out of bed in the morning to if we should brush our teeth at night. Consequently, every decision we make has an outcome that falls into three distinct categories: positive, benign, or negative. We tend to focus on the outcome of our decisions rather than the decision-making process itself, and when we do this, we overlook the importance of the process [Out19]. For example, if an individual decides to drive while drunk and doesn't get into an accident, they may do it again because there wasn't a negative outcome to their poor decision. This occurrence is known as the outcome bias, which was first introduced by Baron and Hershey's publication in the Journal of Personality and Social Psychology. Outcome bias is an error made when people take the outcome of a decision into account that is irrelevant in evaluating the quality of a decision [Bar98].

A study was performed to explain physicians' ability to determine the quality of care if knowledge of the outcome was known. 587 emergency physicians completed a web-based survey that contained six different scenarios that had a mixture of good, no, or bad outcomes [Gup11]. They were asked to rate the quality of care on a 0(poor) to 100(outstanding) point scale based on the information presented. Results from the study displayed a pattern in which ratings were the highest when the outcome was positive and lowest when the outcome was negative. A clear take away was that the outcome of the scenarios directly affected the physicians' perspective of the quality of care. Even when the quality of care was poor, the scenarios were ranked higher if they had a positive result. An interesting find was that the outcome bias tended to inflate ratings when there was a positive outcome more compared to the penalization when there were negative outcomes [Gup11]. This can be explained by understanding how individuals tend to associate positive outcomes with quality decisions, yet when it comes to poor outcomes, individuals don't always view the process poorly because it could be associated with bad luck. While the conception of luck is often ambiguously used,it plays a role in interpreting bad outcomes.

One the one hand, the outcome bias can negatively affect patients' health or unnecessarily waste their money and time. For example, if a patient comes in with a headache and the physician decides to conduct an examination for rabies, an infection with 1 to 3 cases reported annually, it may initially seem unethical. However, if the results show that the patient does indeed have rabies, the physician will associate the positive outcome with a good decision, when in reality, it was just a "lucky call" story [Cla14]. Most doctors have their own "lucky call" story where they requested an additional examination that revealed a rare or unlikely disease. These lucky catches are the exception, not the norm, but doctors will be inclined to make it the norm by requesting the procedure more often in the future because of the one miracle result. This will, for the most part, lead to a waste of time, money, and resources for both the patient and the health care facility. In the example mentioned previously, the physician will now correlate the rabies test as a good decision, even though by just looking at the medical process itself, it is considered unethical. In the future, this could mislead physicians and cause them to view headaches as a sign of rabies instead of a much more common disease like migraines.

On the other hand, when a rational decision leads to a poor outcome, it is easy for physicians to be hard on themselves, and also on others. Jousting, when used as a medical term, occurs when a healthcare professional speaks poorly of another or implies that a decision made by another caregiver was unprofessional [Cla14]. When a negative outcome is publicly known, individuals tend to blame the physician in charge, downplaying any external factors that may have influenced the result. While this can affect a physician's individual confidence, it also decreases trust between doctors who rely on each other for business-like referrals or access to select data. In addition, if a select procedure has produced productive results 364 days in a row but one day it doesn't, changing the entire procedure because of one bad outcome isn't ethical since the procedure has a high efficiency rate and it would be a waste of resources to tackle an insignificant percentage [Fli18].

In Baron and Hershey's publication, they walked through a between-subjects treatment they performed to determine how prominent the outcome bias is in medical decision-making [Bar98]. The subjects were 20 undergraduate students from the University of Pennsylvania who were given a questionnaire with 15 different medical procedures. Each case included the patient's symptoms, the procedure that was conducted, and its outcome. They were asked to rank each decision on a seven point scale from -3 to 3, where -3 correlated to an inexcusable and bad decision and 3 correlated to a correct decision. Case 1 and 2 had the same procedure but in Case 1 the physician's decision to perform a bypass operation was successful and in Case 2 it wasn't. Case 3 and 4 paralleled Case 1 and 2 except that the patient made the decision instead. Cases 5 through 8 were the same as 1 through 4 except it was for a liver ailment rather than a heart ailment. Cases 9 through 11 involved a subscribed test with poor accuracy and outcomes while cases 12 through 15 dealt with deciding which of two diseases to treat given that both were equally likely. Ten of the students evaluated cases in one order(2, 5, 13, 10, 3, 8, 15, 9, 1, 6, 12, 11, 4, 7, 14) and the other ten did it in reverse.

The study's results matched their predictions: cases in which the outcome was a success were ranked higher than cases that failed, even if the procedures were the same [Bar98]. The subjects may have held the physicians more responsible for the bad outcome than the patients because they may have had information the patients didn't; however, those cases still coincided with the outcome bias. Furthermore, the last 8 subjects of the experiment were asked if they should consider the outcome in evaluating the decision. All but one said they shouldn't, but the results of the study highlighted that they did. The outcome bias affected their decision-making skills even when most of them accepted the irrelevance of the result.

While the results may portray outcomes as completely unrelated to the decision, the experiment wasn't performed to argue that outcomes should not be considered when evaluating a medical procedure, but rather whether there are conditions in which it's overused. For example, if employee 1 produces productive results and requests a promotion, the manager should look at the employee's tangible results in evaluating their expertise. However, if employee 2 is also asking for a promotion and has done identical work to employee 1 except with unsuccessful results, the manager should not immediately promote employee 1. The manager should evaluate that employee's work ethic to understand why the same procedure diverged into two different outcomes. Potential reasons include stress, lack of resources, personal engagements, etc. In other words, although the relationship between decisions and outcomes might seem intuitive, the outcome of a decision should not be the sole determinant of its quality [Doh20].

To mitigate the possibility of the outcome bias influencing physician's evaluation process, the DocYoda platform will create a confusion matrix to determine the probability of success of each procedure based on past results. A confusion matrix is a table that visualizes the performance of a classified algorithm in a 2 X 2 table shown below.

	Actual Value: (+)	**Actual Value: (-)**
Predicted Value: (+)	TP	TN
Predicted Value: (-)	FP	FN

Figure 2: TP: True Positive, FP: False Positive, TN: True Negative, FN: False Negative

The predicted value is what the doctor initially diagnosed the patient with along with the medical procedures performed and the actual value is what the actual diagnosis was and the procedures. If the predicted and actual match, then the algorithm will make the probability of success 100 percent, but in the future, if a doctor incorrectly diagnoses a patient, the confusion matrix will decrease the probability of success to 50 percent. In order for the matrix to work efficiently, a larger sample of data needs to be inputted first to ensure the probabilities are as accurate as possible.

This model prevents physicians from placing too much weight on the outcome because each medical procedure is weighed against hundreds of other procedures where the outcome of one examination won't influence the recommended diagnoses and examinations.

The main obstacle to tackle for DocYoda to work intelligently is ensuring a large, heterogeneous population of data is being utilized to prevent the data itself from containing biases. This could be resolved by outsourcing to healthcare clinics across the country or even around the globe. Along with data comes privacy concerns, but since the data is only accessible to the patient's physician unless otherwise requested, it won't be a major issue ethically.

4 Conclusion

Healthcare in the United States is an expensive industry that has exponentially grown in all aspects in just the past decade. Many doctors in the industry make life-or-death decisions almost every day, and their ability to produce successful outcomes is of the utmost importance in determining the quality of care their patients receive. This paper examined how three different cognitive biases—availability, anchoring, and outcome—can unconsciously affect physicians' decision-making skills that can result in inaccurate or biased recommendations.

When doctors rely on their System 1 thinking to determine what procedure to perform or diagnoses to treat, they depend on the information that comes to their mind first. The information that comes to mind may not be the most representative, which makes the recommendation biased and inaccurate. Strategies to reduce the bias involved activating System 2 thinking and simply slowing down. These strategies were implemented into a hypothetical extension, DocYoda, that automates physicians' System 2 thinking by referencing online data points to provide the top 3 diagnoses and examinations. DocYoda also prevents the anchoring effect in which doctors "anchor" to the first piece of information presented and don't adjust their anchor enough to accurately analyze additional information. DocYoda is able to analyze all information available equally via a historical section for physicians to create profiles for each of their patients to enter past medical information, such as a history of smoking, and a modern section with the patient's ongoing medications or symptoms. DocYoda also presents a confusion matrix to determine which procedure and/or diagnosis should be recommended based on past procedures to ensure physicians don't base the procedure on an outcome.

While this paper has focused on three niche biases in doctors' decision-making, numerous other biases need to be studied in order to design solutions that will produce substantial development. Behavioral economics can play a major role in the healthcare industry if future research is explored to positively impact the quality of care the citizens of the United States receive.

References

[Bar98] Hershey J. C. Baron, J. Outcomes biases in decision evaluation. 1998.

[Cla14] Jones Clay. Outcome bias in clinical decision making and the assessment of our peers. *Science-BasedMedicine*, 2014.

[Dep22] Statista Research Department. Topic: Health expenditures in the u.s. - statistics facts. 2022.

[Doh20] Carroll A. E. Doherty, T. S. Believing in overcoming cognitive biases. *Journal of Ethics — American Medical Association*, 2020.

[Eis93] R. Eisenman. Belief that drug usage in the united states is increasing when it is really decreasing: An example of the availability heuristic. *Bulletin of the Psychonomic Society*, 1993.

[Etc15] E. Etchells. Anchoring bias with critical implications.s. *Patient Safety Network*, 2015.

[Fli18] J. Flinchbaugh. Overcoming outcome bias. 2018.

[Gup11] Schriger D. L. Tabas J. A. Gupta, M. The presence of outcome bias in emergency physician retrospective judgments of the quality of care. *Annals of emergency medicine*, 2011.

[Kah11] D. Kahneman. Part i. two systems. *Thinking, fast and slow (pp. 21–96)*, 2011.

[Mam10] Gog T. van Berge K. van den Rikers R. Saase J. van Guldener C. van Schmidt H. G. Mamede, S. Effect of availability bias and reflective reasoning on diagnostic accuracy among internal medicine residents. *JAMA*, 2010.

[Med16] Farnam Street Median. The conjunctive and disjunctive events bias. 2016.

[Mic22] F. Michas. Inpatient day hospital costs in the u.s. by type 2019. *Statista*, 2022.

[Mye22] E. Myers. How anchoring bias psychology affects decision making. anchoring bias heuristic: Definition and examples. *Simply Psychology*, 2022.

[O'S18] Schofield S. J. O'Sullivan, E. D. Cognitive bias in clinical medicine. 2018.

[Out19] Outcome bias and how to avoid it. *Snaps: Journal*, 2019.

[O8] Schofield S. J. O'Sullivan, E. D. Cognitive bias in clinical medicine. *Journal of the Royal College of Physicians of Edinburgh*, 2018.

[Sap16] Redelmeier D. Ruff C. C. Tobler P. N. Saposnik, G. Cognitive biases associated with medical decisions: A systematic review. bmc medical informatics and decision making. 2016.

[Sar19] S. Sarkis. Anchoring bias can weigh you down and make you settle for less. *Forbes*, 2019.

[Tve74] Kahneman Tversky, A. Judgment under uncertainty: Heuristics and biases. 1974.