Erschienen in: Medical Decision Making (MDM) ; 41 (2021), 7
https://dx.doi.org/10.1177/0272989X21996342

Current Challenges When Using Numbers in Patient Decision Aids: Advanced Concepts

Lyndal J. Trevena, Carissa Bonner, Yasmina Okan, Ellen Peters, Wolfgang Gaissmaier, Paul K. J. Han, Elissa Ozanne, Danielle Timmermans, and Brian J. Zikmund-Fisher

Background. Decision aid developers have to convey complex task-specific numeric information in a way that minimizes bias and promotes understanding of the options available within a particular decision. Whereas our companion paper summarizes fundamental issues, this article focuses on more complex, task-specific aspects of presenting numeric information in patient decision aids. **Methods.** As part of the International Patient Decision Aids Standards third evidence update, we gathered an expert panel of 9 international experts who revised and expanded the topics covered in the 2013 review working in groups of 2 to 3 to update the evidence, based on their expertise and targeted searches of the literature. The full panel then reviewed and provided additional revisions, reaching consensus on the final version. **Results.** Five of the 10 topics addressed more complex task-specific issues. We found strong evidence for using independent event rates and/or incremental absolute risk differences for the effect size of test and screening outcomes. Simple visual formats can help to reduce common judgment biases and enhance comprehension but can be misleading if not well designed. Graph literacy can moderate the effectiveness of visual formats and hence should be considered in tool design. There is less evidence supporting the inclusion of personalized and interactive risk estimates. **Discussion.** More complex numeric information. such as the size of the benefits and harms for decision options, can be better understood by using incremental absolute risk differences alongside well-designed visual formats that consider the graph literacy of the intended audience. More research is needed into when and how to use personalized and/or interactive risk estimates because their complexity and accessibility may affect their feasibility in clinical practice.

Keywords
decision aids, risk communication, standards

A large body of evidence now exists demonstrating that patient decision aids are an effective way to increase informed choice across a range of health decisions.[1] Good-quality decision aids provide balanced information about the available options, the benefits and harms of each option, and how likely they are to occur.[2] By quantifying the outcomes of different options using best practice methods, patients will have a more accurate perception and understanding of the size of those benefits and harms.[1,3] This is obviously a fundamental component of good-quality health decisions.

However, unless the science of risk communication is appropriately applied, decision aids can introduce bias, manipulate, and persuade patients to choose one option over another. Since a core premise of patient decision aids is to enable patients to make an informed decision

Corresponding Author
Lyndal J. Trevena, Faculty of Medicine and Health, School of Public Health, The University of Sydney, Room 121A, Edward Ford Building (A27), Sydney, NSW 2006, Australia (lyndal.trevena@sydney.edu.au).

that aligns with their preferences and values, such biases should be minimized wherever possible.[4]

As part of the updating of the background evidence for the International Patient Decision Aids Standards (IPDAS), we undertook a broad review of the evidence related to approaches for conveying numeric information for maximal understanding. Because the literature on presenting probability information is both broad and rapidly growing, we divided our findings into 2 articles. The first, our companion article in this special issue, focuses on fundamental principles.

However, even if decision aid developers understand and incorporate fundamental principles in data communication, they often grapple with how best to implement task-specific risk communication within their tools. As health decisions become more complex, technology becomes more advanced, and our ability to estimate risks becomes more sophisticated, we face a tradeoff between the desire to develop a state-of-the-art tool and the need for feasibility and equitable accessibility in real-world clinical settings. While acknowledging the relevance of fundamental concepts in communicating using numbers that we summarized in our companion article, we focus here on the evidence base for applying these principles in varied risk communication contexts and discuss a number of emerging areas for further research.

Methods

This article is the second half of the evidence update for IPDAS chapter, "Communicating Probabilities." The original standards were developed in 2005 and updated in 2013.[2,5] Our current chapter update followed the same approach as previously, with an invitation to previous authors initiated in early 2019 and new coauthors invited to cover all aspects of the chapter. The authors are experts from North America, Europe, and Australia who convened over several teleconferences, one meeting at the International Shared Decision-Making Conference in July 2019, and via email. Several opportunities were also provided for the chapter leads (L.J.T. and B.J.Z.-F.) to liaise with other chapter lead authors about overlap and gaps between the standards.

As before, the team reviewed the previous chapter sections and decided whether to remove, merge, or add any further issues. Ten topics were agreed as covering the key aspects of communicating numeric information in patient decision aids. Five of these were considered to be fundamental principles and are detailed in our first article. The remainder apply numeric information in more complex contexts and are outlined in this second article. Authors worked in groups of 2 or 3 on sections of the chapter that most closely reflected their areas of expertise and developed a series of narrative reviews. We have continued to provide this update as a nonsystematic expert review of the literature on these 10 topics, drawing on the depth and breadth of the authors' expertise. Following the development of the expert-written section updates, all coauthors further contributed to the update, which includes more than 230 references.

Results

The science in some aspects of this field has remained relatively unchanged since the previous update (effect sizes for treatment options, interactive and web-based formats), so we have provided a brief overview and a statement about the strength and quality of the evidence. Other aspects have seen considerable advancement since the previous update (visual formats, graph literacy, personalized risk estimates), and we have provided more detail along with an indication of the strength and quality of the evidence. Where emerging issues for future research and/or future systematic reviews were identified, these were highlighted and expanded further in the Discussion section.

The key recommendations where stronger evidence exists are summarized in Table 1 below.

How Should the Effect Sizes of Treatment and Screening Options Be Presented?

Patient decision aids usually require communication of the benefits and harms of options within a particular health decision. For example, this might be the amount by which the chance of dying from breast cancer is

Faculty of Medicine and Health, School of Public Health, The University of Sydney, Sydney, NSW, Australia (LJT, CB); Ask Share Know NHMRC Centre for Research Excellence, The University of Sydney, Australia (LJT, CB); Centre for Decision Research, University of Leeds, Leeds, UK (YO); University of Oregon, Eugene, OR, USA (EP); University of Konstanz, Konstanz, Baden-Wurttemberg, Germany (WG); Center for Outcomes Research and Evaluation, Maine Medical Center Research Institute, Portland, ME, USA (PKJH); School of Medicine, Tufts University, Medford, MA, USA (PKJH); University of Utah, Salt Lake City, UT, USA (EO); Amsterdam UMC, Vrije Universiteit Amsterdam, Amsterdam, North Holland, The Netherlands (DT); University of Michigan, Ann Arbor, MI, USA (BJZ-F).
The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article. The authors disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was completed with no external funding. The authors received their usual salaries from the organizations outlined under their affiliations.

Table 1 Key Recommendations for Decision Aid Developers

Topic	Recommendations
Presenting the effect sizes of treatment and screening options	• Use either independent event rates (with simple frequencies or percentages) and/or an incremental increase/decrease (absolute) from baseline risk estimates • Try to minimize framing (loss and gain used equally, see visual formats below)
How and when visual formats should be used	• Visual formats for event rates (e.g., icon arrays, bar charts, etc.) generally improve understanding of numeric estimates and minimize bias from framing and denominator neglect • Ideally convey the "part-to-whole" relationship by displaying background and foreground estimates (e.g., through icon arrays or stacked bar charts); this promotes transparency and supports understanding of absolute risk magnitudes • Ensure that spatial features (e.g., heights of bars) convey the same meaning as conventional features (e.g., titles, axes labels, legends, numerical values on scales); this implies avoiding potentially misleading features such as inverted or truncated scales • Where multiple estimates are conveyed, preferably use the same denominator • Label axes clearly and complement visual formats with information that describes what is seen • No one visual format is optimal for every situation; therefore, consider the task at hand and the magnitude of the probabilities when using and selecting visual formats
The role of graph literacy in decision aid development	• Consider that people vary in their ability to extract data and meaning from visual formats • To support understanding among the less graph literate, ensure that visual formats are simple and include clear explanations to convey the meaning of important information and bring attention to it • If possible, conduct pilot testing of visual formats for understanding with the intended audience; however, avoid relying solely on reported preferences for different formats • If feasible, measure graph literacy of prospective users, as patients who lack graph literacy could in some cases be better off with numbers
How and when risks should be personalized	• Personalized risk calculators are highly variable in their accuracy and should be carefully evaluated before use in decision aids • When deciding whether to personalize risk estimates within decision aids, consider both the feasibility of use in practice and clinical context
When and how to use interactive web-based formats	• There is limited and mixed evidence on the use of interactive web-based formats for numeric information, and therefore, we offer no clear recommendation on their use at this time

reduced if you have treatment x or the amount by which your chance of a side effect is increased by taking drug y (this can also be described as the "effect size" or the "magnitude of effect").

Where possible in decision aids, effect sizes should be presented as either independent event rates (using simple frequencies or percentage formats) and/or as an incremental (or absolute) risk increase or decrease from a baseline risk frequency.[3,6,7] A hypothetical example would be that 5 out of 100 (5%) people in a particular population group are likely to die from disease X over the next year without receiving treatment A. This could be described as the baseline frequency or control event rate. By contrast, if these 100 people receive treatment A, their chance of dying from disease X over the next year becomes 4 out of 100 (4%). This second frequency is the event rate with the intervention or treatment. To illustrate how to present the size of the benefit of treatment A, the absolute (incremental) risk reduction would be to say that 1 less person out of 100 will die of disease X over the next year if treatment A is received. (Note that the relative risk reduction with treatment A in this example is 20%.) It has been consistently recommended that relative risk presentations alone should be avoided as they tend to magnify risk perceptions and decrease understanding in both patients and clinicians.[7–13] Similarly, the number needed to treat and number needed to harm formats should also be avoided in patient decision aids, as they lead to overestimates of treatment effects and are poorly understood.[14] There is no advantage to providing baseline risk alongside relative risks, and this practice should continue to be avoided.[15,16] These recommendations are based on 2 systematic reviews and 5 additional randomized controlled trials (RCTs).[3,6,8,11–13]

The framing of outcomes in terms of losses or gains also affects people's choices.[17] Framing outcomes in terms of potential gains (e.g., the chances of survival) often generates risk-averse choices, whereas framing outcomes in terms of potential losses (e.g., the chances of death) often generates risk-seeking choices. This guidance is based on a systematic review and 2 RCTs.[18–20]

The principle of using absolute rates also applies for reporting the benefits and harms of testing and screening. Screening decision aids should include estimates of 1) disease and disease-specific mortality with and without screening, 2) false-positives, and 3) false-negatives. The presentation formats in screening decision aids should reflect the type of information being conveyed. For example, the baseline risk of getting breast cancer should have the reference group clearly defined over time and will probably be best understood as a simple frequency since it will be a relatively rare event. As a percentage, it will be less than 1% and may be less well understood because of the use of decimal points.

Despite consistent evidence about best formats, many clinical guidelines continue to use treatment effect formats incorrectly and inconsistently. In fact, a review of US cancer screening and prevention guidelines[21] found that many guidelines presented benefit information in relative risk terms and harm information in absolute risk terms. This imbalance has the potential to overemphasize testing and treatment benefits relative to their harms. Care needs to be taken to present information in a neutral manner in the development of patient decision aids.

An emerging issue for screening decision aids is the inclusion of estimates of "overdiagnosis." Overdiagnosis can be caused by overdetection or overdefinition,[22] and some countries now recommend that it be included in cancer screening information for the general public.[23] However, this concept is not well understood and can influence screening decisions.[23,24] Misperceptions about cancer risk and patient preferences may also play a role in responses to information about overdiagnosis and subsequent cancer screening decisions.[25] Early trials that have included information about overdiagnosis in cancer screening decision aids have shown an improvement in understanding of this concept.[26,27]

One trial of a mammography decision aid evaluated the effect of including overdetection estimates as simple frequencies with icon arrays on screening decisions.[27] The estimate for overdetection provided in the decision aid was 19 per 1000 women over 20 y, and the decision aid included wording to explain the difference between overdetection and false-positives. There was an improvement in understanding of overdetection when estimates were included in the decision aid.[28] Optimal presentation formats for overdiagnosis estimates and their effects on decision outcomes in screening decision aids are an emerging area for the field and should be flagged for future research.

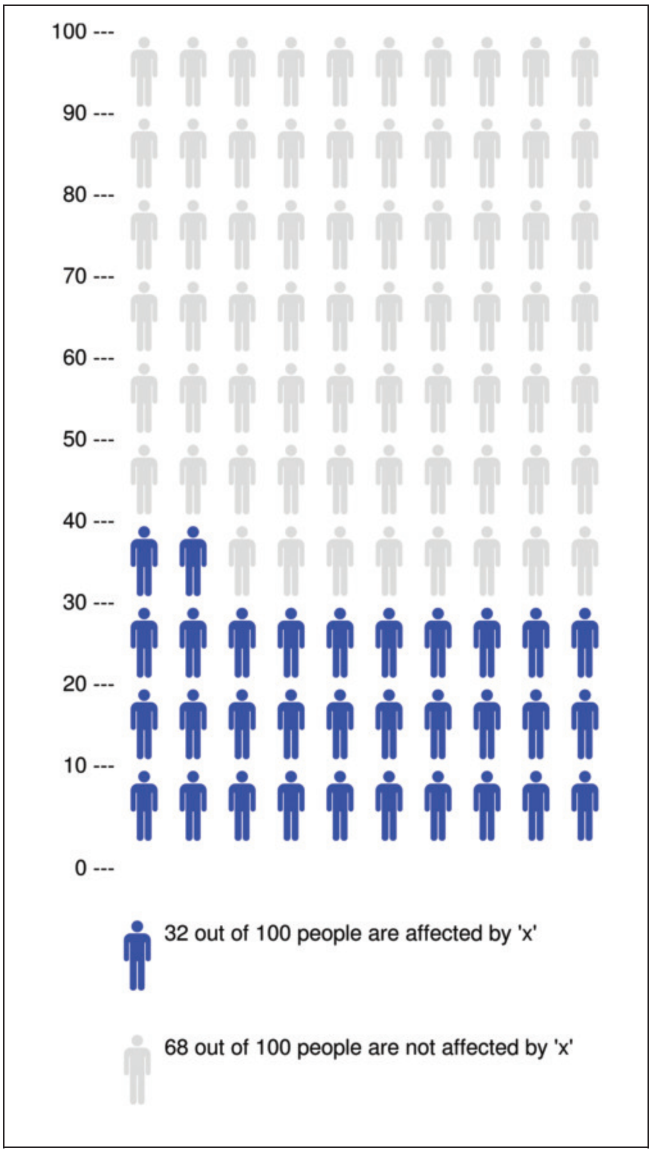

Figure 1 Example of an icon array with background and foreground estimates displayed. Derived using iconarray.com.

How and When Should Visual Formats Be Used?

Presenting event rates with visual formats such as icon arrays (e.g., where stick figures of different colors represent those affected v. not affected by a disease; see Figure 1), bar charts, or flow diagrams is generally recommended to support the interpretation of numerical data.[29–32] This general recommendation is based on strong and often high-quality evidence, much of which we will summarize subsequently. This recommendation has also been put forward in recent systematic review.[30] As caveats, it should be noted that the effect sizes in these studies are typically small to moderate and that the evidence is less clear-cut for more specific recommendations (such as which graph to use exactly for which purpose and for whom). Future systematic reviews on this topic could aim to quantify the strength of existing evidence and identify precisely which specific questions need more research.

Visual formats can help reduce biases such as denominator neglect,[33,34] framing effects,[35,36] and the undue influence of anecdotes,[37] and they can aid the comprehension of more complicated concepts such as incremental risk.[6] Graphs can also improve accuracy in Bayesian reasoning tasks, such as inferring the positive predictive value of a test.[38–44] Even for experts (here, surgeons), transparent visual aids can help to reduce judgment biases in interpreting the scientific medical literature, which still frequently represents risk information in a misleading fashion.[45] People also often prefer graphs over numbers[46] and rate them as more attractive, likeable, or helpful.[40,47–49]

The beneficial effects of visual displays can be partly attributed to their cognitive and motivational advantages, that is, to being easier to process in some cases and attracting more attention. As compared with numerical risk information, graphs can require less cognitive effort to understand.[50] Graphs can also reduce the required processing time relative to tables, particularly for more complex data.[51] They can reveal data patterns that may otherwise go undetected and evoke automatic mathematical operations (e.g., subtraction in comparing the heights of 2 bars).[52,53] In addition, graphs can attract more attention than numerical risk information,[50] particularly among the less numerate.[54] Hence, they may increase the time that people invest in assessing the information compared with mere numbers.[55]

Graphs have sometimes been shown to be suited best to convey the essential aspects of the information (i.e., gross-level information),[56,57] bottom-line meaning, or gist,[58] whereas numerical representations can be better suited to convey more precise aspects of the information (i.e., detailed-level information or verbatim).[56,59,60] The value of visual displays can thus depend on the risk communication goal; a potential weakness of visual displays is that people may focus more on the pattern of data than the precise values, if that is the main objective. For instance, patients presented with a bar graph may make gist-based judgments by comparing the heights of bars and only pay attention to specific numerical details if reminded.[58] This can lead to misinterpretations of displays such as risk ladders that include logarithmic scales, as these may be neglected in some cases.[61] To illustrate, a recent RCT showed that graphs using a log scale to depict the evolution of COVID-19 deaths were associated with less accurate understanding and predictions than graphs using a linear scale.[62]

The effectiveness of specific visual displays depends crucially on how they are designed. Developers of patient decision aids should be aware that graphical display features that promote risk understanding may have other effects such as reducing risk perceptions or intentions for behavior change, depending on the context. The most important general principle to improve understanding is that visual displays should be transparent, which means that they promote unbiased risk understanding and evaluation.[63,64] Transparency requires that all elements of the display are well defined and that part-to-whole relationships in the data are visually available and comparable to accurately and clearly represent the essential risk information. This can be accomplished by using displays that depict both the number of people affected by a risk (the foreground) and the number of people at risk (the background), such as icon arrays or stacked bar charts. Such displays can reduce overestimations of risk,[65,66] particularly among less numerate individuals.[55] In contrast, foreground-only displays (e.g., simple bar graphs representing only those affected) can decrease understanding of absolute risk magnitudes relative to foreground-background displays[36,67] and to purely numerical information.[68] At the same time, foreground-only displays tend to increase perceived risk and risk aversion (e.g., willingness to take a drug to prevent disease or to pay for an improved product).[67,69,70] A recent RCT, however, found that this tendency becomes weaker as the size of the probability conveyed increases.[71]

Another important principle to support understanding is to ensure that spatial features (e.g., heights of bars) convey the same meaning as conventional features such as titles, axes labels, legends, and numerical values on scales. Violations of this principle occur, for example, when scales are inverted or truncated (e.g., where the *y*-axis scale does not start at 0) , which can lead to systematic misinterpretations, particularly among less graph literate individuals.[72] Such graphs can be misleading, and hence, this principle should always be followed if the goal is to improve risk understanding. It should be noted, though, that in some cases, truncation of the *y*-axis may be needed to depict meaningful differences that may be unnoticeable using a zero baseline (e.g., mean differences in quantitative laboratory test results, where there is no meaningful zero). There might also be instances in which space constraints prevent showing the full range of values in scales. In all cases, designers should consider the range and magnitude of effect sizes they wish to communicate and take steps to avoid misinterpretations, such as including clear marks to indicate axes breaks.

Enhancing the accuracy in estimates can also generally be aided by displaying the most crucial elements, hence omitting redundant information.[73,74] In some cases, however, redundant elements (e.g., numerical labels above bars) may be useful to draw people's attention to information that otherwise may be neglected (e.g., axes scales).[69] Indeed, there is some evidence that complementing visual displays with numerical and textual information that describes what is seen may also improve performance and reduce the association between numeracy and accuracy.[75,76]

When informing about different risks, visual displays such as icon arrays should ideally use equal denominators to facilitate comprehension. Whereas displays using different denominators can reduce denominator neglect among more graph-literate individuals, they are less effective among people with low graph literacy. This tendency has been documented in RCTs involving student samples[33,73] as well as surgeons and patients.[72]

For icon arrays, accuracy can be enhanced by using icons that are arranged as groups in a block instead of scattered randomly throughout the array, the latter of which is useful to convey the concept that events (e.g., who is afflicted by disease) occur at random[77] and can increase subjective uncertainty about risk, if that is the communication goal.[78] Studies have also examined whether the specific type of icon used matters, yielding mixed findings. Whereas some studies found that more concrete, high-iconicity arrays (e.g., person-like icons) improve outcomes such as risk recall,[79,80] others found no effects of icon type.[48,81]

The relative effectiveness of different displays also depends on the type of graph used and the task at hand. For instance, some studies found that bar graphs and icon arrays with grouped icons are perceived more accurately and easily by patients than pie charts or icon arrays with ungrouped icons.[56,75] Pie charts, however, may not necessarily hinder understanding of the gist or bottom-line meaning (e.g., which treatment is better).[59,82] Recent work also found better risk understanding for icon arrays and bar charts, relative to other graph types (e.g., line graphs).[76] A unique aspect of icon arrays is that they show frequency information and at the same time convey numbers in a graphical way. This may in some cases result in both better verbatim and gist understanding as compared with text or tables.[49] However, several studies suggest that bar graphs can often be equally beneficial to improve the accuracy of risk understanding and reduce overestimations.[35,55,76] In addition, 2 reviews have highlighted that line graphs are generally better suited for conveying trends over time, whereas bar graphs are often better suited for comparisons across groups.[52,53] However, as noted earlier, the evidence for specific recommendations concerning which graph to use exactly for which purpose is not always clear-cut.

There is also some evidence that the magnitude of probabilities may affect the relative effectiveness of different graph types. For instance, icon arrays have been shown to lead to better accuracy of understanding than bar graphs when probabilities are not too small (e.g., 1% or larger)[83] and numerators are not too large (e.g., less than 100/1000).[84] Studies also suggest that graphs may have a limited influence on people's perceptions of very rare risks (e.g., 0.2%)[85] or relatively large risks (>20%),[55] but more research is needed examining this issue.

A recent study also tested novel visual formats such as "spinners," in which people must evaluate the probability that an arrow would land on a colored segment. Results provide initial evidence that the spinner format can improve gist understanding across numeracy levels.[47] Future research could further investigate the role of this format or related formats to communicate the gist of a risk. Recent work has also examined formats designed to combine the benefits of different graph types such as icon arrays and bar graphs.[86] Although such formats are promising, more research is needed to determine whether they can improve risk understanding over and above more classical formats. The use of multiple icon arrays within a decision aid has had undergone only limited evaluation, and it is unclear at what point people reach cognitive overload.[87] When evaluating novel or uncommon formats, it should be considered that participants may need to get used to these novel formats, so that researchers may want to include a learning or habituation phase to ensure a fair comparison with more classical formats.[7]

Although some research indicates that people may have a slightly better understanding of risk when receiving a format that they prefer (e.g., numbers only v. numbers and graphical displays),[88] it is important to note that individuals' preferences for different visual displays are not always aligned with their performance. That is, the graph types that people prefer or evaluate more positively may not necessarily lead to better performance for a given task.[56,84,89] For instance, pie and clock charts are often preferred but generally not well understood, whereas mere tables are often not preferred but are well understood in general and even best among older adults.[90] Hence, it is not advisable to rely solely on the preferences of patients when designing visual displays to communicate risks.

What Is the Role of Graph Literacy in Developing Decision Aids?

While people vary in their ability to understand and apply mathematical concepts (i.e., numeracy),[91] they also vary in their ability to extract data and meaning from visual formats, whether static or interactive. Graph literacy refers to the ability to understand graphically presented information[92] and can be assessed using objective[92,93] and subjective instruments.[94] Objective instruments assess the ability to understand graphs where a correct answer exists, whereas subjective instruments assess respondents' self-perceived ability to process and use graphs. Higher objective graph literacy is associated with higher education, white ethnicity, and being male.[92,93] Although graph literacy is far less researched than numeracy, the evidence that it predicts the comprehension of graphically displayed information is strong and of high quality, typically with a moderate effect size that could be scrutinized by a systematic review. Less is known about differences in graph literacy across countries.

Graph literacy can moderate the effectiveness of visual formats in improving health risk comprehension[34,36,48] and promoting health management tasks[95] and healthy behaviors.[95–97] High graph literacy is also linked with better performance in Bayesian reasoning tasks that involve visual formats,[98] as well as with doctors' and patients' self-reported use of graphs to communicate health risks to others[94] and of health portals containing graphs.[95,97] As compared with numeracy, less is known about how graph literacy affects information processing and decision making. Existing evidence suggests that higher graph literacy is associated with a stronger tendency to attend to regions of visual formats that have key information for accurate interpretations (e.g., titles, labels, and scales). Instead, individuals who are less graph literate tend to rely more on salient spatial features (e.g., heights of bars).[72] Although numeracy can also affect how people process visual formats,[61,99,100] graph literacy independently predicts the understanding and use of such formats.[90,93,97,101–103] In addition, graph literacy may affect patients' reactions to graphically presented risks. For instance, in a study involving risk ladders, individuals with low graph literacy viewed the risks as larger and more severe, and they expressed more worry.[93]

These research findings imply that visual formats may have limited effectiveness for improving risk comprehension among patients who lack graph literacy, who could in some cases be better off with mere numbers.[48] Visual formats that do not follow general principles of effective design can be particularly misleading for less graph-literate patients. When designing a decision aid, measuring objective numeracy and subjective numeracy, graph literacy, and possibly other aspects of the health literacy[104,105] of the prospective users can help in designing presentation formats that are suitable for their combination of skills. For example, visual formats can be particularly helpful for patients with lower numeracy who have high graph literacy.[36,48] However, it may not always be feasible to measure users' skills and personalize presentation formats accordingly. In such cases, any visual formats in decision aids should be simple and provide clear explanations to convey the meaning of important information and bring patients' attention to it.[31] Simple design features such as explanatory labels may enhance understanding of visual formats even among less graph-literate individuals.[106]

How and When Should Personalized Risk Estimates be Presented?

Personalized risk estimates take into account characteristics that are unique to an individual patient. With the growing availability of increasingly precise, personalized estimates of individuals' risks of various diseases and health outcomes, based on personal characteristics and clinical data including genomic information, personalized risk communication will likely become increasingly important and common. In theory, personalized risk information is more relevant to an individual and may therefore be better processed and understood.[107]

In recent times, there has been a plethora of risk calculators published online enabling the calculation of more personalized estimates of the risk of disease and other health outcomes. By entering individual variables (e.g., age, gender, smoking status, blood test results, etc.), people can find out a more precise estimate of their chance of disease (or disease-related event) over a designated time period. However, a systematic review of online cardiovascular disease risk calculators found that they varied in accuracy and reliability, with the same clinical data producing different results.[108] It also found that only 18% of these tools provided graphical representations of risks in a manner consistent with risk communication guidelines. Similar results have been found in a systematic review of online diabetes risk calculators.[109] An analysis of personalized cancer risk tools also found that their outputs varied in the use of best practice risk communication formats, leading to poor comprehension, misperception of cancer risks, and potentially inappropriate actions.[110] Both experimental and qualitative studies have also shown that clinicians and patients do not necessarily believe or trust personalized risk estimates and may disregard them.[111–113] Thus, efforts to use risk calculators in patient decision aids to produce personalized risk estimates should consider and acknowledge any known limitations in their accuracy and reliability and use accepted best practices to communicate and explain the meaning of these estimates.[5,114]

A Cochrane review concluded that personalized risk estimates appear to have variable effects on health decisions and behaviors such as cancer screening.[107] Another large systematic review and meta-analysis indicated that communicating personalized genetic disease risks has little or no effect on health behavior as compared with generalized risk estimates across a spectrum of behaviors, including cancer screening, alcohol consumption, sun-protection behaviors, diet, and physical activity.[115] Limited evidence suggests that individual characteristics, such as worry about breast cancer and educational status, may moderate the effects of personalized risk messages. For example, Bodurtha et al.[116] found that a brief, personalized intervention regarding mammography adherence had no overall effect on mammography intentions, actual uptake, clinical breast examination, or self-examination but increased mammography rates in the intervention group among patients with higher worry.

Personalized decision aids for a number of health decisions, such as stroke treatment,[117] cardiovascular disease, and diabetes care,[118] have used decision-analytic techniques and embedded decision aids within electronic medical records. Personalized estimates in decision aids also often use web-based delivery methods. Although these tools can be feasible and acceptable to clinicians and patients, their implementation in routine clinical practice remains challenging. Hence, the ability of personalized risk estimates to be used in real-world clinical settings requires further research. Furthermore, the effects of personalized risk information have not been well studied, and more research is needed to understand its value for clinicians and patients and its influence on risk perceptions and decision making. One systematic review suggests that personalized or tailored risk estimates may be discounted or distrusted by patients and thus detrimental to decision making.[119]

In summary, personalized risk estimates are an increasingly common form of information, but important questions remain about their accuracy and reliability (both actual and perceived), effects on decisions and decision makers, and optimal clinical use. Ideally, efforts to integrate personalized risk estimates in decision aids should help patients to understand the meaning and potential value of these estimates as well as the inherent limits in their accuracy and reliability. Decision aid developers and clinicians should also determine whether the potential precision of personalized risk estimates is actually useful for particular decisions.

When and How to Use Interactive and Web-Based Formats in Decision Aids?

Decision aids are often delivered through the use of digital technology, including computers, tablets, and mobile devices. A series of environmental scans have found a large number of decision aids available online, some of which are interactive (e.g., showing the effects of different interventions on reducing cardiovascular disease risk or selecting different outcomes to compare diabetes medications).[109,120–122] This includes 25 for cardiovascular disease prevention, 7 for diabetes medication, 25 for common musculoskeletal conditions, and 4 for prenatal testing.

The online format allows for the use of interactivity within decision aids. The use of these formats is increasing, despite limited evidence of their effectiveness. A systematic review evaluated this issue and assessed whether computer-based decision aids were associated with high-quality decision making (improved knowledge and reduced decisional conflict).[119] This review also looked at whether different features of these tools were more effective in achieving high-quality decision making. This review of 25 RCTs found that computer-based decision aids were more effective than their comparators (usual care or alternative aid controls). Further, specific features of these tools were assessed for effectiveness and found that tailoring of decision aids was negatively associated with patient knowledge. The methods of tailoring incorporated in the decision aids included in the review were superficial and did not provide risks in context of population risks. The authors suggested that the level of tailoring was not sufficient to be useful by the patients who used them.

A recent RCT of an interactive decision aid designed to increase shared decision making for colorectal cancer screening compared with a similar noninteractive decision aid found that patient decision-making outcomes were not improved in the group that used the interactive decision aid.[123] This group of investigators concluded that the resources required to develop and maintain the interactive component of the decision aid were not justified. A study of 5 interactive decision aids found that some patients changed their preferences for treatments and that patients became more risk averse or uncertain after use. However, this study did not have a comparison group.[124]

Overall, early evidence is mixed on the use of interactive web-based formats to communicate probability in decision aids. Use of interactivity in computer-based decision aids may improve some aspects of decision making. However, this limited evidence must be weighed against the evidence indicating that tailoring formats may reduce knowledge when compared with evidence-based static formats.[125,126] Some limited research also assessed whether the animation of icon arrays might improve understanding (verbatim and gist), particularly in people with lower numeracy and lower health literacy, but this was not the case.[127] There is very limited evidence on the effect of animated and interactive formats versus static, and this component of decision aid design is an emerging field and area deserving future research.[128]

The cost of developing and maintaining interactive decision aids can be significant, and the value of such investments should be better understood. In terms of implementation, interactive online formats for decision aids may be easier to tailor to patient characteristics and quicker to update with emerging evidence. However, they may also be classified as a "medical device" requiring additional regulation and resources to maintain them under emerging guidelines.[129]

Discussion

The topics in this article address several key issues that commonly arise in the process of applying best practices in the communication of probability information to specific design requirements of patient decision aids. Given that the aim of patient decision aids is to present balanced information about available options, the strategies discussed here all seek to minimize biases and maximize understanding of the benefits and harms. However, the efficacy of these strategies needs to be weighed against the complexity of the decision, the end users, and the clinical context of implementation. Despite the wider uptake of patient decision aids in practice and a greater level of sophistication in many new tools, there are also a number of key areas that require further research.

The science for how to communicate the effect size of a test or treatment (difference in probabilities) consistently calls for the use of absolute risk differences and the avoidance of relative risks and number needed-to-treat/-harm formats.[5] This is relatively straightforward where outcomes are expressed as proportions, but there remains a paucity of evidence about how to communicate standardized mean differences, which are often used when reporting continuous outcomes in systematic reviews (e.g., pain, function, blood pressure, etc.).[130]

Decision aid developers may also wish to personalize the risk estimates and effects of options within their tools, but this personalization has uncertain and inconsistent effects on knowledge, risk perceptions, and informed choice. It is an issue that needs more research. However, despite this lack of evidence for personalizing risk, there is a burgeoning availability of online personalized risk calculators for consumers to access. These have variable accuracy and need careful consideration when integrated into patient decision aids. If used, personalized risk estimates should be presented in formats that are consistent with this IPDAS update and guidance. Risk calculators should display their results using simple frequencies or percentages and perhaps visual formats such as icon arrays to convey their results and should be linked to actionable outcomes within decision aids as risk-relevant options. More research is needed to explore how people understand personalized risk information, how it should be communicated, and when, why, and for whom personalized risk information is effective in supporting decision making. Finally, it remains an open question whether individuals actually require the added precision of personalized risk information to make informed medical decisions.[131,132] The need for more complex web-based formats for patient decision aids with personalized outcome estimates may best be reserved for particular clinical decisions and contexts, and this is an important area for future research.

Another consideration for decision aid developers is whether to include graphs and visual formats within their tool, and, if so, which formats are most effective at enhancing the accuracy of risk understanding. In short, visual displays often have beneficial effects, and they can help to support interpretation of numerical data. However, the effectiveness of different graph types and visual formats depends on communication goals, features of the task, and/or the magnitude of the probabilities. When considering whether to use visual displays, decision aid developers should also consider the levels of numeracy and graph literacy of prospective users. It is also important to remember that patient decision aids are, by definition, neutral in their presentation of options.

Regardless of context, however, visual displays that follow the general principles outlined in this article should help patients to improve their risk understanding and avoid misinterpretations. Visual formats should be transparent and ideally show the part-to-whole relationship. Icon arrays or stacked bar charts allow foreground as well as background estimates to be represented visually. Visual formats should be pilot tested for understanding, and developers should take care to avoid using misleading images (such as graphs with misleading scales) or using different scales within the same patient decision aid. Testing should evaluate whether audience members miss key messages or draw unintended conclusions.[133] Finally, the field is still in dire need of a more systematic theoretical understanding of why, when, and for whom visual displays are effective.[30,53] This could be achieved by building on recent efforts to develop a unifying framework for understanding decision making with visualizations.[134]

There is also an increasing body of research in numeracy, graph literacy, and related skills of the end users of decision aids. Several issues are worthy of future research attention. First, there is a need to identify effective ways to communicate probabilities to individuals and support decision making among who lack both basic numeracy and graph literacy skills. Second, research on effective methods to improve both numeracy and graph literacy skills would be of high value to patient decision aids. Finally, more research is needed to examine the links between objective and subjective skills and how their interplay affects the emotional response, use, and interpretation of probabilities in decision aids.

In conclusion, there is a well-established evidence base confirming the importance of including numeric estimates of outcomes within patient decision aids.[1] When presented in a way that minimizes bias, this component of decision aid design significantly improves patients' understanding and accuracy of risk perception. Some aspects of numeric presentation are clearly effective and important and should be considered wherever possible in the development of decision aids. Conversely, there are numeric and visual formats that should be avoided because they introduce bias. As this article has outlined, there are also decision and context-specific issues that can guide the inclusion of additional features in patient decision aids and many areas requiring further research.

Acknowledgments

We would like to acknowledge the authors of the previous review on which this article is based, who were not able to contribute to the update: Adrian Edwards, Mirta Galesic, John King, Margaret L. Lawson, Suzanne K. Linder, Isaac Lipkus, and Steven Woloshin.

ORCID iDs

Lyndal J. Trevena https://orcid.org/0000-0003-1419-1832
Carissa Bonner https://orcid.org/0000-0002-4797-6460
Yasmina Okan https://orcid.org/0000-0001-7963-1363
Wolfgang Gaissmaier https://orcid.org/0000-0001-6273-178X
Paul K. J. Han https://orcid.org/0000-0003-0165-1940
Elissa Ozanne https://orcid.org/0000-0001-5352-9459
Danielle Timmermans https://orcid.org/0000-0002-3602-3875
Brian J. Zikmund-Fisher https://orcid.org/0000-0002-1637-4176

References

1. Stacey D, Légaré F, Lewis K, et al. Decision aids for people facing health treatment or screening decisions. *Cochrane Database Syst Rev*. 2017;4(4):CD001431.
2. Elwyn G, O'Connor A, Stacey D, et al. Developing a quality criteria framework for patient decision aids: online international Delphi consensus process. *BMJ*. 2006;333(7565):417.
3. Brick C, McDowell M, Freeman ALJ. Risk communication in tables versus text: a registered report randomized trial on 'fact boxes.' *R Soc Open Sci*. 2020;7(3):190876.
4. Stiggelbout AM, Van der Weijden T, De Wit MP, et al. Shared decision making: really putting patients at the centre of healthcare. *BMJ*. 2012;344:e256.
5. Trevena LJ, Zikmund-Fisher BJ, Edwards A, et al. Presenting quantitative information about decision outcomes: a risk communication primer for patient decision aid developers. *BMC Med Inform Decis Mak*. 2013;13(suppl 2):S7.
6. Zikmund-Fisher BJ, Fagerlin A, Roberts TR, Derry HA, Ubel PA. Alternate methods of framing information about medication side effects: incremental risk versus total risk of occurrence. *J Health Commun*. 2008;13(2):107–24.
7. Tiede KE, Ripke F, Degen N, Gaissmaier W. When does the incremental risk format aid informed medical decisions? The role of learning, feedback, and number of treatment options. *Med Decis Making*. 2020;40(2):212–21.
8. Akl EA, Oxman AD, Herrin J, et al. Using alternative statistical formats for presenting risks and risk reductions. *Cochrane Database Syst Rev*. 2011;2011(3):CD006776.
9. Malenka DJ, Baron JA, Johansen S, Wahrenberger JW, Ross JM. The framing effect of relative and absolute risk. *J Gen Intern Med*. 1993;8(10):543–8.
10. Naylor CD, Chen E, Strauss B. Measured enthusiasm: does the method of reporting trial results alter perceptions of therapeutic effectiveness? *Ann Intern Med*. 1992;117(11):916–21.
11. Covey J. A meta-analysis of the effects of presenting treatment benefits in different formats. *Med Decis Making*. 2007;27(5):638–54.
12. Johnston BC, Alonso-Coello P, Friedrich JO, et al. Do clinicians understand the size of treatment effects? A randomized survey across 8 countries. *CMAJ*. 2016;188(1):25–32.
13. Schwartz LM, Woloshin S, Welch HG. Using a drug facts box to communicate drug benefits and harms: two randomized trials. *Ann Intern Med*. 2009;150(8):516–27.
14. Halvorsen PA, Selmer R, Kristiansen IS. Different ways to describe the benefits of risk-reducing treatments: a randomized trial. *Ann Intern Med*. 2007;146(12):848–56.

15. Marcatto F, Rolison J, Ferrante D. Communicating clinical trial outcomes: effects of presentation method on physicians' evaluations of new treatments. *Judg Decis Making*. 2013;8(1):29–33.
16. Bodemer N, Meder B, Gigerenzer G. Communicating relative risk changes with baseline risk: presentation format and numeracy matter. *Med Decis Making*. 2014;34(5):615–26.
17. Tversky A, Kahneman D. The framing of decisions and the psychology of choice. *Science*. 1981;211(4481):453–8.
18. Lee MJ, Kang H. Designing skin cancer prevention messages: should we emphasize gains or losses? Message framing, risk type, and prior experience. *Am J Health Promot*. 2018;32(4):939–48.
19. Michalovic E, Hall S, Duncan LR, Bassett-Gunter R, Sweet SN. Understanding the effects of message framing on physical activity action planning: the role of risk perception and elaboration. *Int J Behav Med*. 2018;25(6):626–36.
20. Akl EA, Oxman AD, Herrin J, et al. Framing of health information messages. *Cochrane Database Syst Rev*. 2011 (12):CD006777.
21. Caverly TJ, Hayward RA, Reamer E, et al. Presentation of benefits and harms in US cancer screening and prevention guidelines: systematic review. *J Natl Cancer Inst*. 2016; 108(6):djv436.
22. Brodersen J, Schwartz LM, Heneghan C, O'Sullivan JW, Aronson JK, Woloshin S. Overdiagnosis: what it is and what it isn't. *BMJ Evid Based Med*. 2018;23(1):1–3.
23. Waller J, Whitaker KL, Winstanley K, Power E, Wardle J. A survey study of women's responses to information about overdiagnosis in breast cancer screening in Britain. *Br J Cancer*. 2014;111(9):1831–5.
24. Ghanouni A, Renzi C, Waller J. Improving public understanding of 'overdiagnosis' in England: a population survey assessing familiarity with possible terms for labelling the concept and perceptions of appropriate terminology. *BMJ Open*. 2018;8(6):e021260.
25. Phillips K, Hersch J, Turner R, Jansen J, McCaffery K. The influence of the 'cancer effect' on young women's responses to overdiagnosis in cervical screening. *Patient Educ Couns*. 2016;99(10):1568–75.
26. Hoffman AS, Hempstead AP, Housten AJ, et al. Using a patient decision aid video to assess current and former smokers' values about the harms and benefits of lung cancer screening with low-dose computed tomography. *MDM Policy Pract*. 2018;3(1):2381468318769886.
27. Hersch J, Barratt A, Jansen J, et al. Use of a decision aid including information on overdetection to support informed choice about breast cancer screening: a randomised controlled trial. *Lancet*. 2015;385(9978):1642–52.
28. Hersch J, McGeechan K, Barratt A, et al. How information about overdetection changes breast cancer screening decisions: a mediation analysis within a randomised controlled trial. *BMJ Open*. 2017;7(10):e016246.
29. Paling J. Strategies to help patients understand risks. *BMJ*. 2003;327(7417):745–8.
30. Spiegelhalter D. Risk and uncertainty communication. *Annual Review of Statistics and Its Application*. 2017;4(1): 31–60.
31. Garcia-Retamero R, Cokely ET. Designing visual aids that promote risk literacy: a systematic review of health research and evidence-based design heuristics. *Hum Factors*. 2017; 59(4):582–627.
32. Spiegelhalter D, Pearson M, Short I. Visualizing uncertainty about the future. *Science*. 2011;333(6048):1393–400.
33. Garcia-Retamero R, Galesic M, Gigerenzer G. Do icon arrays help reduce denominator neglect? *Med Decis Making*. 2010;30(6):672–84.
34. Okan Y, Garcia-Retamero R, Cokely E, Maldonado A. Individual differences in graph literacy: overcoming denominator neglect in risk comprehension. *J Behav Decis Making*. 2012;25:390–401.
35. Garcia-Retamero R, Cokely ET. Effective communication of risks to young adults: using message framing and visual aids to increase condom use and STD screening. *J Exp Psychol Appl*. 2011;17(3):270–87.
36. Garcia-Retamero R, Galesic M. How to reduce the effect of framing on messages about health. *J Gen Intern Med*. 2010;25(12):1323–9.
37. Fagerlin A, Wang C, Ubel PA. Reducing the influence of anecdotal reasoning on people's health care decisions: is a picture worth a thousand statistics? *Med Decis Making*. 2005;25(4):398-405.
38. Barbey AK, Sloman SA. Base-rate respect: from ecological rationality to dual processes. *Behav Brain Sci*. 2007;30(3): 241–54.
39. Brase G. The power of representation and interpretation: doubling statistical reasoning performance with icons and frequentist interpretations of ambiguous numbers. *J Cogn Psychol*. 2014;26(1):81–97.
40. Garcia-Retamero R, Hoffrage U. Visual representation of statistical information improves diagnostic inferences in doctors and their patients. *Soc Sci Med*. 2013;83:27–33.
41. Garcia-Retamero R, Cokely ET, Hoffrage U. Visual aids improve diagnostic inferences and metacognitive judgment calibration. *Front Psychol*. 2015;6:932.
42. McDowell M, Jacobs P. Meta-analysis of the effect of natural frequencies on Bayesian reasoning. *Psychol Bull*. 2017;143(12):1273–312.
43. Sloman S, Over D, Slovak L, Stibel J. Frequency illusions and other fallacies. *Organ Behav Hum Decis Process*. 2003;91(2):296–309.
44. Tubau E, Rodríguez-Ferreiro J, Barberia I, Colomé À. From reading numbers to seeing ratios: a benefit of icons for risk comprehension. *Psychol Res*. 2019;83(8):1808–16.
45. Garcia-Retamero R, Petrova D, Cokely ET, Joeris A. Scientific risk reporting in medical journals can bias expert judgment: comparing surgeons' risk comprehension across reporting formats. *J Exp Psychol Appl*. 2020;26(2):283–99.
46. Tait AR, Voepel-Lewis T, Brennan-Martinez C, McGonegal M, Levine R. Using animated computer-generated text

and graphics to depict the risks and benefits of medical treatment. *Am J Med*. 2012;125(11):1103–10.
47. Eyler RF, Cordes S, Szymanski BR, Fraenkel L. Utilization of continuous "spinners" to communicate risk. *Med Decis Making*. 2017;37(6):725–9.
48. Gaissmaier W, Wegwarth O, Skopec D, Müller A-S, Broschinski S, Politi M. Numbers can be worth a thousand pictures: individual differences in understanding graphical and numerical representations of health-related information. *Health Psychol*. 2012;31(3):286–96.
49. Tait AR, Voepel-Lewis T, Zikmund-Fisher BJ, Fagerlin A. The effect of format on parents' understanding of the risks and benefits of clinical research: a comparison between text, tables, and graphics. *J Health Commun*. 2010;15(5):487–501.
50. Smerecnik CM, Mesters I, Kessels LT, Ruiter RA, De Vries NK, De Vries H. Understanding the positive effects of graphical risk information on comprehension: measuring attention directed to written, tabular, and graphical risk information. *Risk Anal*. 2010;30(9):1387–98.
51. Brewer NT, Gilkey MB, Lillie SE, Hesse BW, Sheridan SL. Tables or bar graphs? Presenting test results in electronic medical records. *Med Decis Making*. 2012;32(4):545–53.
52. Lipkus IM, Hollands JG. The visual communication of risk. *J Natl Cancer Inst Monogr*. 1999(25):149–63.
53. Lipkus IM. Numeric, verbal, and visual formats of conveying health risks: suggested best practices and future recommendations. *Med Decis Making*. 2007;27(5):696–713.
54. Keller C, Kreuzmair C, Leins-Hess R, Siegrist M. Numeric and graphic risk information processing of high and low numerates in the intuitive and deliberative decision modes: an eye-tracker study. *Judgm Decis Making*. 2014;9(5):420–32.
55. Oudhoff JP, Timmermans DR. The effect of different graphical and numerical likelihood formats on perception of likelihood and choice. *Med Decis Making*. 2015;35(4):487–500.
56. Feldman-Stewart D, Kocovski N, McConnell BA, Brundage MD, Mackillop WJ. Perception of quantitative information for treatment decisions. *Med Decis Making*. 2000;20(2):228–38.
57. Waters EA, Maki J, Liu Y, et al. Risk ladder, table, or bulleted list? Identifying formats that effectively communicate personalized risk and risk reduction information for multiple diseases. *Med Decis Making*. 2021;41(1):74–88.
58. Reyna VF. A theory of medical decision making and health: fuzzy trace theory. *Med Decis Making*. 2008;28(6):850–65.
59. Hawley ST, Zikmund-Fisher B, Ubel P, Jancovic A, Lucas T, Fagerlin A. The impact of the format of graphical presentation on health-related knowledge and treatment choices. *Patient Educ Couns*. 2008;73(3):448–55.
60. Etnel JRG, de Groot JM, El Jabri M, et al. Do risk visualizations improve the understanding of numerical risks? A randomized, investigator-blinded general population survey. *Int J Med Inform*. 2020;135:104005.
61. Hess R, Visschers V, Siegrist M, Keller C. How do people perceive graphical risk communication? The role of subjective numeracy. *J Risk Res*. 2011;14:47–61.
62. Romano A, Sotis C, Dominioni G, Guidi S. The scale of COVID-19 graphs affects understanding, attitudes, and policy preferences. *Health Econ*. 2020. doi:10.1002/hec.4143
63. Garcia-Retamero R, Cokely E. Communicating health risks with visual aids. *Curr Dir Psychol Sci*. 2013;22:392–9.
64. Kurz-Milcke E, Gigerenzer G, Martignon L. Transparency in risk communication: graphical and analog tools. *Ann N Y Acad Sci*. 2008;1128:18–28.
65. Arrick BA, Bloch KJ, Colello LS, Woloshin S, Schwartz LM. Visual representations of risk enhance long-term retention of risk information: a randomized trial. *Med Decis Making*. 2019;39(2):100–7.
66. Keller C, Siegrist M. Effect of risk communication formats on risk perception depending on numeracy. *Med Decis Making*. 2009;29(4):483–90.
67. Stone ER, Bruine de Bruin W, Wilkins AM, Boker EM, MacDonald Gibson J. Designing graphs to communicate risks: understanding how the choice of graphical format influences decision making. *Risk Anal*. 2017;37(4):612–28.
68. Stone ER, Gabard AR, Groves AE, Lipkus IM. Effects of numerical versus foreground-only icon displays on understanding of risk magnitudes. *J Health Commun*. 2015;20(10):1230–41.
69. Okan Y, Stone ER, Bruine de Bruin W. Designing graphs that promote both risk understanding and behavior change. *Risk Anal*. 2018;38(5):929–46.
70. Stone E, Sieck W, Bull B, Yates J, Parks S, Rush C. Foreground:background salience: Explaining the effects of graphical displays on risk avoidance. *Organ Behav Hum Decis Process*. 2003;90(1):19–36.
71. Okan Y, Stone ER, Parillo J, Bruine de Bruin W, Parker AM. Probability size matters: the effect of foreground-only versus foreground + background graphs on risk aversion diminishes with larger probabilities. *Risk Anal*. 2020;40(4):771–88.
72. Okan Y, Galesic M, Garcia-Retamero R. How people with low and high graph literacy process health graphs: evidence from eye-tracking. *J Behav Decis Making*. 2016;29:271–94.
73. Zikmund-Fisher BJ, Fagerlin A, Ubel PA. Improving understanding of adjuvant therapy options by using simpler risk graphics. *Cancer*. 2008;113(12):3382–90.
74. Zikmund-Fisher BJ, Fagerlin A, Ubel PA. A demonstration of "less can be more" in risk graphics. *Med Decis Making*. 2010;30(6):661–71.
75. Feldman-Stewart D, Brundage MD, Zotov V. Further insight into the perception of quantitative information: judgments of gist in treatment decisions. *Med Decis Making*. 2007;27(1):34–43.
76. Hamstra DA, Johnson SB, Daignault S, et al. The impact of numeracy on verbatim knowledge of the longitudinal risk for prostate cancer recurrence following radiation therapy. *Med Decis Making*. 2015;35(1):27–36.

77. Ancker JS, Weber EU, Kukafka R. Effects of game-like interactive graphics on risk perceptions and decisions. *Med Decis Making*. 2011;31(1):130–42.
78. Han PK, Klein WM, Killam B, Lehman T, Massett H, Freedman AN. Representing randomness in the communication of individualized cancer risk estimates: effects on cancer risk perceptions, worry, and subjective uncertainty about risk. *Patient Educ Couns*. 2012;86(1):106–13.
79. Kreuzmair C, Siegrist M, Keller C. High numerates count icons and low numerates process large areas in pictographs: results of an eye-tracking study. *Risk Anal*. 2016;36(8): 1599–614.
80. Zikmund-Fisher BJ, Witteman HO, Dickson M, et al. Blocks, ovals, or people? Icon type affects risk perceptions and recall of pictographs. *Med Decis Making*. 2014;34(4): 443–53.
81. Sirota M, Kostovičová L, Juanchich M. The effect of iconicity of visual displays on statistical reasoning: evidence in favor of the null hypothesis. *Psychon Bull Rev*. 2014;21(4): 961–8.
82. Schonlau M, Peters E. Comprehension of graphs and tables depend on the task: empirical evidence from two web-based studies. *Stat Politics Policy*. 2012;3(2).
83. Dolan JG, Qian F, Veazie PJ. How well do commonly used data presentation formats support comparative effectiveness evaluations? *Med Decis Making*. 2012;32(6):840–50.
84. McCaffery KJ, Dixon A, Hayen A, Jansen J, Smith S, Simpson JM. The influence of graphic display format on the interpretations of quantitative risk information among adults with lower education and literacy: a randomized experimental study. *Med Decis Making*. 2012;32(4):532–44.
85. Fraenkel L, Reyna V, Cozmuta R, Cornell D, Nolte J, Wilhelms E. Do visual aids influenced patients' risk perceptions for rare and very rare risks? *Patient Educ Couns*. 2018;101(11):1900–5.
86. Kasper J, van de Roemer A, Pöttgen J, et al. A new graphical format to communicate treatment effects to patients: a web-based randomized controlled trial. *Health Expect*. 2017;20(4):797–804.
87. McDowell M, Gigerenzer G, Wegwarth O, Rebitschek FG. Effect of tabular and icon fact box formats on comprehension of benefits and harms of prostate cancer screening: a randomized trial. *Med Decis Making*. 2019;39(1):41–56.
88. Henneman L, van Asperen CJ, Oosterwijk JC, Menko FH, Claassen L, Timmermans DR. Do preferred risk formats lead to better understanding? A multicenter controlled trial on communicating familial breast cancer risks using different risk formats. *Patient Prefer Adherence*. 2020;14:333–42.
89. Poirier MW, Decker C, Spertus JA, McDowd JM. What eye-tracking methods can reveal about the role of information format in decision-aid processing: an exploratory study. *Patient Educ Couns*. 2019;102(11):1977–84.
90. van Weert JCM, Alblas MC, van Dijk L, Jansen J. Preference for and understanding of graphs presenting health risk information: the role of age, health literacy, numeracy and graph literacy. *Patient Educ Couns*. 2020;104(1):109–17.
91. Peters E. Beyond comprehension: the role of numeracy in judgments and decisions. *Curr Dir Psychol Sci*. 2012;21: 31–5.
92. Galesic M, Garcia-Retamero R. Graph literacy: a cross-cultural comparison. *Med Decis Making*. 2011;31(3): 444–57.
93. Okan Y, Janssen E, Galesic M, Waters EA. Using the short graph literacy scale to predict precursors of health behavior change. *Med Decis Making*. 2019;39(3):183–95.
94. Garcia-Retamero R, Cokely ET, Ghazal S, Joeris A. Measuring graph literacy without a test: a brief subjective assessment. *Med Decis Making*. 2016;36(7):854–67.
95. Sharit J, Lisigurski M, Andrade A, Karanam C, Nazi K, Lewis J, et al. The roles of health literacy, numeracy, and graph literacy on the usability of the VA's personal health record by veterans. *J Usability Studies*. 2014;9(4):173–93.
96. Garcia-Retamero R, Cokely ET. The influence of skills, message frame, and visual aids on prevention of sexually transmitted diseases. *J Behav Decis Making*. 2014;27(2): 179–89.
97. Ruiz JG, Andrade AD, Hogue C, et al. The association of graph literacy with use of and skills using an online personal health record in outpatient veterans. *J Health Commun*. 2016;21(suppl 2):83–90.
98. Reani M, Davies A, Peek N, Jay C. How do people use information presentation to make decisions in Bayesian reasoning tasks? *Int J Hum Comput Stud*. 2018;111:62–77.
99. Kreuzmair C, Siegrist M, Keller C. Does iconicity in pictographs matter? The influence of iconicity and numeracy on information processing, decision making, and liking in an eye-tracking study. *Risk Anal*. 2017;37(3):546–56.
100. Keller C, Junghans A. Does guiding toward task-relevant information help improve graph processing and graph comprehension of individuals with low or high numeracy? An eye-tracker experiment. *Med Decis Making*. 2017;37(8):942–54.
101. Dowding D, Merrill JA, Onorato N, Barrón Y, Rosati RJ, Russell D. The impact of home care nurses' numeracy and graph literacy on comprehension of visual display information: implications for dashboard design. *J Am Med Inform Assoc*. 2018;25(2):175–82.
102. Nayak JG, Hartzler AL, Macleod LC, Izard JP, Dalkin BM, Gore JL. Relevance of graph literacy in the development of patient-centered communication tools. *Patient Educ Couns*. 2016;99(3):448–54.
103. Durand MA, Yen RW, O'Malley J, Elwyn G, Mancini J. Graph literacy matters: examining the association between graph literacy, health literacy, and numeracy in a Medicaid eligible population. *PLoS One*. 2020;15(11):e0241844.
104. Baker DW. The meaning and the measure of health literacy. *J Gen Intern Med*. 2006;21(8):878–83.
105. Schwartz LM, Woloshin S, Welch HG. Can patients interpret health information? An assessment of the medical data interpretation test. *Med Decis Making*. 2005;25(3): 290–300.
106. Okan Y, Garcia-Retamero R, Cokely E, Maldonado A. Improving risk understanding across ability levels:

encouraging active processing with dynamic icon arrays. *J Exp Psychol Appl*. 2015;21:178–94.
107. Edwards AG, Naik G, Ahmed H, et al. Personalised risk communication for informed decision making about taking screening tests. *Cochrane Database Syst Rev*. 2013;2013(2):CD001865.
108. Bonner C, Fajardo MA, Hui S, Stubbs R, Trevena L. Clinical validity, understandability, and actionability of online cardiovascular disease risk calculators: systematic review. *J Med Internet Res*. 2018;20(2):e29.
109. Fajardo MA, Harris L, Naidoo N, L T, Bonner C. Systematic review and evaluation of freely available online diabetes medication decision aids. *Eur J Person Centered Healthc*. 2019;7(1).
110. Waters EA, Sullivan HW, Nelson W, Hesse BW. What is my cancer risk? How internet-based cancer risk assessment tools communicate individualized risk estimates to the public: content analysis. *J Med Internet Res*. 2009; 11(3):e33.
111. Scherer LD, Ubel PA, McClure J, et al. Belief in numbers: When and why women disbelieve tailored breast cancer risk statistics. *Patient Educ Couns*. 2013;92(2):253–9.
112. Jansen J, Bonner C, McKinn S, et al. General practitioners' use of absolute risk versus individual risk factors in cardiovascular disease prevention: an experimental study. *BMJ Open*. 2014;4(5):e004812.
113. Damman OC, Bogaerts NMM, van den Haak MJ, Timmermans DRM. How lay people understand and make sense of personalized disease risk information. *Health Expect*. 2017;20(5):973–83.
114. Davis KW, Roter DL, Schmidlen T, Scheinfeldt LB, Klein WMP. Testing a best practices risk result format to communicate genetic risks. *Patient Educ Couns*. 2020. doi:10.1016/j.pec.2020.10.021
115. Hollands GJ, French DP, Griffin SJ, et al. The impact of communicating genetic risks of disease on risk-reducing health behaviour: systematic review with meta-analysis. *BMJ*. 2016;352:i1102.
116. Bodurtha J, Quillin JM, Tracy KA, et al. Mammography screening after risk-tailored messages: the women improving screening through education and risk assessment (WISER) randomized, controlled trial. *J Womens Health (Larchmt)*. 2009;18(1):41–7.
117. Flynn D, Nesbitt DJ, Ford GA, et al. Development of a computerised decision aid for thrombolysis in acute stroke care. *BMC Med Inform Decis Mak*. 2015;15:6.
118. Ballard AY, Kessler M, Scheitel M, Montori VM, Chaudhry R. Exploring differences in the use of the statin choice decision aid and diabetes medication choice decision aid in primary care. *BMC Med Inform Decis Mak*. 2017;17(1):118.
119. Syrowatka A, Krömker D, Meguerditchian AN, Tamblyn R. Features of computer-based decision aids: systematic review, thematic synthesis, and meta-analyses. *J Med Internet Res*. 2016;18(1):e20.
120. Bonner C, Patel P, Fajardo MA, Zhuang R, Trevena L. Online decision aids for primary cardiovascular disease prevention: systematic search, evaluation of quality and suitability for low health literacy patients. *BMJ Open*. 2019;9(3):e025173.
121. Fajardo MA, Durayb B, Zhong H, Trevena L, Traeger A, Bonner C. Online decision aids for knee osteoarthritis and low back pain: an environmental scan and evaluation. *Med Decis Making*. 2019;39(4):327–34.
122. Leiva Portocarrero ME, Garvelink MM, Becerra Perez MM, et al. Decision aids that support decisions about prenatal testing for Down syndrome: an environmental scan. *BMC Med Inform Decis Mak*. 2015;15:76.
123. Jimbo M, Sen A, Plegue MA, et al. Interactivity in a decision aid: findings from a decision aid to technologically enhance shared decision making RCT. *Am J Prev Med*. 2019;57(1):77–86.
124. Scalia P, Durand MA, Kremer J, Faber M, Elwyn G. Online, interactive option grid patient decision aids and their effect on user preferences. *Med Decis Making*. 2018; 38(1):56–68.
125. Zikmund-Fisher BJ, Dickson M, Witteman HO. Cool but counterproductive: interactive, web-based risk communications can backfire. *J Med Internet Res*. 2011;13(3):e60.
126. Zikmund-Fisher BJ, Witteman HO, Fuhrel-Forbis A, Exe NL, Kahn VC, Dickson M. Animated graphics for comparing two risks: a cautionary tale. *J Med Internet Res*. 2012;14(4):e106.
127. Housten AJ, Kamath GR, Bevers TB, et al. Does animation improve comprehension of risk information in patients with low health literacy? A randomized trial. *Med Decis Making*. 2020;40(1):17–28.
128. Stellamanns J, Ruetters D, Dahal K, Schillmoeller Z, Huebner J. Visualizing risks in cancer communication: a systematic review of computer-supported visual aids. *Patient Educ Couns*. 2017;100(8):1421–31.
129. IMRF. International Medical Device Regulators Forum. 2019. Available from: http://www.imdrf.org/
130. Leppink J, O'Sullivan P, Winston K. Effect size—large, medium, and small. *Perspect Med Educ*. 2016;5(6):347–9.
131. Zikmund-Fisher BJ. The right tool is what they need, not what we have: a taxonomy of appropriate levels of precision in patient risk communication. *Med Care Res Rev*. 2013;70(1 suppl):37s–49s.
132. Han PKJ, Lary C, Black A, et al. Effects of personalized risk information on patients referred for lung cancer screening with low-dose CT. *Med Decis Making*. 2019; 39(8):950–61.
133. Hallgreen CE, Mt-Isa S, Lieftucht A, et al. Literature review of visual representation of the results of benefit-risk assessments of medicinal products. *Pharmacoepidemiol Drug Saf*. 2016;25(3):238–50.
134. Padilla LM, Creem-Regehr SH, Hegarty M, Stefanucci JK. Decision making with visualizations: a cognitive framework across disciplines. *Cogn Res Princ Implic*. 2018;3:29.