Life and Death: The Effect of Biases and Heuristics on Medical Decision Making

Rajeev Krishnamurthy [*†]

October 17, 2023

Abstract

Doctors' decision making is affected by a variety of cognitive shortcuts and biases. Five biases and heuristics extremely relevant to medical decision making are the availability heuristic, anchoring, sunk cost bias, omission bias, and status quo bias. By conducting literature reviews involving the analysis and evaluation of largely quantitative data, this paper analyses these five biases and the extent to which they affect doctors, as well as the roles they play in medicine. Finally, this paper recommends a range of policies which aim to alleviate the negative effects of these heuristics and biases on medical decision making

1 Introduction

The average doctor-patient consultation takes a mere 18 minutes [ea20a], so it is perhaps not surprising that misdiagnosis is the largest single cause of adverse medical events in the USA, accounting for 34% of the country's total medicolegal claims [LB11]. The current medical system incentivizes doctors to process the highest number of patients possible, and, in order to accomplish this, they unconsciously utilize a number of cognitive shortcuts, or heuristics. While this does indeed speed up the medical processes, it also makes doctors vulnerable to a number of errors and biases – heuristics offer the easiest path from a problem to its solution for the brain, not the most methodical or careful one [ea08]. This can cause anything from a doctor over-diagnosing epilepsy because he took a course on it a week earlier, to one continuing an incorrect medical treatment because of previous investment of time and money into it. Furthermore, the patients whom doctors are treating may have biases too – which can influence doctors and which they must compensate for.

This paper will provide an overview of heuristics and biases within the medical establishment, using both hypothetical and real-world examples to illustrate their causes and effects. By reviewing a wide range of previous literature, the

*Advised by: Dr. Edoardo Gallo of the University of Cambridge
†The International School Bangalore

mechanisms behind these biases can be explored thoroughly, and various policies intended to reduce the effects of biases on and increase the accuracy of doctors' decision-making will be evaluated. Finally, I will provide systemic recommendations which aim to significantly alleviate the negative impact that biases and heuristics cause to the medical establishment. This paper will focus on five cognitive drivers: the availability heuristic, anchoring, sunk cost bias, status quo bias, and omission bias. This paper will contain four main sections – Section 1 will focus on the availability heuristic, Section 2 will focus on anchoring, Section 3 will cover the sunk cost bias, and Section 4 will focus on the status quo and omission biases. Each section will consist of three subsections: the first will define the bias or heuristic covered, the second will be a literature review, and the third will comprise its implications for medical decision making, and recommendations which could potentially alleviate its harmful effects.

2 Availability

2.1 Defining the availability heuristic

Li et al. define the availability heuristic as "the tendency to overestimate the likelihood of events when they readily come to mind". It is an example of base rate neglect – a phenomenon that occurs when people tend to ignore statistical averages in favor of new information [KT73]. A real-word example of this is as follows: students who were asked to retrieve 12 examples of them expressing assertive behavior rated themselves as less assertive than students who were asked to recite 12 examples of their unassertive behavior [ea91] - 12 examples of the stated behavior were not easily available to the students, leading them to underrate themselves. In medicine, the availability heuristic could present as a physician who spent years specializing in tuberculosis being more likely than generalist peers to misdiagnose similarly presenting disorders as tuberculosis [ea20b].

2.2 Literature review

This section will analyze two at-scale studies which examined the role of medicinal availability bias in different contexts - namely the emergency department and general consulting.

Ly's study involved emergency departments in 104 Veterans Affairs hospitals across the US over seven years from 2011 to 2018, where the rate of testing for pulmonary embolisms was compared before and after diagnoses for pulmonary embolisms were issued [Ly21]. Ly hypothesized that, as a result of the availability heuristic, rates of pulmonary embolism testing would increase after a diagnosis of pulmonary embolism [Ly21]. The study's scope was limited to patients 21 years or older presenting with shortness of breath. Multivariate regression was used to compare testing rates between the 60 days before and after a diagnosis. Ly found that rates of testing increased significantly by 1.4

percentage points in absolute terms – a relative increase of 15 percent – in the 10 days following a diagnosis [Ly21]. However, in the following 50 days, no statistically significant change was found. Ly, however, acknowledged that, due to the study's 95 percent confidence elements, an increase below the 5 percent level could not be ruled out [Ly21]. Ly concluded that "These results are consistent with the availability heuristic influencing physician decision making in relation to pulmonary embolism diagnoses".

Li et al. approached their study with a different method – it involved 46 internal medicine residents, divided into two groups, with one being the experimental (EG) and the other the control (CG) [ea20b]. Prior to the experiment, the EG was asked to analyze an article on dengue fever, and then completed a test on it. The control group, however, did not receive any of this information and directly participated in Stage 2 of the study, which occurred six hours later [ea20b]. Li and his colleagues mention that "great care was taken to ensure that stage 2 appeared to be an unrelated study" [ea20b]. The participants were presented with and asked to diagnose eight clinical cases – one of which was dengue fever, three of which appeared similar to it but were actually different conditions, and the remainder of which were unrelated to dengue fever. Finally, in the third stage, participants received three experimental cases and one filler that they had previously diagnosed and were encouraged to reflect on their previous diagnoses and change them if they felt they were incorrect in order to test whether reflection would compensate for availability heuristic-caused errors [ea20b]. Participants were assigned a score of 1 and 0 for each correct and incorrect diagnosis they made, and the mean scores of each group were compared.

In the second stage of the study, the CG significantly outperformed the EG in the experimental cases, 0.80 to 0.66, and slightly underperformed it in the filler cases, 0.59 to 0.64 [ea20b]. The EG misdiagnosed significantly more cases as dengue fever than the CG. Additionally, the participants did not show a statistically significant difference in accuracy after performing reflective reasoning [ea20b]. Li and his colleagues concluded that "the availability bias seemed to account for the bulk of diagnostic errors and was not well repaired by reflective reasoning" [ea20b].

2.3 Implications and recommendations

Both in the emergency room and in the context of consulting, doctors were shown to be affected by the availability heuristic in a statistically significant manner. It caused a significant impact over a period of time – a 15% increase in misdiagnosis sustained over 10 days [Ly21]. Additionally, it is not tied to doctor competence – the EG the study 2 outperformed the CG in non-affected diagnoses, but significantly underperformed it when affected by the heuristic [ea20b]. Thus, it can be concluded that the availability heuristic poses a real danger to the decision making of doctors, both in the emergency room and during normal consulting work. An example of this which occurred in 2022 was presented by Kyere, Kwaku, et al. – a man was incorrectly diagnosed with

COVID-19 despite three negative tests, resulting in him being given excessive doses of antibiotics and requiring supplemental oxygen before being correctly diagnosed and eventually discharged [ea22b]. They described the availability bias as a "significant contributor to poor patient outcomes" and encouraged physicians to be aware of it in order to avoid "inadvertently affecting patient outcomes" [ea22b].

Using reflection and taking additional time to diagnose is not an effective method against this heuristic, resulting in no statistically significant improvement in the accuracy of diagnosis [ea20b]. A possible workaround could be to consult with another doctor who has not seen or diagnosed a recent case of the disease, as only diagnoses of the exact disease cause availability bias, not ones similar to it [Ly21]. However, this would likely not be cost-effective, and it might be difficult to find an unbiased doctor in the case of a common condition, as a result of the relatively long-lasting nature of the bias [Ly21]. Additionally, as the availability bias is an example of base rate neglect [KT73], consulting base rates and ensuring that statistical overdiagnosis is not taking place could be an effective tool for doctors to mitigate the effects of the availability heuristic.

Finally, the current rise of artificial intelligence could provide the future possibility of the consultation of neural networks to ensure that opportunities for differential diagnosis are presented and base rate neglect is avoided [ea21]. Patient details and symptoms reported would be processed by the system, which would present several diagnoses to the doctor, considering their rates of occurrence in the general population as well as their likelihood based on patient history and the symptoms presented. By presenting base rates to doctors, base rate neglect would be mitigated, and, as a result of the system itself theoretically not being subject to human heuristics and cognitive shortcuts, the "second opinion" provided by it would provide an effective antidote to the doctor's availability bias.

However, this would not be a silver bullet – as mentioned previously, taking additional time to reflect after diagnosis did not mitigate the bias's effects on doctors, so the system would likely need to provide fairly forceful suggestions to doctors and play a relatively large role in the decision making process in order to have an impact. Moreover, at the end of the day, systems are merely an aid to doctors, and a biased doctor will inevitably make biased decisions – while using AI as an aid might improve the accuracy of diagnoses, systemic training in order to make doctors less susceptible to the effects of the availability heuristic would still be necessary.

Additionally, precautions would need to be taken while integrating AI into the medical decision-making process. It has been demonstrated that, when trained on biased datasets, AI-based systems can produce biased results [ea19]. However, measures to alleviate these inherent biases do exist [ea19], and would need to be integrated into a hypothetical medical system in order to provide relatively unbiased advice to help mitigate the effects of the availability heuristic upon doctors.

3 Anchoring

3.1 Defining Anchoring

Anchoring was originally described by Kahneman and Tversky, as the tendency of people to make estimates “by starting from an initial value that is adjusted to yield the final answer”; this adjustment is “typically insufficient” [TK74]. An example of this is as follows: participants who were anchored with the value “65” estimated 20% more African countries in the United Nations than participants anchored with the value “10” [TK74]. Dargahi et al. define anchoring in the context of medicine as “the excessive weighting of initial information and the inability to adjust the initial diagnostic hypothesis when further information becomes available” [ea22a]. A hypothetical example of this could be a doctor misdiagnosing a patient with depression because the patient seemed depressed to him upon first impressions, and the doctor did not make a sufficient adjustment away from the first impression.

3.2 Literature review

This section will analyze two studies associated with anchoring in medicine, in different contexts – namely the emergency room and general consulting.

A study by Dargahi et al. involved 77 faculty members and residents in Emergency Medicine [ea22a]. The participants were presented with nine commonly misdiagnosed written clinical cases and were asked to provide a diagnosis for each case. Each case was scored on a 1-7 scale on difficulty of diagnosis by an expert panel [ea22a]. Participants were given a three-page document and asked to provide a diagnosis after each page – intended to simulate the gradual acquisition of information in real-world contexts [ea22a]. The study found that, while the faculty members made far fewer errors overall – 34% as opposed to a total average of 57% - a much higher proportion of their errors were anchoring errors – 75% as compared to an overall average of 38% [ea22a]. Dargahi and her colleagues concluded that “The results show that the anchoring error rate in the faculties is meaningfully higher than in the residents”, and that while the faculty members were “better than the residents in focusing on the relevant and related information and generating more links to relate critical cues”, their diagnostic process was “dominated by heuristic thinking”. They hypothesized that this could be caused by “their more clinical exposures to diagnoses in emergency situations”, and that they were “not looking for ways to strengthen and support their decisions” [ea22a].

A study conducted by Voytovich et al. examined rates of anchoring in students, residents, and faculty members in Connecticut State University [ea85]. The study involved participants asked to generate “precise problem lists” for four cases, and the problems were then judged by independent raters, and mistakes were categorized [ea85]. The authors found that, while the other errors tracked decreased consistently with increased experience, the frequency of anchoring-induced errors “seemed... independent of training and level of ability". They recommended that "physicians should encourage independent review of their conclusions and realize that knowledge provides no shield against premature closure", and that anchoring might be able to be avoided with "good interrater ability" [ea85].

3.3 Implications and recommendations

In both situations analyzed, doctors and medical students were found to be affected by anchoring in a statistically significant manner. Similarly to availability, it also has the potential to cause poor patient outcomes, as evidenced by a 2021 case presented by Rehana and Huda: a patient with a brain tumor was assumed to be on drugs by his family and doctors, leading to delayed medical intervention, misdiagnosis, and ultimately his death [RH21].

What makes anchoring a uniquely dangerous heuristic is the fact that error rates associated with it do not improve with training and experience – respectively, the studies reviewed showed an increase in error proportion and no change when the experience of doctors surveyed increased [ea22a] [ea85]. As a result of other errors decreasing, inexperienced doctors might universally regard more experienced individuals as less fallible than themselves – when it is not true with anchoring. Moreover, the fact that senior doctors' decision-making processes were "dominated by heuristic thinking" [ea22a] suggests that the medical establishment implicitly encourages the adoption of anchoring, which would require systemic change to fix.

As with availability, consulting base rates could be an effective solution to alleviate the effects of anchoring and prevent misdiagnosis via preventing overdiagnosis. Consulting a colleague not involved with the case or a computerized, A.I. based system would, as mentioned by Voytovich and his colleagues [ea85], likely also be effective, possible financial and technological limitations aside. This hypothetical colleague or system, as a result of seeing the case as a whole from the outset, would not have an "anchor" from which they would have to adjust and therefore would largely be free from the effects of anchoring. In the case of A.I, the same limitations mentioned in Section 2.3 would apply – it would function as an aid, and would not be able to wholly counteract biased doctors, and the precautions mentioned therein would have to be taken to ensure an effective implementation which would help alleviate the effects of anchoring on doctors. Finally, systemic training involving asking senior doctors to question their initial judgements and evaluate new evidence with higher weight would likely lessen the effects on anchoring on them.

4 Sunk Cost Bias

4.1 Defining sunk cost bias

Bornstein et al. define sunk cost bias as occurring "when a decision maker continues to invest resources into a previously selected action or plan even after the plan has proven to be the suboptimal option" [ea99]. This, for example, could take the form of sitting through a boring movie in order to "get more value" out of your ticket. This may seem logical; however, by continuing to sit in the movie, you are impacting your future enjoyment as well. Thus, despite the sunk cost, the best option is always to switch immediately to the optimal course of action. In medicine, sunk cost bias could take the form of a doctor continuing a course of ineffective prescription because their patient has already spent time at their office and money in buying the medicine.

4.2 Literature review

This section will analyze two studies – one on the side of the patient, and one on the side of the doctor. Sunk cost has a complex effect on medical decision making, and analysis must be done from both perspectives in order to evaluate the issue completely and issue sound recommendations.

A 2010 study by Coleman analyzed the sunk cost effect on university undergraduates by making them run a computer program, which simulated spending one of three things – money, time, or effort – in three different quantities – under, on, or over budget - to book sessions with a chiropractor [Col10]. Then, an option for a slightly more effective treatment for free was revealed, and the students decided whether they would cut their losses or invest more in the hope of the sessions starting to work [Col10]. When the students invested money, AVANOVA analysis revealed a strong positive correlation overall, with students who spent more money willing to invest more time into the sessions. Invested time did not show an effect with AVANOVA, but did have a 90% probability of detecting a medium effect size when used with power analysis. Finally, previously invested effort showed the strongest correlation of all with time; future willingness to invest increased steadily with past effort invested [Col10]. Coleman concluded that money invested produced a sunk cost effect, while effort produced a similar relationship but due to a different cognitive mechanism [Col10].

A 2012 study by Braverman and Blumenthal-Barby analyzed the effect of sunk cost on doctors, and its implications for clinical decision making [BBB12]. The study involved 389 healthcare providers, who were each given one of four hypothetical clinical scenarios, and asked to give a 1-5 answer, where 1 was a strong recommendation to discontinue treatment and 5 was a strong recommendation to continue treatment. All scenarios involved an unsuccessful medical treatment but varied in investment. The first scenario involved investment of money, the second time, the third both, and the fourth neither [BBB12]. The expected result consistent with the sunk cost effect would have been for the doctors in the scenarios with the most investment recommending continuation, however, the opposite transpired, and the doctors in the scenario with no investment were the most likely to recommend continuing the treatment – an "overcompensation" for the sunk cost effect [BBB12]. In spite of this, 11% of those surveyed stated that they would recommend continuing the treatment – which the authors describe as "unrealistic optimism". The authors hypothesized that "the participants' response to the scenario given in the study may not be reflective of their behaviour when faced with a similar situation in practice" due to the "close-ended nature of the available responses" and concluded that "further research is necessary" [BBB12].

4.3 Implications and recommendations

The sunk cost fallacy affects both patients and doctors, which makes it a particularly tricky problem to solve. With invested time and effort, patient show clear evidence of a sunk-cost or sunk-cost like effect [Col10], but the evidence in the case of doctors is much more inconclusive [BBB12]. The vast majority of doctors seem to overcompensate for the sunk cost effect in theoretical scenarios, which is not necessarily a negative, as it might provide an effective counter for the fallibility of patients [BBB12]. Indeed, given the extent of the effect of sunk cost on patients, it might be the best course of action for doctors to overcompensate to a greater extent against their own sunk cost effects in order to fight those of their patients [Col10]. However, their behavior in practice remains unknown, due to a lack of observational studies [Col10]. Moreover, a significant portion of doctors still display "unrealistic optimism" in pursuing clearly unsuccessful courses of action [Col10].

Thus, the only concrete recommendation that can be made regarding sunk cost bias is for medical establishments to commission research in the area, as based on current unknowns it is impossible to know the extent to which doctors are affected by it in the real world. However, there is no downside to conducting campaigns to both doctors and the general public which promote awareness of the effect, and how to reduce its negative impact.

5 Omission bias and status quo biases

5.1 Defining the omission and status quo biases

Ritov and Baron define an omission bias as occurring when a decision-maker prefers a harmful outcome resulting from inaction to a less harmful one involving an action [RB92]; status quo bias is defined as a preference to maintain one's state as opposed to changing it in any way [SZ88]. These biases are closely related in the field of medicine, and indeed elsewhere; inaction often leads to a worse outcome than taking action [ea05]. An example of the status quo bias in medicine would be a doctor choosing not to prescribe a patient a new, improved medication as the patient had been on the previous medication for several years; one of omission could involve not treating a patient who is having a heart attack as they are being treated for pneumothorax already.

5.2 Literature review

This section will analyze two studies; one focused on omission bias and one on status quo bias.

A 2005 study by Aberegg et al. focused on the impact of the omission bias on medical decision making. The study was conducted on 500 randomly selected pulmonologists from the Royal College of Chest Medicine, of whom 125 responded to the survey [ea05]. The study involved the creation of two pairs of case vignettes, which contained one option relating to keeping a status quo, and one with a course of action involving either action or omission depending on the form [ea05]. In the first case described, participants were almost twice as likely to pick the same option when it was presented as an omission as opposed to an action [ea05]. The second case also showed a trend nearly as strong, but the third did not – which the paper hypothesizes may be due to the "perceived psychological burden of the decision it involved". The study concluded that pulmonologists "may be susceptible to cognitive biases such as omission and status quo bias" and that the "suboptimal decisions" made as a result of this could have "far-reaching implications for patient outcomes, cost-effectiveness, clinical practice variability, and medical errors." [ea05].

A 2021 study by Camilleri and Shah focused on analyzing the effect of the status quo bias on physicians and the general population in Australia. It involved giving 302 physicians and 733 non-physicians three scenarios: one related to medicine and two unrelated to it [CS21]. There were two versions of each question; one with a status quo option and one without it, and participants were randomly allocated one version. After completing the survey, participants were also asked to state their confidence in their decision on a five-point scale [CS21]. The results of the study showed that, in the medical scenario, physicians and the non-medical population surveyed both exhibited more status quo bias than in the other scenarios. The physicians, however, proved significantly more susceptible to this bias in medical scenarios than the non-physicians; they showed a 35% absolute increase in preference for an option presented as the status quo, while the non-physicians only showed 18% [CS21]. The authors of the study suggest that this is because "experts often review a decision made by a prior expert", which is why it was not present in "non-expert domains". The paper cautions that this may lead to "the treatment patients receive being suboptimal" and states that "it is important that physicians not fall prey to the status quo bias just because their colleague has reviewed the patient themselves" [CS21]. In order to reduce the impact of the status quo bias on medical decision making, the paper suggests making physicians "effectively 'blind' to prior treatment decisions", or to make primary care physicians "unaware that their first treatment decision will be reviewed by another", or, finally, to ask physicians to "consider why the preferred option may be wrong" [CS21].

5.3 Implications and recommendations

Both omission bias and status quo bias affect physicians to a very significant extent and are therefore likely propagated by systemic factors within the medical establishment. If initial treatment plans are correct, these biases do not necessarily cause any problems – however, if an incorrect diagnosis or prescription is made in the first place, omission and status quo biases threaten to keep patients from getting the treatment they need [ea05]. These are potentially changing lives for the worse every day – take the example of a woman who would have received an unnecessarily disabling colostomy if not for seeking a second opinion from a doctor resistant to status quo bias, as presented by Camilleri and Sah [CS21].

There are several courses of action which could have the capability to reduce the impact of the omission and status quo biases on medical decision making. As suggested by Camilleri and Sah, making previous decisions invisible to physicians would likely remove the impact of these biases, as is the case with consulting an uninvolved colleague [CS21]. This, however, has the disadvantage of likely adding significant cost and hassle to the medical process.

Alternatively, integrating artificial intelligence to provide a constant "second opinion" to doctors could possibly go a long way towards alleviating these biases, assuming its evolution proceeds at current rates without being impeded by currently unknown technological limitations [ea21]. This A.I. would analyze the case without any weight being placed on previous investment into treatment plans, thereby being free from the omission and status quo bias and being able to alleviate the effects of these biases upon the doctor. However, the same limitations mentioned in Section 2 would apply – the AI would not be able to completely counter a biased doctor and would instead function as an aid, and precautions would need to be taken during its implementation to ensure the minimization of systemic bias.

6 Conclusion

While most doctors get the vast majority of their diagnoses and prescriptions right, the consequences of failure are so severe that any rate of misdiagnosis and failure to pursue optimal courses of action is too high. In order to make our medical decision making process as sound as possible, the impact of a variety of cognitive shortcuts and biases that doctors utilize, such as availability, anchoring, omission bias, and status quo bias on the process must be minimized through personal and systemic change. This would be on the parts of patients, doctors, and the medical establishment, and would involve awareness campaigns, doctor training, and additional measures intended to help doctors make more objective judgements. However, the impacts of biases like the sunk cost effect remain unresearched and unknown, and real-world observational studies must be conducted in order to reveal their effects and develop recommendations.

References

[BBB12] Jennifer A. Braverman and J.S. Blumenthal-Barby. Assessment of the sunk-cost effect in clinical decision-making. *Social Science & Medicine*, 2012.

[Col10] Martin D. Coleman. Sunk cost and commitment to medical treatment. *Current Psychology*, 2010.

[CS21] Adrian R. Camilleri and Sunita Sah. Amplification of the status quo bias among physicians making medical decisions. *Applied Cognitive Psychology*, 2021.

[ea85] A E Voytovich et al. Premature conclusions in diagnostic reasoning. *Academic Medicine*, 1985.

[ea91] Norbert Schwartz et al. Ease of retrieval as information: Another look at the availability heuristic. *Journal of Personality and Social Psychology*, 1991.

[ea99] Brian H. Bornstein et al. Rationality in medical treatment decisions: Is there a sunk-cost effect? *Social Science & Medicine*, 1999.

[ea05] Scott K. Abergg et al. Omission bias and decision making in pulmonary and critical care medicine. *Chest*, 2005.

[ea08] Omar Merlo et al. Heuristics revisited: Implications for marketing research and practice. *Marketing Theory*, 2008.

[ea19] Drew Roselli et al. Managing bias in ai. *Companion Proceedings of The 2019 World Wide Web Conference*, 2019.

[ea20a] Hannah T. Neprash et al. Measuring primary care exam length using electronic health record data. *Medical Care*, 2020.

[ea20b] Ping Li et al. Availability bias causes misdiagnoses by physicians: Direct evidence from a randomized controlled trial. *Internal Medicine*, 2020.

[ea21] Silvana Secinaro et al. The role of artificial intelligence in healthcare: a structured literature review. *BMC Medical Informatics and Decision Making 21*, 2021.

[ea22a] Helen Dargahi et al. Anchoring errors in emergency medicine residents and faculties. *Medical Journal of the Islamic Republic of Iran*, 2022.

[ea22b] Kwaku Kyere et al. Availability bias and the covid-19 pandemic: A case study of legionella pneumonia. *Cureus*, 2022.

[KT73] Daniel Kahneman and Amos Tversky. On the psychology od prediction. *Psychological Review*, 1973.

[LB11] David Levine and Alan Bleakley. Misdiagnosis: Analysis based on case record review with proposals aimed to improve diagnostic processes. *Clinical Medicine*, 2011.

[Ly21] Dan P. Ly. The influence of the availability heuristic on physicians in the emergency department. *Annals of Emergency Medicine*, 2021.

[RB92] Ilana Ritov and Jonathan Baron. Status-quo and omission biases. *Journal of Risk and Uncertainty*, 1992.

[RH21] Rita W. Rehana and Najia Huda. A common heuristic in medicine: Anchoring. *Annals of Medical and Health Sciences Research*, 2021.

[SZ88] William Samuelson and Richard Zeckhauser. Status quo bias in decision making. *Journal of Risk and Uncertainty*, 1988.

[TK74] Amos Tversky and Daniel Kahneman. Judgment under uncertainty: Heuristics and biases. *Judgment under Uncertainty*, 1974.