Risk & Danger

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Improving risk literacy

Developing risk literacy could greatly benefit healthcare.

Mirjam Jenny

Head Research Scientist,
Harding Center for Risk Literacy
Max Planck Institute for Human
Development, Germany

jenny@mpib-berlin.mpg.de

@Risk_Literacy

harding-center.mpg.de/de

What research is undertaken at the Harding Center for Risk Literacy?

Our goal is to help people in their struggle to understand and assess risks and to facilitate better risk-related decisions. Our primary focus has been on healthcare where transparent risk communication can support patients to make informed decisions about their own health. More recently, we've started addressing additional areas such as consumer risks, financial risks, and digital risks. By conducting studies, experiments, and surveys, we investigate people's problems with understanding numbers and find solutions to these. We strive to raise the number of risk-literate citizens, that is, informed citizens who can critically interpret and question the risks communicated to them by experts or the media. We also offer special training for physicians and journalists, who need to know how to interpret and communicate risks to their patients, readers, and the general public.

How best can health professionals communicate risk?

One of the most important principles of risk communication is that numbers need to be made transparent. For example, changes in risk should be communicated using absolute risks and base rates instead of relative risks. Let's consider the risks associated with eating processed meat like bacon or sausages. The World Health Organization warns that processed meat is carcinogenic because it was found that eating 50 grams of processed meat a day increased the chance of developing colorectal cancer by 18%. Looking at this relative risk increase of 18%, eating processed meat seems risky. This number leaves out two important risk aspects, however: the baseline risk that one develops colorectal cancer and the absolute increase caused by eating processed meat. What does the 18% mean? A relative increase of 18% could mean an increase from 500 in 1000 people to 600 in 1000 people that get diagnosed with the cancer, for example. It could also mean an increase from five in 1000 to six in 1000. While the former risk increase would result in 100 additional diagnoses in 1000 people, the latter and correct risk increase results in one additional diagnosis in 1000 people. Stated in absolute terms, the risk increase of one in 1000 people is more transparent than the 18% relative risk increase because it provides more information. It provides the base rate, in other words, how often the cancer occurs (five in 1000 people get diagnosed with colorectal cancer) as well as the absolute risk increase attributable to processed meat (one additional diagnosis in 1000 people). There are many more non-transparent formats that are often used but that would have more transparent counterparts. Communicators need to understand why some numerical formats are more transparent than others and make more conscious efforts to choose transparent formats. Unfortunately, experts are often not aware of these differences and can themselves be misled by non-transparent formats. In addition to our work on risk perception and risk communication, we develop decision tools that help people make better decisions. These tools help, for example, emergency physicians to make good decisions quickly.

Can you tell us more about the fact boxes that the Harding Center has developed to help patients and physicians assess the benefits and harms of treatments? Do these also include risks of no treatment?

Fact boxes communicate the best available evidence about a specific topic in an easily-understandable manner. The most important benefits and harms of screenings, diagnostic and therapeutic interventions, or treatments are contrasted with each other in a tabular format thus allowing even people with no medical or statistical background to make informed decisions. Some of our own fact boxes contain graphical representations of the benefits and harms, so-called icon arrays, in addition to tables. The resulting mix of text, tables, and icon arrays make the most important numbers accessible to both patients and physicians.

The simple tabular format was originally developed to illustrate the benefits and harms of colorectal cancer screening and later adopted to improve direct-to-consumer drug advertisements. Building on that work, the Harding Center for Risk Literacy builds and disseminates fact boxes on various health topics and highlights the need for transparent risk communication in health care. Several studies show that fact boxes are effective tools for informing the general public about the harms and benefits of medical interventions.

Fact boxes are based on the best available scientific evidence on a specific topic. Ideally they are based on systematic reviews and meta-analyses. Whenever possible, we rely on the Cochrane Database of Systematic Reviews, which is currently the leading resource for systematic reviews in healthcare.

Whether a fact box includes the risk of no treatment depends on the specific question that it addresses and

on the scientific evidence available to address the question. Fact boxes on topics such as general health checks or childhood vaccinations, for example, contain information about the risk of no treatment in the sense of taking no preventive measures. Our fact box on general health checks is based on a Cochrane Systematic Review from 2012 that includes adults aged 18 or older who were followed up between four and 22 years. Amongst other things, it compares how many adults who underwent a general health check and died of cardiovascular disease to the number of people who did not undergo a general health check and died of cardiovascular disease (no treatment group). The same number of people (about 75 in 1000) died of cancer in both groups.

Other systematic reviews and meta-analyses on topics such as breast or colon cancer screening compare screening groups to groups that were not screened or received standard care. Systematic reviews addressing topics such as dietary supplements or influenza vaccinations compare intervention groups to people who received either a placebo or no intervention. In those cases we cannot disentangle the risk of no intervention from the risk of standard care or placebo and thus cannot communicate the risk of no intervention. To sum up, the information included in a fact box depends on the medical evidence that is available.

Please tell us more about your research in emergency medicine.

Emergency physicians frequently encounter patients with nonspecific complaints who report vague conditions such as feelings of weakness or fatigue. These patients are difficult to accurately triage, risk stratify, and diagnose, and their treatment is often delayed. To investigate whether key medical outcomes can be predicted in these patients, we tested an array of statistical and machine learning models in a large group of patients. Collaborating with the university hospital in Basel, Switzerland, and surrounding hospitals, we found that our models could indeed accurately predict patient outcomes. The models also predicted these outcomes more accurately than did physicians' intuitive judgments on how ill the patients looked. These results lay the groundwork for further refining triage and risk-stratification tools for patients with nonspecific complaints. Building on these findings, we are currently investigating whether we can build readily applicable clinical decision support tools such as fast-and-frugal decision trees that physicians can use for patients with nonspecific symptoms. Electronic health records could facilitate the use of such tools.

What are fast-and-frugal decision trees and how might they be applied in clinical practice?

Fast-and-frugal decision trees resemble hierarchically ordered checklists. On the basis of a few key questions to be answered with yes or no, they quickly lead to a recommendation. The yes/no questions are listed in a specific order so that the most important questions are asked first. In many cases it suffices to ask only the top few questions. In this manner, it is possible to make clear recommendations in little time on the basis of a few criteria.

In medical decision trees, each question tackles, for instance, an observed symptom. Depending on the patient's symptoms that are checked by the tree, an initial decision is made, such as whether a patient is an emergency case or not. This is helpful, for example, when doctors need to decide relatively quickly which station to allocate a patient to or which further tests are needed, or in helping patients at home decide on the basis of a small number of observed symptoms whether to consult with a doctor.

Decision trees can hence be advantageous to different groups in medicine. As mentioned, they can be used by patients to decide whether they should seek medical help, but also by medical professionals in their first consultation with a patient to rule out particular illnesses or to take the next corresponding steps.

Not all medical scenarios lend themselves to being described in this way. But in many cases, where time is limited and the most important criteria can be reduced to just a small number of questions, it is possible to make solid decisions using this method.

A couple of years ago, we developed a decision tree that detects clinically relevant depressed moods in young women. In addition to the emergency medicine setting mentioned above, we are also testing whether we can apply these methods to improve the allocation of patients after surgeries. This addresses the problem that many patients who died after surgery were never treated in the intensive care unit and were probably not monitored well enough. In summary, fast-and-frugal trees are simple and versatile decision tools. Due to their simple structure medical professionals could memorise those decision trees that they need particularly often. Due to their simple graphical structure, the trees can also be implemented in the form of posters that are put up on the walls of the emergency room, for example. Finally, due to their simple algorithmic structure, they can easily be implemented into computer software in the form of software agents and made available via mobile apps. ∎

Mirjam Jenny
After receiving her PhD at the University of Basel, spent her postdoc at the Max Planck Institute for Human Development where she won the Otto Hahn Medal. Before joining the Harding Center, she spent one year at the National Association of Statutory Health Insurance Physicians as a data scientist.