CHAPTER SIX

# Nudge 2.0: Unveiling Better Health Outcomes with AI-Enhanced Personalized Default Nudges

Sara Roman

**Introduction**

Medical mistakes – human errors in healthcare that harm patients – are common.[1] According to research conducted in 2016 by researchers at Johns Hopkins School of Medicine, medical mistakes rank as the third most prevalent cause of death in the U.S.[2] The economic impact of medical error on the U.S. economy is estimated to be around $20 billion, with 87% of this amount representing direct increases in the medical expenses incurred in treating patients affected by medical error.[3] A 1999 report from the Institute of Medicine approximated that medical mistakes lead to a range of 44,000 to 98,000 avoidable fatalities and an excess of 1,000,000 injuries occurring annually within U.S. hospitals. [4] On a similar note, a 2001 study conducted across seven Department of Veterans Affairs medical centers projected that out of every 10,000 patients admitted to these specific hospitals, approximately one patient's life could have been extended by three months or more in good cognitive health if they had received "optimal" care.[5] Addressing medical mistake is thus of high importance: improvements could save thousands of lives annually in the U.S.

A significant sub-category of medical mistake is diagnostic error, which is characterized by Graber et al. as an incorrect, significantly delayed, or entirely overlooked medical diagnosis.[6] In the same vein as addressing medical mistake, addressing diagnostic error would yield significant benefits for society. Chicago, for instance, is the third-largest city in the United States, with heart disease being the leading cause of death in the region – an issue extensively documented by government data from 2017 and 2021.[7, 8, 9] People die both from heart disease itself but also frequently from the misdiagnosis of heart disease, as concluded in a systematic review of the literature on heart failure misdiagnosis.[10] The literature review emphasizes the necessity for research to improve the understanding of missed opportunities in accurately diagnosing heart disease.[11] Implementing innovative strategies to minimize diagnostic errors in heart disease could significantly decrease the prevalence of mortality from heart disease in the Chicago area and elsewhere.

A compelling intervention to address the prevalence of mortality from heart disease could be drawn from Chicago sources, specifically from work conducted at the University of Chicago.[12, 13] This chapter will build upon the concept of "nudge," first introduced by economist Richard Thaler, who is associated with the University, along with another (former) University of Chicago academic, law professor Cass Sunstein. A nudge, according to Thaler and Sunstein, can be defined as "any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives".[14] I argue for the implementation of what I call Nudge 2.0, a personalized default nudge enhanced by contributions from Artificial Intelligence (AI).

**Nudge 2.0 Proposal: Addressing Medical Diagnostic Error in Heart Disease**

The concept of a nudge is applicable to health policy and to heart disease, in part because of the unavoidably bounded rationality of doctors, which can lead to diagnostic errors.[15] A nudge in this domain would be a non-coercive intervention that would improve diagnoses. Nudge 2.0 is an example of a personalized nudge[16], one that uses patient-specific information to provide better guidance. The volume of general and patient-specific information is so great that medical professionals alone cannot process the data and respond appropriately.[17] AI, however, can process this data, and generate a high-quality, personalized diagnostic suggestion.

The medical Nudge 2.0 is an example of a common type of nudge, establishing a default setting. The nudge to the medical team would consist of a diagnostic suggestion, the "default." In keeping with the notion of default, however, it will be easy for cardiologists to override the suggestion. Doctors will retain their individual judgement in making diagnoses and designing treatment plans; however, Nudge 2.0 would complement the physician's private information, with the goal of leading to improved health outcomes.

The proposal of Nudge 2.0 in this paper builds from a wide range of explorations of past health care interventions, their shortcomings, and nudge-related policies. A closely related notion is explored in an article by Sendhil Mullainathan and Ziad Obermeyer, "Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care." Mullainathan and Obermeyer indicate the potential to use AI for more efficient nudging, within the ambit of medical errors. When applied to heart disease diagnosis, Nudge 2.0 could reduce the prevalence of mortality from heart disease in Chicago, and hence contribute to better controlling Chicago's leading cause of death.

**Addressing the Issue: Past Policy Measures Without the Concept of Nudge**

Policy reforms (separate from nudging) have been implemented to address the issue of medical errors, but the problem of medical errors persists. The 2009 article "A National Survey of Medical Error Reporting Laws," documents healthcare policies in light of the Institute of Medicine's (IOM) recommendations for addressing this problem.[18] IOM proposed a two-part reporting system to gather policy-relevant information. First, IOM suggested that Congress create a national system managed by the National Forum for Health Care Quality Measurement and Reporting, which would compile reports from individual states about the most severe errors occurring in healthcare facilities. The IOM hoped to identify serious adverse events, allowing state health departments to hold facilities accountable and assist them in developing protocols to reduce future errors. The IOM also recommended making the analyses of the root causes of these adverse events publicly available. Second, the IOM recommended that the Center for Patient Safety establish a voluntary reporting mechanism for less severe medical errors. This approach would protect the confidentiality of the reports, allowing data to be collected for analysis and identifying the causes of errors, thus facilitating improvements.[19]As a result of such recommendations, by 2014, mandatory reporting systems for adverse medical events were required in 27 US states, including Illinois.[20] The reporting systems aimed to facilitate collaboration between state health departments and healthcare facilities to investigate the factors that lead to error.[21]

Despite such efforts, there is a lack of evidence demonstrating subsequent improvements in health outcomes.[22] While the technologies implemented since the release of the IOM report have been significant, it is evident that they are not producing the same level of benefits as observed in earlier periods.[23] If a better policy to mitigate medical and diagnostic errors had been identified and adopted, there would have been an opportunity to reduce heart disease deaths. New solutions are needed.

**Nudge Theory for Better Outcomes in Health Care**

Recall that a nudge is defined as "any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives".[24]A nudge is a sort of suggestion, but it only counts as a nudge if it is easy for people to ignore the suggestion. Nudges lack the coercive element associated with taxes, fines, subsidies, bans, or mandates. "Putting the fruit at eye level counts as a nudge. Banning junk food does not."[25]

Jean Baptiste Point du Sable Lake Shore Drive provides a surprising illustration of a generalized approach to nudging. Chicago's DuSable Lake Shore Drive features an S curve, which can pose driving hazards. The risk here lies in drivers potentially failing to slow down sufficiently, leading to a car crash. A policy that takes the form of a nudge was applied to address the problem and improve driving outcomes. Several white stripes were painted onto the road as visual cues. The lines, perpendicular to the direction of travel, appear to drivers in moving vehicles to be equally spaced. As drivers progress, the lines get closer together. These series of white stripes were intended to create the sensation in drivers of increased speed, as the next white line arrives more quickly, an effect designed to occur as drivers reach the riskiest portion of the road. Drivers slow down as a result; they are being "nudged."[26]

Like drivers, doctors can be nudged toward better health outcomes, too. A nudge is a method of subtly reducing the risk of human fallibility. In the medical field, where misdiagnosis in heart disease is documented to primarily stem from automatic thinking and a doctor's reliance on coarse rule-of-thumb guidelines in complex cases, appropriate nudges would be well-suited to improve outcomes.[27] Physicians could be guided toward a suggested diagnosis – one that would be as accurate as possible given all the data at hand – rather than relying on the current approaches to medical diagnosis that often lead to errors.

The premise that nudges can work in the medical field has been demonstrated in the past fifteen years, with nudges having been applied to many areas of healthcare. The Center for Health Incentives and Behavioral Economics at the University of Pennsylvania, for instance, has implemented and studied a host of nudges with respect to various public health challenges, such as tobacco dependence, obesity, and medication non-adherence.[28]

**Defaults: A Crucial Feature of Nudge 2.0 for Better Health Outcomes**

A crucial feature of the Nudge 2.0 proposal is leveraging the stickiness of default settings. The default refers to the option that is automatically applied unless an overt decision is made or action is taken to override the default.[29] In line with the concept of the nudge, default nudges preserve freedom of choice, with no explicit hindrance or prohibition applied to the choice of other alternatives.[30]

Numerous nudges taking advantage of the stickiness of defaults have been implemented in various areas of private and public institutions to promote beneficial behaviors.[31]A classic example of default nudges is in the field of retirement savings: many individuals indicate that they believe that they do not put aside enough savings for retirement. Brigitte Madrian and Dennis Shea's article, "The Power of Suggestion: Inertia in 401(k) Participation and Savings Behavior," analyzes the 401(k) savings behavior of employees in a large U.S. corporation.[32] Madrian and Shea study the effect of changing the default setting from opt-in – where employees had to explicitly enroll in the 401(k) plan – to opt-out, where employees were automatically enrolled in the savings plan but could choose to opt-out. The shift to automatic enrollment had a significant impact on employees' savings habits in various ways. First, under automatic enrollment, 401(k) participation increased significantly. Second, the default contribution rate and fund allocation under automatic enrollment had substantial staying power as well. Notably, employees hired before the implementation of automatic enrollment did not show the same inclination to enroll or to choose what later became the default saving rates and allocations[33]. The findings of the paper point to "the power of suggestion" behind default nudges, where defaults have been employed to encourage numerous beneficial behaviors.

In healthcare, an emblematic example that highlights the powerful impact of default nudges is an opt-out vaccination policy. Consider the context of the Covid-19 pandemic, which, as of November 2021, resulted in over 200 million diagnosed cases and more than 5 million deaths worldwide. [34] Vaccination emerged as a potential solution in this context, standing as a critical infection protective measure. With widespread vaccination uptake, a sufficiently large portion of the population would become immune, generating social "herd immunity" and thereby reducing morbidity and mortality.[35] Nevertheless, many people remained reluctant or unwilling to receive the COVID-19 vaccine, despite the potential personal and social benefits. Liu, Zhao, Li, and Zheng, in their article "Opt-out policy and its improvements promote COVID-19 vaccinations," explore whether using default nudges – specifically, an opt-out vaccination scheme – could increase intentions to get vaccinated. The results of the researchers' online survey indicate that a default nudge did indeed increase the willingness of Chinese people to be vaccinated, compared to the opt-in vaccination policy in place at the time; these findings are in line with related research on default nudges in the context of flu vaccination.[36, 37]

## Default Nudges Applied in Heart Disease Diagnosis

Nudge 2.0 is a personalized default nudge empowered by contributions from AI. A key characteristic of Nudge 2.0 in heart disease is the default nudge's power of suggestion, the potential for which has just been illustrated. Applied in the world of heart disease diagnosis, a Nudge 2.0 involves generating a default or baseline diagnosis, individually personalized for patients at risk of heart disease. The sensible choice of defaults is a staple of nudge-based policy, and it would "only" provide a default diagnosis, complementing rather than replacing the doctor's judgment. The stickiness of the default in the context of heart disease would function as follows: Nudge 2.0, akin to any default nudge, would represent the best diagnosis available to an extremely well-informed (including personalized patient information) and cognitively sophisticated (able to digest the mass of global evidence) physician. The created default nudge would guide cardiologists toward a diagnosis, which could be crucial when an overload of information or a shortage of time might lead to diagnostic mistakes. Nudge 2.0 is, in this context, predicted to produce improved diagnoses. Recommendations generated by Nudge 2.0 could be incorrect, despite the algorithmic sophistication, but it is only a default, medical professionals could override it if they choose. Nudge 2.0, with its default feature, does not replace the doctor's judgment; instead, it complements the physician's own analysis.

## Diving Deeper: The Specifics of Nudge 2.0 and its Default Mechanism

As previously suggested, with Nudge 2.0, doctors will preserve their freedom of choice. When making a final diagnostic decision, doctors can decide, in light of their private information, judgment and knowledge, to accept or reject Nudge 2.0. Nudge 2.0 would, in other words, offer an opt-out option for physicians. Similar to a GPS[38], Nudge 2.0 would suggest, but not impose, an effective route: a default diagnosis becomes available for the doctor's consideration.

The body of research exploring concepts similar to Nudge 2.0 can suggest further design features that could aid in its effectiveness, such as the kind of information that would be most beneficial to accompany a default diagnosis.[39, 40] "Transparency effects on policy compliance: Disclosing how defaults work can enhance their effectiveness" for example, is a study by Paunov, Wänke, & Vogel. Amidst debate among scholars on whether the effectiveness of nudges might be undermined by transparency, these authors find that transparency can instead enhance the effectiveness of default nudges. Transparency reduces or eliminates the feeling that one is being manipulated. With transparency, policymakers can signal their intention not to trick people into a desired behavior, but rather to assist them in making an informed choice.[41]

A recent working paper by Desiraju and Dietvorst, "Reason Defaults: Presenting defaults with reasons for choosing each option helps decision-makers with minority interests", aims to explore a default intervention where the option chosen as the default is not the best option for some of the targets of the nudge. Are defaults too sticky, or can people who are not well-served by a default opt-out of the default and into an alternative that is better for them?[42]

Desiraju and Dietvorst's "reason defaults" examine a standard default – the pre-selected option best suited for most individuals in a population – paired with information that explains why the default was chosen and provides additional information as to the sort of individual circumstances under which an alternative option should be carefully considered.[43] The idea is that reason defaults might improve targeting, where people who are well-served by the default continue to take that option but those for whom the default is unattractive opt into a better choice.

Desiraju and Dietvorst find that reason defaults can be highly effective in directing decision-makers toward suitable options. Reason defaults that provide the reasoning behind the choice of the default enable people to preserve their freedom of choice, while retaining the advantages of sticking to the standard defaults if desired. Reason defaults are themselves a form of transparency, explaining when each option is beneficial and why the default was chosen. The study finds that reason defaults improve participant outcomes,[44] which is in accord with previous studies that establish a link between transparency and the increase in the efficacy of default nudges.[45]

The characteristics of reason defaults could enhance the efficiency and specificity of Nudge 2.0 in the field of heart disease diagnosis. Nudge 2.0 can provide, alongside a default diagnosis, information that communicates to the medical staff, in the spirit of transparency, why the proposed default diagnosis was chosen. Further, it can identify the sort of circumstances in which a different diagnosis would be more appropriate, guiding physicians on when to be particularly vigilant in looking for signals that suggest the default diagnosis is untrustworthy. The default nudge, along with information used in formulating the default diagnosis, could also provide a quantitative assessment, the level of confidence that the AI algorithm has in the default. By incorporating these features of reason defaults, Nudge 2.0 will have enhanced potential to reduce medical errors in cardiology.

**Personalized Default Nudge: Default as a Key Feature of Nudge 2.0**

Let us go back to Chicago's Lake Shore Drive example for a moment. One can argue that the reason why the line-painting nudging works in the context of Chicago's DuSable Lake Shore Drive is because nudging doesn't require the consideration of specific information about drivers to efficiently nudge them: slowing down is more-or-less universally beneficial. This approach might not, however, be the best choice for the medical field, where the patient population is diverse and heterogeneous, and each patient's situation is unique.

Personalized nudges – one of the features of Nudge 2.0 – hold the potential to lead to better outcomes, helping to overcome the challenge posed by an excessively general nudge.[46] In a 2013 journal article, Sunstein himself explores this challenge to general nudges and suggests "personalized nudges" as a response to heterogeneity.[47] Sunstein sees the opportunity for personalized nudges to arise when enough information is available about an individual's circumstances to enable effective targeting.[48] In contrast to a general nudge, personalized nudges would produce tailored nudges specific to each individual and increase the effectiveness of nudge interventions.[49]

In the field of heart disease diagnosis, personalization is possible and even necessary. In cardiology and in healthcare at large, the population is comprised of individuals with varying medical characteristics and histories, which can influence appropriate diagnoses and treatment plans. Effective nudges must be personalized in the sense of taking this complex and multidimensional information into account. Instead of producing a uniform nudge based on coarse information, personalization recognizes the uniqueness of each patient in terms of backgrounds and needs, and can produce a suggestion that reflects the medically-important elements of that information.

**Personalized Nudging and Medical Data Privacy**

Given that Nudge 2.0, in implementing a personalized nudging approach, takes into consideration sensitive medical information, ensuring the privacy and security of this information become a paramount consideration. The sensitivity of health data has already generated significant data protection regulations in the United States. The Health Insurance Portability and Accountability Act of 1996 (HIPAA) is a federal law which required the establishment of national standards to safeguard confidential patient health information.[50] One of the goals of HIPAA is preventing unauthorized disclosure without patient consent, and the resulting HIPAA Privacy Rule was issued by the US Department of Health and Human Services (HHS) to serve that end.[51] HIPAA rules are regularly updated to reflect improvements in cybersecurity and changes to threats to information privacy.[52] To add an extra layer of protection against the risks that personalized nudging might bring, state-of-the-art data encryption and secure infrastructure technologies for the storage and transmission of sensitive data must continue to be adopted.

**AI-assistance for Personalized Default Nudges**

The value of the personalization of nudges for improved outcomes is intuitively reasonable and backed by research. Desiraju and Dietvorst, however, note the difficulties of collecting detailed information during the decision-making process and making sense of this information in a predictive way.[53]

Advances in AI in recent years suggest that the challenge of processing large amounts of information can be overcome, and hence that decision nudges themselves can be greatly improved. In a vast sea of medical data, more concretely, AI stands as a crucial tool for efficiently analyzing and appropriately responding to a multitude of patient-specific and related cases – a task challenging for doctors alone. In the medical arena, professionals encounter challenges synthesizing large and diverse pieces of information.[54] Decisions often have to be made quickly and under pressure, rendering it hard to effectively deliberate. Doctors are people, and hence are subject to "bounded rationality"[55], where the immense overload of information becomes unmanageable for them[56]. In short, medical diagnosis is a context in which decision errors can be (and empirically are) common. Thaler and Sunstein's basic nudges, personalized and enhanced with AI – Nudge 2.0 – represent a potential game-changer in reducing misdiagnoses of heart disease. Improved coronary diagnosis, in turn, could significantly reduce the prevalence of mortality from heart disease.

Nudge 2.0 can be used not just for diagnosis but for generating information that will be helpful for diagnosis and treatment. A frequent medical quandary is when to recommend that a patient undergo a potentially intrusive and expensive test, one that, it is hoped, will provide more information about the nature of the medical problems and appropriate treatments. Errors are costly on both sides, testing when there is little to be gained or not testing when the benefits exceed the costs. Once again, personalized default recommendations, powered by AI, can improve targeting and reduce both errors of testing. These Nudges 2.0, too, can be accompanied with explanations, degrees of confidence, and markers for potential errors. And as always, the recommendations can be overridden in light of the private information of the patient and physician.

**Navigating Concerns: Addressing Issues Related to AI in the Implementation of Nudge 2.0**

When machines become competent at a task previously the exclusive domain of humans, humans are likely to reduce their own inputs into the task. Nudge 2.0, which relies on AI for diagnosis suggestions, raises concerns regarding the erosion of doctors' skills. Nudge 2.0 may diminish the necessity of certain skills associated with doctors, and possibly reduce their overall proficiency as they increasingly depend upon technology for medical diagnoses. Since Nudge 2.0 is designed to complement physician judgment rather than replace it, there would seem to be a built-in constraint on the erosion of doctors' skills. (Further, the problem only arises to the extent that Nudge 2.0 generally works, that is, that patients and physicians become comfortable with the quality of the recommendations.) In the long run, however, a shift in physician training to ensure that they become especially proficient in areas where AI does not excel could prove beneficial.

**The Demonstrated Success of Using Machine Learning as a Tool to Reduce Medical Error in Heart Attacks**

Machine learning – a subfield of AI – already has been used by researchers to identify shortcomings in testing in the context of heart attacks.[57] An article that employs machine learning methods is especially enlightening in tying together many features of Nudge 2.0 and indirectly illustrating how default recommendations might improve testing decisions in a heart disease setting.

Sendhil Mullainathan and Ziad Obermeyer published in 2022 the article "Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care". Mullainathan and Obermeyer note that physicians' testing decisions deviate from what predicted risk would prescribe with respect to heart attacks. The authors employ machine learning to identify decision shortfalls. Mullainathan and Obermeyer present the reader with a situation in which a patient arrives at the emergency room with nausea and chest pain[58]. In predicting the chances of a heart attack, the doctor must consider a diverse set of information. The physician's decision is crucial: the patient can die from not being tested, while testing brings its own risks. Testing for heart disease, for example, can result in a new blockage in the coronary arteries.[59]

Mullainathan and Obermeyer describe the decision-making situation for doctors as being especially difficult. Many medical conditions possess symptoms that are similar to those of a heart attack. [60] The difficult decision-making environment leads to errors in both directions, where low-risk patients receive tests and where high-risk patients are not tested.[61] Doctors appear to adopt an overly simplistic model when making medical diagnostic decisions.[62] Because the errors are not systematically of one type, imposing a simple rule like "lower the threshold for testing" or "raise the threshold for testing" would not improve matters. Further, the machine learning algorithm does not always perform better than physicians: information unavailable to the machine but available to physicians and patients often is important. Doctors need to maintain discretion.

Chicago ranks among the most heterogeneous populations in the U.S. Heterogeneity is significant from a medical perspective, as the complexity of information that needs to be considered for an accurate medical diagnostic increases with diversity among patients and their circumstances.[63] Coarse decision heuristics become even more of an issue.

In addressing medical diagnostic errors in heart disease in Chicago, all aspects of Nudge 2.0 would come into play. First, "personalization," or a personalized default nudge would allow for specific information about Chicago's diverse population of patients to be considered in the diagnosis process: diagnoses and treatment plans can be individually specific, and data based. The diagnosis default generated by Nudge 2.0 would draw from (as in Mullainathan and Obermeyer's article) demographics, historical health information on diagnoses, procedures, laboratory results, and quantitative vital signs. Nudge 2.0 would also be responsive to symptoms documented at the triage desk when the visit commenced.[64] AI would be used to construct such a personalized nudge – a task impossible for humans on their own to replicate[65].

Nudge 2.0 would provide a default diagnosis to guide cardiologists, with the goal of increased diagnostic accuracy. Doctors would retain individual judgment and autonomy. By incorporating successful findings in the field, the default feature of Nudge 2.0 will present, alongside a default diagnosis, information that will be provided to the medical staff. The information will consist of the rationale as to why the proposed default diagnosis was chosen by Nudge 2.0, the health information that the personalized nudge considered most relevant when making a diagnosis, along with information about specifics that Nudge 2.0 identifies as unusual within the multitude of data. Complementary to this information will be the level of confidence the AI algorithm has in generating its Nudge 2.0. Transparency would thus be enabled, and physicians will be able to use their private information to override the default recommendation when they deem such an override appropriate.

## Conclusion

I propose Nudge 2.0 as a personalized default nudge enhanced by contributions from AI in response to the high toll imposed by heart disease in Chicago and elsewhere. To address the feasibility of Nudge 2.0 in tackling this problem, I demonstrated that the incorporation of a nudge is appropriate in the context of health policy and heart disease, where current modes of decision making lead to a surfeit of diagnostic errors. A personalized nudge is requisite to respond appropriately to individual patient characteristics. The personalization could be operationalized and enhanced through AI, which can usefully synthesize the multitudinous amount of pertinent information. The resulting diagnostic suggestion, Nudge 2.0, could complement but not override the physician's private information and judgment, with the promise of enhanced health outcomes.

### References

Alotaibi, Yasser K., and Federico Federico. "The Impact of Health Information Technology on Patient Safety." Saudi Medical Journal 38, no. 12 (2017): 1173–1180. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5787626/

Bates, David W., and Hardeep Singh. "Two Decades Since To Err Is Human: An Assessment Of Progress And Emerging Priorities In Patient Safety." (2018) https://www.healthaffairs.org/doi/10.1377/hlthaff.2018.0738

Böhm, Robert, Cornelia Betsch, Lars Korn, Cindy Holtmann. "Exploring and Promoting Prosocial Vaccination: A Cross-Cultural Experiment on Vaccination of Health Care Personnel." BioMed Research International, vol. 2016, Article ID 6870984, 9 pages, 2016. https://doi.org/10.1155/2016/6870984

Centers for Disease Control and Prevention. "Health Insurance Portability and Accountability Act (HIPAA)." CDC Public Health Law Program. https://www.cdc.gov/phlp/publications/topic/hipaa.html

Chapman GB, Li M, Colby H, Yoon H. "Opting In vs Opting Out of Influenza Vaccination." JAMA. 2010;304(1):43–44. doi:10.1001/jama.2010.892

Cherone, Heather. "How Did Chicago Become So Segregated? By Inventing Modern Segregation." WTTW News. https://interactive.wttw.com/firsthand/segregation/how-did-chicago-become-so-segregated-by-inventing-modern-segregation

City of Chicago. "Healthy Chicago 2025 Data Compendium." City of Chicago Department of Public Health, October 22, 2019. https://www.chicago.gov/content/dam/city/depts/cdph/CDPH/Healthy_Chicago_2025_Data-Compendium_10222019.pdf

City of Chicago. "Leading Causes of Death in Chicago, 2006." Chicago Department of Public Health, https://www.chicago.gov/dam/city/depts/cdph/statistics_and_reports/SR_leading%20causes%20of%20death%202006.pdf

Desiraju, S., & Dietvorst, B. J. (2023). "Reason defaults: Presenting defaults with reasons for choosing each option helps decision makers with minority interests." https://journals.sagepub.com/doi/abs/10.1177/09567976231198184

Graber, Mark L., Nancy Franklin, and Richard Gordon. "Diagnostic error in internal medicine." Archives of Internal Medicine 165, no. 13 (2005): 1493-1499. https://www.researchgate.net/publication/298348382_Diagnostic_Error_in_Internal_Medicine

Hayward, R., Hofer, T. "Estimating hospital deaths due to medical errors: preventability is in the eye of the reviewer." JAMA 286, no. 4 (2001): 415–20. https://pubmed.ncbi.nlm.nih.gov/11466119/

Institute of Medicine. To Err Is Human: Building a Safer Health System. National Academy Press, 1999. https://nap.nationalacademies.org/resource/9728/To-Err-is-Human-1999--report-brief.pdf

Jon Shreve, Jill Van Den Bos, Travis Gray, Michael Halford, Karan Rustagi, Eva Ziemkiewicz. "The Economic Measurement of Medical Errors." Society of Actuaries' Health Section, June 2010. https://docplayer.net/5172892-The-economic-measurement-of-medical-errors-sponsored-by-society-of-actuaries-health-section-prepared-by.html

Makary, Martin A. and Michael Daniel. "Medical error—the third leading cause of death in the US." British Medical Journal 353 (2016) https://www.bmj.com/content/353/bmj.i2139

Madrian, Brigitte C., and Dennis F. Shea. "The Power of Suggestion: Inertia in 401(K) Participation And Savings Behavior." (2001) Pages 1149-1187 https://www.jstor.org/stable/2696456

Mills, S. "Personalized Nudging." Behavioural Public Policy 6, no. 1 (2020): 150-159. doi:10.1017/bpp.2020.7 doi:10.1017/bpp.2020.7

Mullainathan, Sendhil, and Ziad Obermeyer. "Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care." Quarterly Journal of Economics 137, no. 2 (2022) Page 682 https://academic.oup.com/qje/issue/137/2

"A National Survey of Medical Error Reporting Laws." Yale Journal of Health Policy, Law, and Ethics 9, no. 1 (2009): 201–86. https://openyls.law.yale.edu/handle/20.500.13051/6099

Paunov, Y., Wänke, M., & Vogel, T. (2018). "Transparency effects on policy compliance: Disclosing how defaults work can enhance their effectiveness." Behavioural Public Policy, Pages 1–22. https://www.cambridge.org/core/journals/behavioural-public-policy/article/transparency-effects-on-policy-compliance-disclosing-how-defaults-work-can-enhance-their-effectiveness/C09BD43EA7FE06BA6DD27AE1D783FB12

Robert Böhm, Cornelia Betsch, Lars Korn, Cindy Holtmann, "Exploring and Promoting Prosocial Vaccination: A Cross-Cultural Experiment on Vaccination of Health Care Personnel", BioMed Research International, vol. 2016, Article ID 6870984, 9 pages, 2016. https://doi.org/10.1155/2016/6870984

Sunstein, Cass R. "Behavioral Economics and Paternalism." Yale Law Journal 122, no. 7 (2013): Pages 1867-1899. https://www.yalelawjournal.org/feature/the-storrs-lectures-behavioral-economics-and-paternalism

Thaler, Richard H., and Cass R. Sunstein. Nudge: The Final Edition. Penguin Books, 2021. https://www.penguinrandomhouse.com/books/623739/nudge-the-final-edition-by-richard-h-thaler-and-cass-r-sunstein/

The HIPAA Journal. https://www.hipaajournal.com/

**Notes**

[1] Zhang, J., Patel, V. L., and Johnson, T. R. 2002. "Medical error: Is the solution medical or cognitive?" Journal of the American Medical Informatics Association: JAMIA 9 (6 Suppl): S75–S77. https://doi.org/10.1197/jamia.m1232.
[2] Makary, Martin A. and Michael Daniel. "Medical error—the third leading cause of death in the US." British Medical Journal 353 (2016) https://www.bmj.com/content/353/bmj.i2139
[3] Jon Shreve, Jill Van Den Bos, Travis Gray, Michael Halford, Karan Rustagi, Eva Ziemkiewicz. "The Economic Measurement of Medical Errors." Society of Actuaries' Health Section, June 2010

https://docplayer.net/5172892-The-economic-measurement-of-medical-errors-sponsored-by-society-of-actuaries-health-section-prepared-by.html
[4] Institute of Medicine. To Err Is Human: Building a Safer Health System. National Academy Press, 1999. https://nap.nationalacademies.org/resource/9728/To-Err-is-Human-1999--report-brief.pdf
[5] Hayward, R., Hofer, T. "Estimating hospital deaths due to medical errors: preventability is in the eye of the reviewer." JAMA 286, no. 4 (2001): 415–20.
https://pubmed.ncbi.nlm.nih.gov/11466119/
[6] Graber, Mark L., Nancy Franklin, and Richard Gordon. "Diagnostic error in internal medicine." Archives of Internal Medicine 165, no. 13 (2005): 1493-1499.
https://www.researchgate.net/publication/298348382_Diagnostic_Error_in_Internal_Medicine
[7] City of Chicago. "Healthy Chicago 2025 Data Compendium." City of Chicago Department of Public Health, October 22, 2019.
https://www.chicago.gov/content/dam/city/depts/cdph/CDPH/Healthy_Chicago_2025_Data-Compendium_10222019.pdf.
[8] Illinois GOV, Leading Causes of Death by Age Group, Illinois Residents, 2021
https://dph.illinois.gov/content/dam/soi/en/web/idph/publications/idph/data-and-statistics/vital-statistics/death-statistics/Leading-causes-by-age-2021.pdf
[9] Illinois GOV, Diseases of the Heart and Stroke: Illinois' Leading Killers
https://dph.illinois.gov/topics-services/diseases-and-conditions/heart-stroke.html.
[10] Chun Wai Wong, Jacopo Tafuro, Ziyad Azam, Duwarakan Satchithananda, Simon Duckett, Diane Barker, Ashish Patwala, Fozia Z. Ahmed, Christian Mallen, Chun Shing Kwok,
"Misdiagnosis of Heart Failure: A Systematic Review of the Literature."
Journal of Cardiac Failure, Volume 27, Issue 9, 2021, Pages 925-933, ISSN 1071-9164,
https://doi.org/10.1016/j.cardfail.2021.05.014.
[11] Chun Wai Wong, Jacopo Tafuro, Ziyad Azam, Duwarakan Satchithananda, Simon Duckett, Diane Barker, Ashish Patwala, Fozia Z. Ahmed, Christian Mallen, Chun Shing Kwok,
"Misdiagnosis of Heart Failure: A Systematic Review of the Literature."
Journal of Cardiac Failure, Volume 27, Issue 9, 2021, Pages 925-933, ISSN 1071-9164,
https://doi.org/10.1016/j.cardfail.2021.05.014.
[12] City of Chicago. "Leading Causes of Death in Chicago, 2006." Chicago Department of Public Health,
https://www.chicago.gov/dam/city/depts/cdph/statistics_and_reports/SR_leading%20causes%20of%20death%202006.pdf.
[13] Illinois Department of Public Health. "Leading Causes of Death by Age in Illinois, 2021."https://dph.illinois.gov/content/dam/soi/en/web/idph/publications/idph/data-and-statistics/vital-statistics/death-statistics/Leading-causes-by-age-2021.pdf.
[14] Thaler, Richard H., and Cass R. Sunstein. Nudge: The Final Edition. Penguin Books, 2021. Page 10
[15] Mullainathan, Sendhil, and Ziad Obermeyer. "Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care." Quarterly Journal of Economics 137, no. 2 (2022) Page 682
https://academic.oup.com/qje/issue/137/2
[16] Mills, S. "Personalized Nudging." Behavioural Public Policy 6, no. 1 (2020): 150-159. doi:10.1017/bpp.2020.7
[17] Mullainathan, Sendhil, and Ziad Obermeyer. "Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care." Quarterly Journal of Economics 137, no. 2 (2022) Page 682
https://academic.oup.com/qje/issue/137/2

[18] "A National Survey of Medical Error Reporting Laws." Yale Journal of Health Policy, Law, and Ethics 9, no. 1 (2009): 201–86. https://openyls.law.yale.edu/handle/20.500.13051/6099
[19] "A National Survey of Medical Error Reporting Laws." Yale Journal of Health Policy, Law, and Ethics 9, no. 1 (2009): 201–86. https://openyls.law.yale.edu/handle/20.500.13051/6099
[20] "A National Survey of Medical Error Reporting Laws." Yale Journal of Health Policy, Law, and Ethics 9, no. 1 (2009): 201–86. https://openyls.law.yale.edu/handle/20.500.13051/6099
[21] "A National Survey of Medical Error Reporting Laws." Yale Journal of Health Policy, Law, and Ethics 9, no. 1 (2009): 201–86 https://openyls.law.yale.edu/handle/20.500.13051/6099
[22] Alotaibi, Yasser K., and Federico Federico. "The Impact of Health Information Technology on Patient Safety." Saudi Medical Journal 38, no. 12 (2017): 1173–1180. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5787626/
[23] Alotaibi, Yasser K., and Federico Federico. "The Impact of Health Information Technology on Patient Safety." Saudi Medical Journal 38, no. 12 (2017): 1173–1180. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5787626/
Bates, David W., and Hardeep Singh. "Two Decades Since To Err Is Human: An Assessment Of Progress And Emerging Priorities In Patient Safety." (2018) https://www.healthaffairs.org/doi/10.1377/hlthaff.2018.0738
Also see Wang SJ, Middleton B, Prosser LA, Bardon CG, Spurr CD, Carchidi PJet al. "A cost-benefit analysis of electronic medical records in primary care." Am J Med. 2003;114(5):397–403. Crossref, Medline, Google Scholar https://pubmed.ncbi.nlm.nih.gov/12714130/
[24] Thaler, Richard H., and Cass R. Sunstein. Nudge: The Final Edition. Penguin Books, 2021. Page 10
[25] Thaler, Richard H., and Cass R. Sunstein. Nudge: The Final Edition. Penguin Books, 2021. Page 10
[26] Thaler, Richard H., and Cass R. Sunstein. Nudge: The Final Edition. Penguin Books, 2021. Page 22-23
[27] Mullainathan, Sendhil, Ziad Obermeyer, "Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care," The Quarterly Journal of Economics, Volume 137, Issue 2, May 2022, Pages 679–727, https://doi.org/10.1093/qje/qjab046
[28] Center for Health Incentives and Behavioral Economics - About. Center for Health Incentives and Behavioral Economics, University of Pennsylvania. Accessed November 3, 2023. https://chibe.upenn.edu/about/.
[29] Eric J. Johnson, Daniel Goldstein, "Do Defaults Save Lives?." Science 302,1338-1339 (2003) https://www.science.org/doi/10.1126/science.1091721
[30] Thaler, Richard H., and Cass R. Sunstein. Nudge: The Final Edition. Penguin Books, 2021. Page 88
[31] Sunstein, Cass R. "Deciding by Default." Formerly American Law Register, December 2013. 2013 by the University of Pennsylvania Law Review. Accessed November 3, 2023. https://scholarship.law.upenn.edu/cgi/viewcontent.cgi?article=1000&context=penn_law_review/. Page 1
[32] Madrian, Brigitte C., and Dennis F. Shea. "The Power of Suggestion: Inertia in 401(K) Participation and Savings Behavior." (2001) Pages. 1149-1187 https://www.jstor.org/stable/2696456
[33] Madrian, Brigitte C., and Dennis F. Shea. "The Power of Suggestion: Inertia in 401(K) Participation and Savings Behavior." (2001) Pages. 1149-1187 https://www.jstor.org/stable/2696456

[34] Xin Liu, Ning Zhao, Shu Li, Rui Zheng, "Opt-out policy and its improvements promote COVID-19 vaccinations," Social Science & Medicine, Volume 307, 2022, https://doi.org/10.1016/j.socscimed.2022.115120.
[35] Xin Liu, Ning Zhao, Shu Li, Rui Zheng, "Opt-out policy and its improvements promote COVID-19 vaccinations," Social Science & Medicine, Volume 307, 2022, https://doi.org/10.1016/j.socscimed.2022.115120.
[36] Robert Böhm, Cornelia Betsch, Lars Korn, Cindy Holtmann, "Exploring and Promoting Prosocial Vaccination: A Cross-Cultural Experiment on Vaccination of Health Care Personnel", BioMed Research International, vol. 2016, Article ID 6870984, 9 pages, 2016. https://doi.org/10.1155/2016/6870984
[37] Chapman GB, Li M, Colby H, Yoon H. "Opting In vs Opting Out of Influenza Vaccination." JAMA.2010; 304(1):43–44. doi:10.1001/jama.2010.892, Pages 43–44, 2010
[38] Sunstein, Cass R. "Deciding by Default." Formerly American Law Register, December 2013.  2013 by the University of Pennsylvania Law Review. Accessed November 3, 2023. https://scholarship.law.upenn.edu/cgi/viewcontent.cgi?article=1000&context=penn_law_review/. Page 5.
[39] Paunov, Y., Wänke, M., & Vogel, T. (2018). "Transparency effects on policy compliance: Disclosing how defaults work can enhance their effectiveness." Behavioural Public Policy, Pages 1–22. (2018) https://www.cambridge.org/core/journals/behavioural-public-policy/article/transparency-effects-on-policy-compliance-disclosing-how-defaults-work-can-enhance-their-effectiveness/C09BD43EA7FE06BA6DD27AE1D783FB12
[40] Desiraju, S., & Dietvorst, B. J. (2023). "Reason defaults: Presenting defaults with reasons for choosing each option helps decision-makers with minority interests." https://journals.sagepub.com/doi/abs/10.1177/09567976231198184
[41] Paunov, Y., Wänke, M., & Vogel, T. (2018). "Transparency effects on policy compliance: Disclosing how defaults work can enhance their effectiveness." Behavioural Public Policy, Pages 1–22. (2018) https://www.cambridge.org/core/journals/behavioural-public-policy/article/transparency-effects-on-policy-compliance-disclosing-how-defaults-work-can-enhance-their-effectiveness/C09BD43EA7FE06BA6DD27AE1D783FB12
[42] Desiraju, S., & Dietvorst, B. J. (2023). "Reason defaults: Presenting defaults with reasons for choosing each option helps decision-makers with minority interests." https://journals.sagepub.com/doi/abs/10.1177/09567976231198184
[43] Desiraju, S., & Dietvorst, B. J. (2023). "Reason defaults: Presenting defaults with reasons for choosing each option helps decision-makers with minority interests." https://journals.sagepub.com/doi/abs/10.1177/09567976231198184
[44] Desiraju, S., & Dietvorst, B. J. (2023). "Reason defaults: Presenting defaults with reasons for choosing each option helps decision-makers with minority interests." https://journals.sagepub.com/doi/abs/10.1177/09567976231198184
[45] Paunov, Y., Wänke, M., & Vogel, T. (2018). "Transparency effects on policy compliance: Disclosing how defaults work can enhance their effectiveness." Behavioural Public Policy, Pages 1–22. (2018) https://www.cambridge.org/core/journals/behavioural-public-policy/article/transparency-effects-on-policy-compliance-disclosing-how-defaults-work-can-enhance-their-effectiveness/C09BD43EA7FE06BA6DD27AE1D783FB12
[46] Mills, Stuart. "Personalized nudging." Behavioural Public Policy 6 (2020): Page 150 doi:10.1017/bpp.2020.7

[47] Sunstein, Cass R. "Behavioral Economics and Paternalism." Yale Law Journal 122, no. 7 (2013): Pages 1867-1899. https://www.yalelawjournal.org/feature/the-storrs-lectures-behavioral-economics-and-paternalism
Mills, Stuart. "Personalized Nudging." Behavioural Public Policy 6 (2020): Pages 150-159 doi:10.1017/bpp.2020.7
[48] Sunstein, Cass R. "Behavioral Economics and Paternalism." Yale Law Journal 122, no. 7 (2013): Pages 1867-1899. https://www.yalelawjournal.org/feature/the-storrs-lectures-behavioral-economics-and-paternalism
[49] Mills, Stuart. "Personalized Nudging." Behavioural Public Policy 6 (2020): Pages 150-159. doi:10.1017/bpp.2020.7
[50] Centers for Disease Control and Prevention. "Health Insurance Portability and Accountability Act (HIPAA)." CDC Public Health Law Program. https://www.cdc.gov/phlp/publications/topic/hipaa.html.
[51] Centers for Disease Control and Prevention. "Health Insurance Portability and Accountability Act (HIPAA)." CDC Public Health Law Program. https://www.cdc.gov/phlp/publications/topic/hipaa.html.
[52] The HIPAA Journal. https://www.hipaajournal.com/.
[53] Desiraju, S., & Dietvorst, B. J. (2023). "Reason defaults: Presenting defaults with reasons for choosing each option helps decision makers with minority interests." https://journals.sagepub.com/doi/abs/10.1177/09567976231198184
[54] Mullainathan, Sendhil, and Ziad Obermeyer. "Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care." Quarterly Journal of Economics 137, no. 2 (2022) Page 682, https://doi.org/10.1093/qje/qjab046.
[55] Mullainathan, Sendhil, and Ziad Obermeyer. "Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care." Quarterly Journal of Economics 137, no. 2 (2022) Page 682, https://doi.org/10.1093/qje/qjab046.
[56] Mills, Stuart. "Personalized nudging." Behavioural Public Policy 6 (2020): pages 150 – 159 doi:10.1017/bpp.2020.7
[57] Mullainathan, Sendhil, and Ziad Obermeyer. "Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care." Quarterly Journal of Economics 137, no. 2 (2022) Page 679, https://doi.org/10.1093/qje/qjab046.
[58] Mullainathan, Sendhil, and Ziad Obermeyer. "Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care." Quarterly Journal of Economics 137, no. 2 (2022) Page 680, https://doi.org/10.1093/qje/qjab046.
[59] Mullainathan, Sendhil, and Ziad Obermeyer. "Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care." Quarterly Journal of Economics 137, no. 2 (2022) Page 680, https://doi.org/10.1093/qje/qjab046.
[60] Mullainathan, Sendhil, and Ziad Obermeyer. "Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care." Quarterly Journal of Economics 137, no. 2 (2022) Page 680, https://doi.org/10.1093/qje/qjab046.
[61] Mullainathan, Sendhil, and Ziad Obermeyer. "Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care." Quarterly Journal of Economics 137, no. 2 (2022) Page 710, https://doi.org/10.1093/qje/qjab046.
[62] Mullainathan, Sendhil, and Ziad Obermeyer. "Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care." Quarterly Journal of Economics 137, no. 2 (2022) Page 679, https://doi.org/10.1093/qje/qjab046.

[63] Cherone, Heather. "How Did Chicago Become So Segregated? By Inventing Modern Segregation." WTTW News. Accessed 3 October 2023 https://interactive.wttw.com/firsthand/segregation/how-did-chicago-become-so-segregated-by-inventing-modern-segregation

[64] Mullainathan, Sendhil, and Ziad Obermeyer. "Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care." Quarterly Journal of Economics 137, no. 2 (2022) Page 693, https://doi.org/10.1093/qje/qjab046.

[65] Mullainathan, Sendhil, and Ziad Obermeyer. "Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care." Quarterly Journal of Economics 137, no. 2 (2022) Page 711, https://doi.org/10.1093/qje/qjab046.