CHAPTER

12 Human Decision-Making is Rarely Rational

Theories of decision-making and economics were historically based on the assumption that decision-making is rational, selfish, and stable over time. However, research in cognitive science has shown that at least two of those attributes—rationality and stability—are not attributes of *human* decision-making (Kahneman, 2011; Eagleman, 2012, 2015). These findings have had a strong impact on economic and decision theories.

Chapter 10 explained that we have two separate minds, which psychologists call *system one* (automatic, unconscious, unmonitored, highly parallel, irrational, approximate, fast) and *system two* (controlled, conscious, monitored, single-process, rational, precise, slow). Although system two believes that it governs our thoughts and actions, it only rarely does. Its main roles are:

- override the quick-and-dirty and often faulty judgments of system one,
- resolve conflicts when different automatic processes in system one produce conflicting results,
- figure out how to respond in novel situations where system one has no automatic response.

However, system two is lazy[1] and intervenes only when necessary (Eagleman, 2015).

PEOPLE ARE OFTEN IRRATIONAL

Classic decision and economic theories are based on studies of people's choices between simple gambles. Economists and decision scientists do this to simplify their

[1] System Two is also a source of individual differences. Some people have a more proactive System Two than others (Kahneman, 2011; Eagleman, 2012, 2015).

Designing with the Mind in Mind. https://doi.org/10.1016/B978-0-12-818202-4.00012-X

research just as some biologists study fruit flies, flatworms, and white rats to help them understand more general biological processes. A basic axiom of rational decision-making is this—if you prefer an X to a Y, then you will prefer a 40% chance of winning an X over a 40% chance of winning a Y. From this and similar basic axioms, plus the assumptions that humans are rational, selfish, and stable in their preferences, economists and decision theorists derived complex economic and decision theories. Those theories are useful for calculating how people and organizations *should* make decisions, but when it comes to predicting how humans *actually* make decisions, they are just plain wrong.

LOSSES MEAN MORE TO US THAN GAINS

If you ask people if they would prefer (1) a 50% chance of winning $100 or nothing or (2) a gift of $45, most choose the gift. A rational agent would choose the bet because its expected value is $50.[2] But for system one—the collection of unconscious processes that actually makes most of our decisions before we are aware of it—the 50% chance of ending up with nothing is just too scary. The gift's value has to be *much* less than the expected value of the bet for people to prefer the bet. An exception is professional gamblers, who would probably choose the bet because they know that over *many* such choices, they would come out ahead. Their system one has learned to accept risky but favorable bets.

Not convinced? Consider this example: A friend offers you a bet based on a coin toss: heads, he pays you $150; tails, you pay him $100. Would you take that bet? Although the odds are in your favor, studies show that most people would *not* take the bet (Kahneman, 2011). They fear losing more than they rejoice at winning. Most people want two-to-one odds (heads you win $200; tails you lose $100) before they will take the bet. Again, professional traders are less risk-averse; they know they will be taking a lot of bets, so if the odds are even slightly in their favor, they will probably come out ahead overall even if they lose many individual bets.

Also, according to Kahneman (2011), the pain people feel from a loss is not linear with the size of the loss. For example, for a cattle rancher, the pain of losing 900 cows is more than 90% of the pain of losing 1000 cows.

Based on years of research on how people actually make decisions on gambles and other risky conditions, such as whether to settle a lawsuit out of court, Daniel Kahneman and his colleague Amos Tversky developed a 2 × 2 matrix, which they called the *fourfold pattern*, to summarize their theory's predictions (see Table 12.1). It says that when we face a big chance of a large gain (top left) or a small chance of a large loss (bottom right), we prefer to play it safe and take the no-gamble sure-thing option (that is, we are risk-averse), but when we face a big chance of a large loss (top right) or a small chance of a large gain (bottom left), we prefer to gamble (that is, we are risk-seeking).

[2]The *expected value* of a bet is the amount you can win multiplied by the probability of winning—in this case $100 × 0.5 = $50. It is what you can expect to win each time, on average, if you bet many times.

Table 12.1 Fourfold Pattern: Predictions of Human Choice under Risk

	Gain	Loss
High probability	**Gamble**: High chance to win $10,000 (but slight chance of winning nothing) **No-gamble option**: Gain $8000 (which is less than long-term gain of gamble) • fear to lose gain • people are risk-averse • most prefer "safe" definite gain	**Gamble**: High chance to lose $10,000 (but slight chance of losing nothing) **No-gamble option**: Lose $8000 (which is less than long-term loss of gamble) • hope to avoid loss • people are risk-seeking • most prefer to gamble
Low probability	**Gamble**: Slight chance to win $10,000 (but high chance of winning nothing) **No-gamble option**: Gain $2000 (which is more than long-term gain of gamble) • hope for large gain • people are risk-seeking • most prefer to gamble	**Gamble**: Slight chance to lose $10,000 (but high chance of losing nothing) **No-gamble option**: Lose $2000 (which is more than long-term loss of gamble) • fear of large loss • people are risk-averse • most prefer "safe" definite loss

Adapted from: Kahneman, D., 2011. Thinking Fast and Slow. Farrar Straus and Giroux, New York.

The fourfold pattern predicts human behavior in risky situations—for example, our willingness to:

- accept settlements in lawsuits;
- buy insurance (when not required);
- play lotteries;
- gamble in casinos.

WE ARE BIASED BY HOW CHOICES ARE WORDED

Imagine that your doctor informs you that you have a terminal disease. She tells you there is a treatment that has a 90% survival rate. Sounds good, doesn't it? Rewind now to the doctor informing you of your terminal illness. In this version, she tells you the treatment has a 10% mortality rate. Sounds bad, doesn't it?

The two statements about the treatment's effectiveness are equivalent. A rational agent's decision would not be affected by how the doctor phrases it. But people's decisions are. That is system one at work, with system two rarely bothering to intervene.

Here is another nice example of biasing by choice of words, adapted from Kahneman (2011). An outbreak of a dangerous flu is about to hit your country. Health officials predict that if the population is not vaccinated against it, about 600 people will die. Two vaccines are available:

- Vaccine A has been used before; an estimated 200 (of the 600) people would be saved.
- Vaccine B is experimental, with a one-third chance of saving all 600 people and a two-thirds chance of saving no one.

Most people presented with this choice choose vaccine A. They like the certainty. Now look at these slightly differently worded options for the same choice:

- Vaccine A has been used before; an estimated 400 (of the 600) people would die.
- Vaccine B is experimental, with a one-third chance of nobody dying and a two-thirds chance of all 600 people dying.

With this alternative wording, most people choose vaccine B. In this case, the certainty is unappealing because it is about deaths. According to Kahneman, system one not only treats losses as more important than gains, it also is risk-averse for gains and risk-seeking for losses. Therefore, people usually prefer a sure thing over a gamble when options are worded as gains, and gambles over sure things when the identical options are worded as losses.

Psychologists call this the *framing* effect: how choices are framed affects people's decisions.

Framing can also bias our decisions by setting—researchers call it *anchoring*—our mental accounting to a certain level, after which we perceive gains and losses from that *new* level. For example, imagine you are on a TV game show and have just won $1000. Before you leave, the game show host offers you a choice: (1) 50% chance (coin toss) to win either $1000 more or $0 more or (2) get $500 more for sure. Most people choose the sure thing; they'd rather end up with a sure $1500 than gamble for $2000 and risk ending up with only $1000. Their mind gets anchored to the idea of getting $1000, so $1500 seems better—probably good enough. Although system one made the decision, system two rationalizes it by thinking, "Why be greedy?"

But now let's start over. Assume you initially won $2000, and now your choice is: (1) a 50% chance you could *lose* either $1000 or $0 of the $2000 just won or (2) lose $500 for sure. In this case, most people don't like the sure loss; they prefer to gamble to keep all $2000, even though there is a good chance they may end up with only $1000. Their mind gets anchored to the idea of getting $2000, so ending up with only $1500 seems worse. Again, system one made the decision, but system two rationalizes by thinking, "I'm hoping to keep it all."

Companies use anchoring to sell products in several ways (Stefanovic, 2018):

- List the most expensive version of a product first, causing shoppers to anchor the price in their minds at that level, making other versions of the product seem like a bargain.

- Offer discounts for buying more than one of the product—e.g., three for the price of two—thereby anchoring that number in shoppers' minds as the "right" number to buy.
- Set a time limit on a discount—anchoring the sale price in customers' minds—and urge customers to "buy now" or lose the discount.
- Set a limit on how many units shoppers can purchase, thereby pushing customers to buy more units than they otherwise would.

Framing effects are one reason people's judgments and preferences are unstable over time: phrase a choice one way, people decide one way; phrase it differently, people decide differently.

WE ARE BIASED BY OUR VIVID IMAGINATIONS AND MEMORIES

In addition to being biased by gain versus loss and by how choices are framed, people tend to overestimate the probability of improbable events, especially when we can picture or easily recall those events. Furthermore, we tend to give more weight to such events in our decisions.

As an example, if people are asked to estimate the number of murders in the US state of Michigan last year, those who remember that Detroit is in Michigan give a larger number than those who don't—but many don't remember that. Many people even estimate the number of murders per year as higher for Detroit than for Michigan. The explanation is that system one gives quick answers based on heuristics, such as how easily relevant information comes to mind. Murders in Detroit are often mentioned in news reports, thereby associating Detroit with murder in people's memories, but news reports about "murders in Michigan" are rare, so "murder" and "Michigan" are not strongly associated in memory. If system one does not recall that Michigan includes Detroit, its estimate is low, and system two rarely intervenes (Kahneman, 2011).

Similarly, if asked whether politicians or pediatricians are more likely to be rich, most people immediately say "politicians, of course." This answer comes from system one, which can easily recall news stories about politicians' wealth due to all the press coverage such stories receive. Unless the person happens to know pediatricians who are rich, system one can't recall any examples because they seldom are reported in the news.

System one is also easily biased by the vividness of imagery and the brain's automatic responses to events. This is why people use vague or euphemistic terms in polite company: it avoids causing strong reactions to terms associated with unpleasant topics. For example, at a dinner party we would say that our spouse was absent because he or she was ill; we wouldn't say that our spouse was vomiting or had diarrhea.

A related bias is that people give more weight to coherent, compelling stories than to statistical evidence. In Chapter 10, the "Uncle Charlie" effect was explained: a person may have seen plenty of statistics showing that a Nissan Leaf is a great car, but if that person's Uncle Charlie (or other relative or friend) had a bad experience with one, the person's system one will consider the car a "lemon," which will bias their opinion of the car unless system two overrides it.

Similarly, system one does not care about sample sizes. If you read that a door-to-door survey of potential voters found 63% support for the US president, your system one doesn't worry about whether 300 or 3000 voters were polled. However, if you read that 30 voters were polled, that will get your system two's attention and it will intervene and override system one, saying, "That's not a valid survey" (Kahneman, 2011).

Finally, system one bases decisions on what is immediately before it: current perceptions and strong, easy-to-recall memories. System one does not—cannot—consider other, possibly contrary evidence and experiences. Since what is immediately available to system one changes over time, its responses and choices are subject to change.

WE ARE BIASED BY OUR (RECENT) PAST BEHAVIOR

Most people try to be consistent. When we make a promise, we feel obligated to keep it. When we make a decision, have an opinion, or act in a particular way, most of us try to make our future behaviors match it. We tend to justify these commitments by seeking confirmation and providing reasons for supporting them. This tendency manifests itself in several ways (Stefanovic, 2018):

- **Stated commitment bias**: People who state publicly that they want to lose weight are significantly more successful. Once you bid on an item, you're likely to keep bidding. Internet users who click "yes" to a small request are more likely to click "yes" to larger requests (e.g., buy). Shopping carts and wish lists increase commitment and therefore the chances of buying. People are more likely to provide sensitive information if they have consented to give you innocuous information first. Once you've declared your intention to get a basic product, upselling add-on options to you is easier.
- **Sunk cost fallacy (escalation of commitment)**: This is our tendency to stick with a decision and even put more resources into a losing cause. We don't want to lose resources already invested and don't want to seem inconsistent: "I will stay on the line, listening to elevator music, waiting for a ticket agent to answer, even though it's been 15 minutes." Learning an app makes it likely you will stay with that app.
- **Ikea effect**: We value things more once we have put effort into them. Letting people try a product—and put effort into learning it—makes them more likely to buy it.
- **Status quo bias**: We prefer familiarity and tend to resist change. We use the current situation as an anchor, so we perceive downward changes as losses and upward changes as gains.

EMOTIONS ARE CRUCIAL TO DECISION-MAKING

Making decisions rationally does *not* mean eliminating emotions from the equation. To evaluate and compare alternatives effectively, people need some sort of emotional response.

For example, when you choose a driving route to a friend's wedding, making a rational choice means that you choose the best route based on some objective metric—e.g., shortest, safest, most familiar, least nerve-wracking, or least use of fuel. Why? Because choosing the best route—whatever your criteria are—makes you feel good, and choosing a bad route makes you feel bad. Similarly, when you choose between alternative products, you may compare the products on several objective criteria: cost, features, quality, reliability, ratings. You do that to buy the product that benefits you most, because that feels good.

Research shows that people who experience few or no emotions—perhaps due to brain injuries or illnesses—have great difficulty making decisions (Hudlicka, 2021). If there is no difference in your emotional response to two alternatives, you will have difficulty choosing between them. Emotional response is essential to decision-making (Eagleman, 2015).

EXPLOITING STRENGTHS AND WEAKNESSES OF HUMAN COGNITION

How can designers use knowledge of the previously described characteristics of human decision-making to achieve their goals? Here are some ways.

Support rational decision-making: help system two override or co-opt system one

People invented computers for the same reason we invented arithmetic, calculators, Rolodexes, and checklists: to augment our weak and unreliable rational thought processes. Early computers performed numerical calculations that were too complex or lengthy for people to perform reliably and quickly, but they now perform for us—or help us perform—a wide variety of information-processing tasks. Computers are good—reliable, fast, and accurate—at precisely what we are bad at: remembering, calculating, deducing, monitoring, searching, enumerating, comparing, and communicating, so people use computers to support those activities. Decision-making is another such activity.

For example, many people won't sign a new home mortgage without first using a mortgage calculator to compare different loan options and compute their monthly payments and the total amount they will pay (see Fig. 12.1). The calculator supports our decision-making.

An example of problems that arise when people *don't* use computer systems to augment their all-too-human capabilities is provided by a recent airliner crash at San

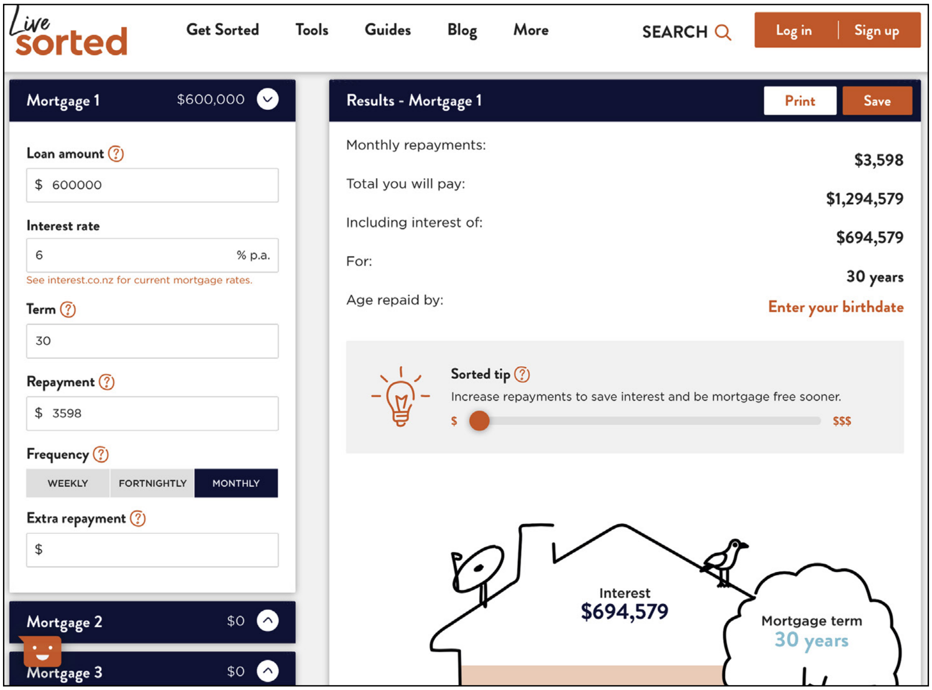

FIGURE 12.1

Sorted.org.nz's mortgage calculator helps people understand and choose a loan.

Francisco International Airport. The crash was allegedly caused at least in part[3] by the pilots trying to land the plane manually rather than with the autopilot (Weber, 2013).

It could be argued that a great many software applications and commercial websites exist to help people make decisions. Usually the decisions supported are mundane, as in apps and websites that help people choose which product to buy (see Fig. 12.2). Such websites support rational choice (system two) by displaying products side by side and allowing people to compare prices, features, and reliability, as well as customer satisfaction based on product ratings and reviews.

However, many software applications support decision-making that is anything but mundane, such as where to drill for oil, how much water to store in a reservoir, what the suggested retail price of a new car should be, how many endangered rhinos and elephants a game reserve can hold, or what the most efficient route for a snowplow is (see Fig. 12.3). In fact, software for supporting complex decision-making is such an important and well-studied category that it has a title and acronym (decision support systems, or DSS), a scientific journal (*Decision Support Systems*), textbooks, regular conferences, and even a Wikipedia page.

Whether the supported decisions are mundane or of monumental importance, the primary goal of decision support software (and websites) is to help people engage their system two, see all their options, evaluate them rationally and fairly, and make

[3]According to preliminary assessments by National Transportation Safety Board (NTSB) officials.

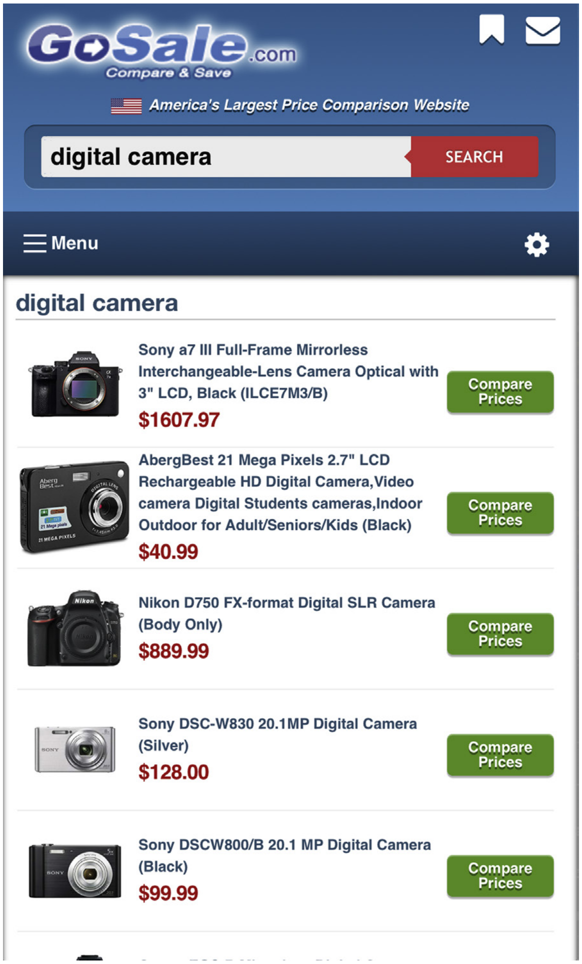

FIGURE 12.2

GoSale.com is a comparison-shopping website.

an unbiased decision. Achieving that goal isn't easy, because as explained earlier and in Chapter 1, human perception and cognition are *usually* biased. But it is possible, if decision support software follows these guidelines:

- ***Provide all options***. If there are too many to simply list, they can be organized or abstracted into categories and subcategories with summary information provided for those so people can evaluate, compare, and possibly eliminate entire categories of options at once.
- ***Help people find alternatives***. Some solutions may be so counterintuitive that people don't consider them. Decision support systems can expose options users

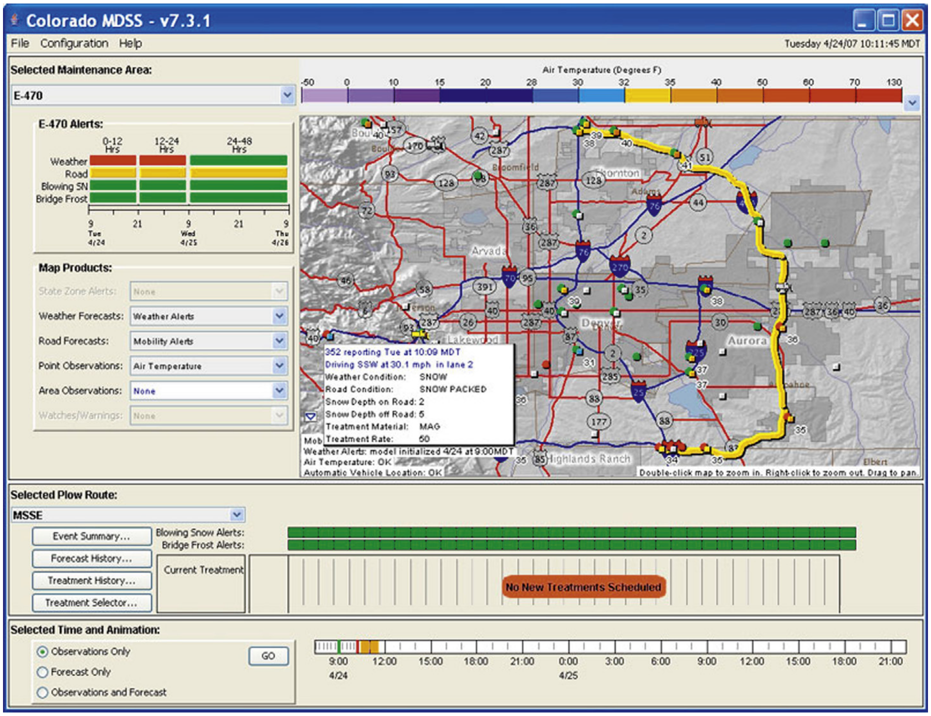

FIGURE 12.3

Decision support system for choosing efficient snowplow routes.

might miss and generate variants on user solutions that are minor or even major improvements.

- ***Provide unbiased data***. That is, data should be created or collected in an objective, reproducible manner.
- ***Don't make people calculate***. Perform calculations, inferences, and deductions for users where possible. Computers are good at that; people aren't.
- ***Check assertions and assumptions***. Decisions are based on not only data but also assumptions and assertions. Decision support systems—especially those supporting critical or complex decisions—should let users declare any assumptions and assertions that will be used for decision-making and "sanity check" them for users.
- ***Explain the system's reasoning***. If users of a decision support system don't understand its results or recommendations, they may not trust the system and therefore will be less likely to follow its suggestions. Therefore, decision support systems should show—if not normally then at least on demand—the rationale for their recommendations.

Make AI-based systems more transparent

The last guideline poses a problem for decision support systems based on artificial intelligence technology, such as machine learning or neural networks. AI-based systems often present themselves to us as black boxes: we see the data that go into the system and the results or recommendations that come out, but we cannot see *which* inputs affected the results or *how* the inputs affected the results (Budiu, 2018; Budiu and Laubheimer, 2018). Because we lack a clear, predictive mental model of how AI-based apps and services work,[4] their advice or recommendations often seem mysterious, off-base, or just plain creepy. For example, most of us have received "You may also like" suggestions or advertisements that cause us to say "Huh!? Where did *that* come from?"

To lose their reputation as being unpredictable and creepy, and to gain widespread acceptance, AI-based apps and services must become more transparent. They must be designed so users can see how the results were derived from inputs (Budiu, 2018). Perhaps they even need to become capable of explaining the reasoning behind their decisions and suggestions.

Data visualization: harnessing system one to support system two

One might assume that a secondary goal of decision support systems is to shut system one—with all its biases, satisficing, and approximating—out of the decision-making loop. In some decision support systems that may indeed be a design goal. However, there is another way.

To understand the other way, one must realize that system one is *not* an inner "evil twin" trying to bias and mess up our decisions. It doesn't have any goal to thwart or undermine system two. In fact, it doesn't have any goals at all. Strictly speaking, it isn't even a single thing. System one is a large collection of semi-independent automatic "robotic" or "zombie" processes, each of which handles a specific situation (Eagleman, 2012). As described earlier, some of those automatic processes have characteristics detrimental to rational decision-making, but overall the brain's collection of automatic processes helps us react, survive, and thrive. Many of those automatic processes are skills that can be harnessed—one could say "hijacked" or "co-opted"—by system two to *support* its analysis. That is the basis of the "other way."

An approach that utilizes this other way is called *data visualization*, or "data viz" for short. Think of it as business graphics on steroids. Data visualization exploits the strengths of the human visual system—which consists mainly of automatic processes—to allow people to perceive relationships in complex data. Some of those strengths were described earlier in this book: perception of structure (Chapter 2), analysis of complex scenes (Chapter 2), edge detection (Chapter 4), motion detection (Chapter 5), and face recognition (Chapter 9). Another strength is three-dimensional

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[4] See Chapter 11, section on conceptual models.

FIGURE 12.4

Maps of the London underground: (A) geographic map, 1919, and (B) schematic map, 2020.

vision. Like decision support, data visualization is a large (and growing) field with a name,[5] regular conferences, journals, textbooks, and a Wikipedia page.

A relatively simple but familiar example of data visualization is provided by schematic (i.e., nongeographic) maps of urban subway systems (see Fig. 12.4), which have largely replaced geographic subway maps over the past 100 years. Geographic location, landmarks,

[5] Some researchers prefer the term “information visualization” or “info viz” for short.

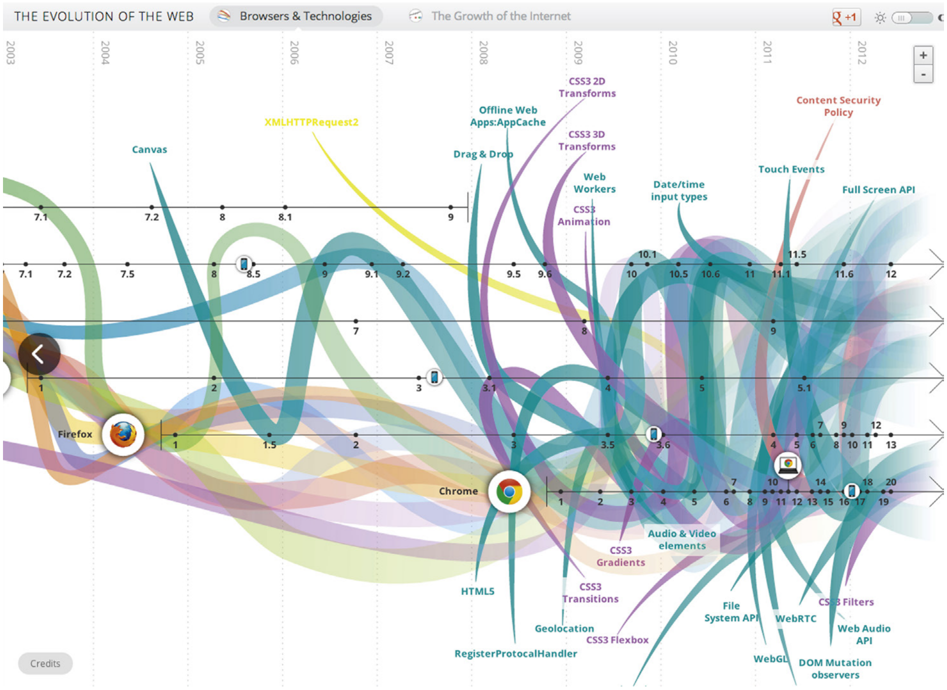

FIGURE 12.5

Evolution of the web (2012). (Source: Hyperakt, Vizzuality, Google Chrome team (http://www.evolutionoftheweb.com).)

and even distances are of little importance on subway maps. All that people usually want to see from these maps is which subway lines go to which stations, where lines connect, and whether a given destination is near or far. Geographic maps confuse the issue by providing unnecessary information. Schematic maps make it easy to see what people want to know.

A more complex and interactive example of data visualization is the Gapminder application described in Chapter 2 (see Fig. 2.21). It exploits human perception of motion and several Gestalt principles to show changes in the socioeconomic status of the world's nations and relationships between nations. It shows how nations and groups of nations have "moved" over the years along the dimensions of average life expectancy, per capita income, gross national product, etc. Another example of interactive data visualization of time-varying data is a graph depicting the evolution of the Web from 2003 to 2012 (see Fig. 12.5). It uses horizontal scrolling along a timeline rather than the animated motion of objects.

Some of the same graphical techniques, except motion, are used in a graph showing important data visualization publications, their relative number of citations, and how they are related to each other, such as in cross-citations (see Fig. 12.6).[6] Motion isn't needed in this visualization because the data depicts a moment in time rather than a time period.

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[6]More data-viz examples at: http://www.webdesignerdepot.com/2009/06/50-great-examples-of-data-visualization.

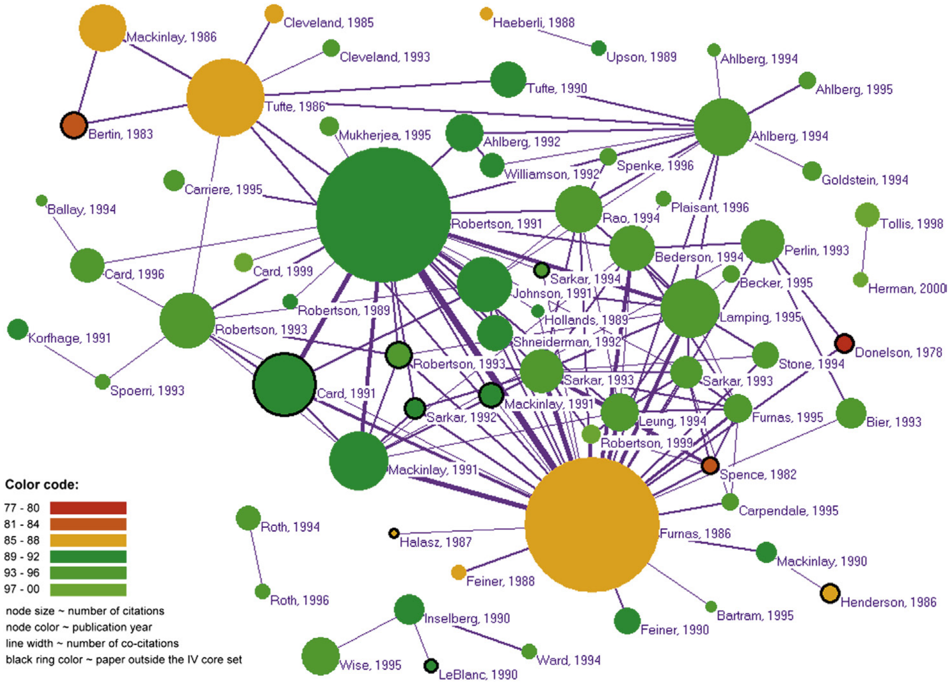

FIGURE 12.6

Visualization of data viz publications, their citations, and their relationships.

An imaginative example of data visualization goes by the name of *Chernoff faces*, named after Herman Chernoff, who invented the idea (Tufte, 2001). Scientists, engineers, and even administrators often must analyze and categorize data in which each data point has many dimensions. A simple example: a person in a police database can be represented by his name, address, phone number, date of birth, height, weight, eye color, hair color, number of traffic citations, number of convictions, and other variables. Bank accounts can be represented by their owner's name, a debit card number, a bank branch number, a balance, an interest rate, a minimum allowed balance, a required term of deposit, date of opening, etc. Displaying data in anything more than three dimensions is difficult, especially if scientists need to be able to see when data points form clusters or follow predictable patterns.

Chernoff realized that human faces are multidimensional: they vary in overall height, width, cheekbone height, nose length, nose width, chin width, eye distance, mouth width, ear height, ear width, ear vertical position, etc. He decided that 18 dimensions could characterize most human faces. He also knew that people are very good at recognizing human faces and differences, even slight differences, between faces. As mentioned in Chapter 9, our ability to recognize faces is hardwired; we don't need to learn it.

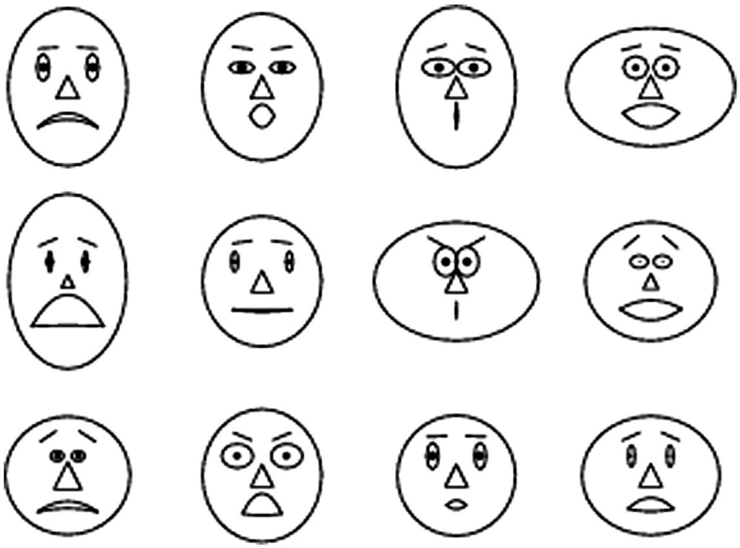

FIGURE 12.7

Chernoff faces are a way to display multidimensional data.

Chernoff reasoned that because human faces are multidimensional, any multidimensional data can be represented as schematic faces, thereby exploiting our built-in face-recognition ability to allow people to recognize similarities, relationships, and patterns. Chernoff faces (see Fig. 12.7) have been used to represent a wide variety of data, from planets in the solar system to financial transactions.

Data visualization is a way to employ automatic visual perception processes built into system one to help system two understand complex data. For a visualization to succeed, it must present data in a way consistent with human visual capabilities and not trigger any of the visual system's flaws (Robertson et al., 1993; Ware, 2012).

Recent research on information visualization provides additional support for Chernoff's use of human faces. Researchers at MIT and Harvard found that data visualizations are much more memorable if they include "human-recognizable objects," such as pictures of people (Borkin et al., 2013).

Convincing and persuading: educing system one and bypassing system two

Given how easily system one can be biased and even fooled, it goes almost without saying that *how* an interactive system presents information influences the decisions and behavior of users *at least* as strongly as *what* information it presents. If designers *want* to influence or persuade people to respond in a specific way—for example, buy a product, join an organization, subscribe to a service, donate to a charity, form a

FIGURE 12.8

Successful ads appeal to our emotions, not to our intellect.

certain political opinion, vote a certain way—they can "exploit" the characteristics of system one to achieve that (Weinschenk, 2009; Kahneman, 2011).

Advertisers and political action committees are well aware of this, and so they *often* design their messages to communicate with their audience's system one (and undermine system two). One can easily distinguish amateur advertisers and neophyte political copywriters from professionals. Amateurs present rational arguments and statistics supporting their point of view, hoping to convince our system two to agree. The pros skip the statistics; they design messages based on powerful stories evoking fear, hope, satisfaction, enjoyment, sex, money, prestige, food, and more fear, thereby bypassing our system two and aiming straight at our system one (see Fig. 12.8).

Software and web designers can do the same if convincing and persuading people is their intent (Weinschenk, 2009). That has given rise to *persuasive* systems (Fogg, 2002), the opposite side of the coin from decision support systems. And, of course, persuasive software is a growing field of study with a name, conferences, textbooks, and—you guessed it—a Wikipedia page.

Contrasting decision support and persuasive systems

To better see the difference between decision support systems and persuasive systems, let's compare one of each, both of which concern charitable donations. One is CharityNavigator.org (see Fig. 12.9), which assesses and compares charitable organizations. The other is Feed My Starving Children (FMSC), one of the charities listed at CharityNavigator.org (see Fig. 12.10).

CharityNavigator.org is a decision support site: it helps people decide, free of bias, which charities to support. To do this, it evaluates charities according to several criteria, such as the percentage of donations used for overhead costs, and assigns each organization an overall score, allowing people to compare the organizations.

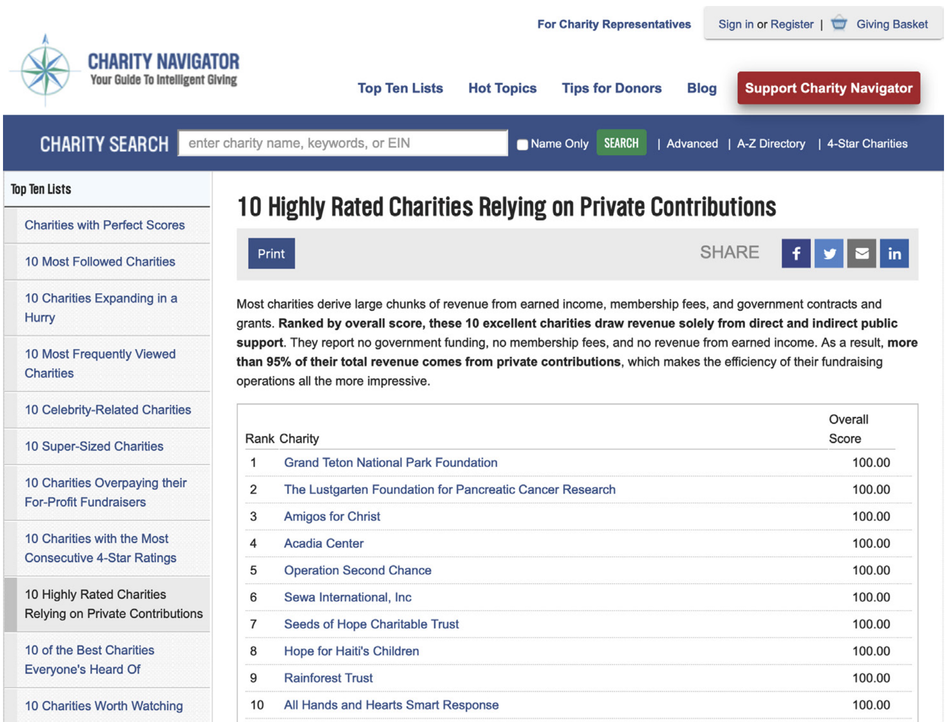

FIGURE 12.9

CharityNavigator.org is a decision support website comparing charities.

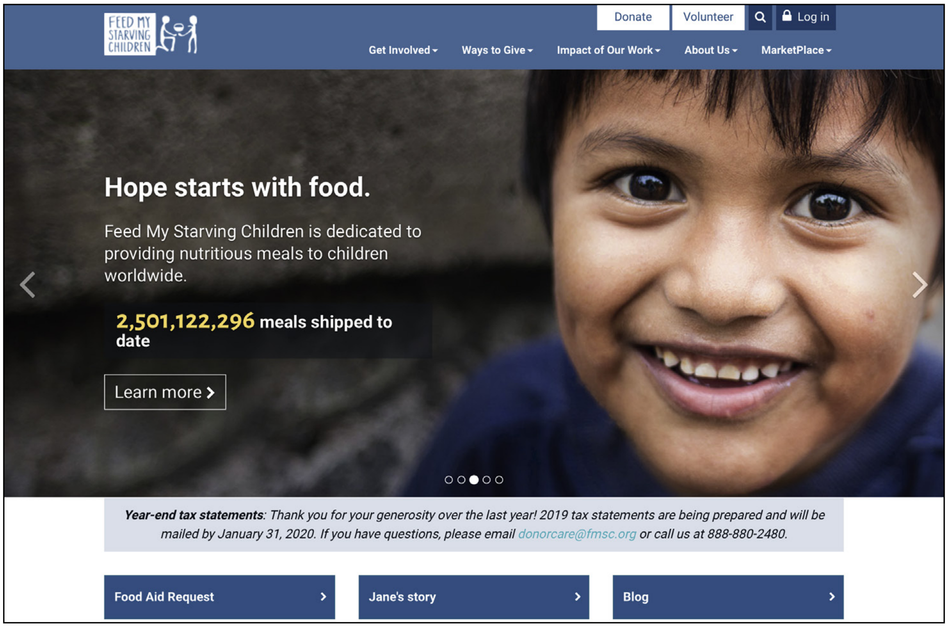

FIGURE 12.10

Feed my starving children (FMSC.org) is a charitable relief organization.

In contrast, the clear goal of FMSC's website is to persuade visitors to donate to the organization so they can provide food-aid to families around the world. Everything on the site—photographs, logos, link labels, textual descriptions, even the organization's name—serves that goal (see Fig. 12.10). Their website is not about helping site visitors make a rational decision about whether to support FMSC versus other food-aid organizations. Decision support is neither their goal nor their responsibility. Their site exists to persuade.

I am not saying decision support is *good* and persuasion is *bad*, or that CharityNavigator.org is good and FMSC.org is bad. Both organizations have worthy missions and do good work. Persuasion can be good and often is necessary. Someone might decide to donate to FMSC because their friend recommended it and they trust their friend. Furthermore, engaging system two to methodically enumerate all options and rationally compare them can be a waste of time if system one can produce an acceptable decision quickly. My only purpose in comparing the two sites is to illustrate the difference between decision support and persuasive systems.

Computer security: worth the cost?

Setting up security (e.g., data backup and virus protection) on computers and smartphones costs time, effort, and money. Using the terms of decision theorists, the setup costs constitute a small to medium loss. People compare that small sure loss to a small chance of a large loss: losing all their data or having unauthorized people access their data. Some people buy the protection, while others decide to take the risk.

This situation seems to fall into the bottom-right cell of Kahneman and Tversky's fourfold pattern: low chance of large loss. The pattern predicts that most people would take the risk-averse path and purchase backup and virus protection systems. In fact, however, many people practice denial and don't bother purchasing protection, and as a result occasionally suffer big losses. Recent surveys found that:

- Between 39% and 51% of American consumers have not backed up their files in over a year, if ever (Budman, 2011; Husted, 2012).
- Of personal computer users, 31% have at some point lost all their files, and those files were on average valued at over $10,000—that is, the files are much more valuable than the computers (McAfee, 2012).
- Of PCs worldwide, 17% have no virus protection; the United States is slightly worse at 19% (McAfee, 2012).

These findings prompt two sets of questions, one for researchers and one for designers. The question for researchers concerns the apparent deviation from Kahneman and Tversky's prediction that people are risk-averse and pay extra for protection when they face a small chance of a large loss. The relatively low percentage of PCs with no virus protection (17%) does not contradict the fourfold pattern: the majority of people (83%) do what the theory predicts. One could argue that even the 39%–51% of PCs that are rarely or never backed up does not contradict the theory because it means that 49%–61% of PCs *are* backed up. However, it *does* seem problematic for the theory that such a high percentage of computer systems—even a slight majority according to some surveys—are not.

Why do so many people not back up their data when the fourfold pattern seems to predict that most people will? How reliable are the surveys that have been conducted? Is the variability in this case related to variability in people's willingness to gamble in casinos, buy lottery tickets (bottom left cell in Table 12.1), ride motorcycles without helmets, install smoke alarms, or fail to purchase insurance or extended product warranties? Knowing the answers to these questions would provide guidance for designers seeking to increase the use of computer security.

For designers, the question is, "How can we design computer and smartphone security (data backup, virus protection, etc.) to get more people to use it?" One way is obvious: reduce the costs of money, time, and effort. Make computer security inexpensive, simple and quick to set up, and easy to use, and more people will use it. For nearly everyone to use it, it would need to be as inexpensive and easy to set up and use as a toaster.

Many companies have tried to simplify backup, and most claim that their backup products and services are easy to set up and use. But the 40% nonbackup and 19% no-virus-protection rates cited here are from surveys conducted in 2011 and 2012, so obviously the various costs of computer security are still not low enough for anything close to universal adoption. This should be seen as a challenge to user-interface designers.

Another answer for designers is less obvious: since people are influenced more by coherent stories than by statistics, companies offering backup and antivirus software should focus less on quoting statistics and instead share stories about how people lost their data or had their computers infected by viruses, or better—how they *recovered* their data and *avoided* viruses.

IMPORTANT TAKEAWAYS

- Human decision-making is strongly biased by unconscious mental processes (system one) that sometimes produce good outcomes quickly but sometimes cause us to make irrational choices. Our rational mind (system two) rarely intervenes.
- Fear of loss influences human decisions more than expectation of gains. This bias affects people's choices in risky situations, like whether to buy insurance, accept lawsuit settlements, gamble, or skydive. Psychologists Kahneman and Tversky conducted experiments demonstrating the pervasiveness and strength of this bias.
- Framing—how a choice is worded—affects how people choose. People prefer a sure thing over a gamble when options are worded as gains, and gambles over sure things when the identical options are worded as losses. This bias makes people susceptible to *anchoring*: a mind trick where someone sets your expectations to a certain level, then shows you either how to improve your outcome or how to avoid a worse outcome.
- People are biased toward options that are easier to recall or envision. A close relative's experience with a product influences our willingness to buy it much more than reading statistics or online reviews about the product.
- Our past decisions bias our future ones, because people try to behave consistently. Therefore, people tend to stay with what is familiar, stick with losing causes longer than they should, and like things better if they put more effort into getting them.
- Emotions are critical to decision-making. Without an emotional response of some sort, it is difficult to make decisions.

- Designing to exploit strengths and weaknesses of human decision-making:
  - Support rational decision-making: Help system two override or co-opt system one by providing all options, showing alternatives, providing unbiased data, performing calculations for users rather than forcing them to calculate, and checking the assumptions underlying the reasoning.
  - Make AI-based systems more transparent.
- Use data visualization to harness system one to support system two.
- Use persuasion ethically. Don't influence people to do what is contrary to their own interests.