Judging the value of the research

When planning a project, researchers face difficult questions that should be confronted explicitly. Is the research really worth doing? Whose interests will it serve? Are there possible negative side effects? What are the justifications: making money, gaining notoriety, advancing theoretical understanding, developing applications, for military purposes, etc.? Researchers should consider if these reasons are morally justifiable and consistent with their obligations and integrity as scientists.

Scientists must make claims to private or public benefactors about the value of their proposed work. The scarcity of funds compared with the abundance of potential scientific pursuits pressures scientists to make exaggerated claims about the import of their work. This poses questions about what constitutes ethical promising and how to distinguish justifiable claims from unjustified hype. This issue has been especially acute with embryonic stem cell research where claims about the potential health benefits have occasionally stretched any reasonable assessment of likely outcomes. Irresponsible promising can not only raise hopes that are later dashed but may even constitute a type of dishonesty on a par with other acts of misconduct.

The flow 2: doing research

Once research has begun, new ethical issues are added to those discussed above. These include: (a) objectivity, inferences, and data management; (b) bias and self-deception; (c) trust; and (d) values embedded in research design.

Objectivity, inferences, and data management

Researchers draw conclusions based on their observations. They make inferences from data that are almost always incomplete and imperfect. How these data should be treated in the process of inference lies at the core of the ethics of doing research. What counts as a valid inference?

Even before a fact or data point is collected, scientists make decisions about where and what to investigate. Interpreting data entails yet further human acts of framing and meaning-making. The data a chemist sees, for example, is a line spiked high on a graph printed out from a gas chromatograph. When she points to this line and says "that is oxygen," she is drawing from a rich theoretical framework to interpret data as meaningful.

For the ideal of objectivity to guide practice it cannot mean that human perspectives are stripped from science. Rather, it means that in making the many unavoidable decisions and interpretations, scientists are guided by scientific norms as discussed in Chapter 3, especially behavioral norms of honesty, carefulness, open-mindedness, and skepticism. This ideal is compromised by dishonesty, carelessness, bias, and self-deception. Furthermore, the ideal means that the scientific community has structures to mitigate these corrupting influences such as peer review and experiment descriptions that allow replication.

Scientists may be tempted to inappropriately alter the data in order to present a case that is stronger than the data warrant. Such dishonesty amounts to clear-cut misconduct when the alterations include the outright fabrication or falsification of data. However, the issue is not often so simple. Disagreements often exist about when certain data may legitimately be considered outliers and thus appropriately ignored in reporting findings. Statistical tests and procedures can be used in questionable ways or ways that are not fully disclosed to the reader. Researchers may manipulate digital images in a variety of ways and to various extents. This was an issue in the Hwang case, as investigators discovered that his team had doctored photos of two authentic stem cell colonies to give the false impression that they had created eleven such colonies.

Misleading data can also result from carelessness in experimental design, measurements, or record-keeping. Responsible researchers must strive to avoid negligence, haste, and inattention in their work. The standards of data collection and management vary between disciplines, but it is widely acknowledged that researchers have an obligation to create an accurate and accessible record of their work sufficiently detailed to allow for checking and replication. This requires that researchers keep orderly and secure notebooks or electronic files. Beginning researchers often receive little or no formal training on these important topics.

Many misconduct investigations have raised questions about standards of care for recording, analyzing, and storing data. For example, in 1986 Nobel Prize-winning biologist and then professor at MIT, David Baltimore, coauthored a paper in the journal *Cell* with five others, including MIT colleague Tereza Imanishi-Kari. The paper reported a novel finding in the genetics of immune systems. Margot O'Toole, a postdoctoral fellow in Imanishi-Kari's lab, reported concerns about the paper after a year of unsuccessful attempts to replicate the study and after some of her own experiments produced contradictory results. When the US Congress subpoenaed Imanishi-Kari's notebooks, she admitted that she did not really have any. She only had disorganized sheets of paper. In the days before the hearing, she quickly bound them into a notebook. The investigators claimed they found clear signs of fraud: data were overwritten in different colors of ink, findings were erased, and dates were changed. At one point, Imanishi-Kari could not even make sense of the meaning of some of her numbers. She admitted to poor record-keeping but always maintained she was innocent of misconduct.[27]

Another example of carelessness is the practice of citing articles without actually reading them. One study found 391 biomedical articles over a ten-year period that cited retracted papers (the papers had often been retracted because of misconduct).[28] Scientists may often not take the time to study the growing reservoir of scientific knowledge. Instead, they may simply copy citations from secondary sources. Responsible conduct would seem to require that researchers actually read any articles that they cite. Otherwise, their own work may be contaminated by the errors or misconduct of others.

Bias and self-deception

Processes of inference can also be distorted by biases, which are systematic or nonrandom errors. For example, Morton's unconscious bias led to invalid inferences. Biases can also stem from consciously made false assumptions, such as the assumption of craniometrists that human head sizes and shapes determine personality traits and intelligence. This indicates why biases can be difficult to identify. They require an independent source of verification outside of a community of practitioners. If an entire field of science accepts the same bias, then it will not be identified. This

[27] See Kevles 1998. [28] See Howard 2011.

means that biases are not always best considered unethical. They may be more akin to hypotheses that are later proven wrong. Craniometrists, for example, may have conducted careful, honest, and responsible research and, as is the case with the progression of science, their biases or hypotheses were eventually discarded. Nonetheless, biases can stem from racial, patriarchal, or other assumptions, which again points out the importance of scientists' skepticism about the assumptions behind their research design and interpretation of data.

Self-deception is perhaps the greatest threat to the ethical ideal of scientific objectivity. It often stems from carelessness and wishful thinking. Hoping that his or her theory is true, a researcher may fall into the trap of experimenter expectancy, or seeing only what he or she wants to see. Self-deception is not intentional fraud – the researcher truly believes that he or she has not manipulated the data to accord with a preferred outcome. Yet there may be some self-awareness involved, as is the case, for example, when a researcher omits data that give the "wrong" answer.

Expectancy contributes to self-deception, which in turn leads to credulity. The Piltdown man hoax is one example of an entire community falling prey to a common delusion. Another example is the 1903 discovery of the N-Ray by the French physicist René Blondlot. Over the next three years over 100 scientists wrote more than 300 papers on N-Rays. Even after the American physicist R.W. Wood demonstrated that N-Rays were nothing more than an "observer effect," several French physicists continued to support Blondlot's work.

So self-deception is dangerous, because it can dupe entire communities into a set of false beliefs. But there is a danger in self-deception even when it leads to beliefs that later prove correct. For example, the English physicist Robert Hooke believed strongly in the Copernican heliocentric theory of the solar system. Proving the theory required observing a stellar parallax – a perceived difference in the position of a star due to the Earth's motion around the Sun. Hooke observed a star with a parallax of almost 30 seconds of arc. Yet, as it turns out he only observed what he wanted to see. There is a stellar parallax, but it is very small (about 1 second of arc); in fact, it is too small to be detected by Hooke's relatively crude telescope.[29]

[29] See Broad and Wade 1983 for more on the N-Ray and Hooke stories.

That heliocentrism later proved correct does not justify holding that belief as a result of credulousness or wishful thinking. For the ethical ideal of objectivity, getting the right answer is not most important. How that answer is derived is the key. It cannot be the result of blind faith or obedience, of expediency, or of deception, intentional or otherwise. As Jacob Bronowski exhorted his fellow scientists, “If we silence one scruple about our means, we infect ourselves and our ends together.”[30] One landmark study reported that bias in science trends toward a pervasive over-reporting and over-selection of false positive results.[31] Another study in 2012 reported that researchers were only able to confirm six of fifty-three “landmark studies” in preclinical cancer research.[32]

Trust

Trust is essential to the conduct of science because understanding the world is a task that is far too big for any single individual to undertake successfully. Even describing the particulars of a small slice of reality – say, cellular metabolism or the marriage customs of a tribe – requires the collective efforts of several researchers. As Newton remarked in a 1676 letter to Hooke, “If I have seen a little further it is by standing on the shoulders of Giants.” Because scientific knowledge is built up communally, its objectivity depends on the intersubjectivity of human communication. It follows that scientists must be able to rely on one another to be truthful. As Bronowski put the point: “We OUGHT to act in such a way that what IS true can be verified to be so.”[33] In short, facts about what is the case rely on the values necessary for “objectivity.”

If scientific predecessors conduct careless or dishonest work, then their shoulders will not be reliable perches for seeing further. Each member of an increasingly networked scientific community that relies on more and more specialized domains of expertise must trust in the work of all the others. Scientists have neither the time nor the expertise to independently verify every finding derived from the work of others; and in an endeavor that values priority of discovery, they certainly do not have the motivation.

[30] Bronowski 1956, p. 66. [31] Ioannidis 2005. [32] Begley, Glenn, and Ellis 2012.
[33] Bronowski 1956, p. 58.

Values embedded in research design

We have argued that the ideal of objectivity does not mean the absence of values or a view of the world somehow removed from human interests and perspectives. Rather, the ideal requires a critical awareness, explicit recognition, and rational defense of the values and perspectives that are unavoidable aspects of the human quest for knowledge. When scientists make decisions about equations, models, constants, and variables, they often must make certain assumptions that amount to the embedding of values in their experimental design. The ideal of objectivity demands self-awareness and an explicit justification of such choices.

The example of integrated assessment models (IAMs) to analyze climate change management strategies will illustrate the point.[34] IAMs are models of the global climate–society system. Environmental scientists and economists use IAMs to study various social responses to climate change and identify an economically optimal trajectory of investments in reducing greenhouse gas emissions. This requires choices about the criteria to define "optimality" (the objective function of the underlying optimization equation), and these choices are necessarily value-laden.

For example, some IAMs frame the goal of climate management strategies in terms of optimizing "utility" as a measure of time-aggregated societal wealth. These models sometimes assume a definition of utility that does not distinguish between situations of evenly distributed consumption and those where the wealthy consume a lot more than the poor. In other words, the scientific model makes a typical utilitarian value calculation where total utility matters, but the distribution of utility does not. The model may further assume that utility is a sufficient proxy metric for human happiness and that this can be adequately measured in terms of money and consumption. In other words, the model assumes that aggregated global utility is the ultimate social goal. These are all value judgments that are intrinsic to the model.

IAMs entail other value judgments as well, such as the choice of a utility discount rate (used to compare the value of future utility with that of present utility). Those who design the equations that govern the model must also make choices about how to quantify climate-related damages. Some,

[34] See Schienke et al. 2010.

for example, convert various climate change impacts such as droughts and floods into units of money and utility, and this conversion of course entails further assumptions about values. There are further value judgments to be made about the reliability of the model for guiding policy decisions.

For any scientific method or model that attempts to measure costs, risks, and benefits, these terms can be defined in a variety of ways and the chosen definition creates a certain way of framing the issue. In making one decision rather than another, a researcher creates and measures one reality rather than another. What counts as a cost, a benefit, a risk? Whose interests are included? The ideal of objectivity is not to avoid or eliminate these value judgments. Rather, it is to make them transparent and explicit and to justify them rationally while remaining open to the potential merits of alternative formulations. For example, perhaps a better way to structure IAMs is not with globally aggregated utility, but with utilities disaggregated by region or nation. African utility and consumption could be optimized separately and weighted equally with North American utility and consumption. This may be a more just or fair calculation given the high probability that damage from climate change will be borne primarily by poorer populations where people benefit little from the fossil fuel consumption by the wealthy that causes the damage.

The flow 3: disseminating research

As a communal enterprise, science depends on outlets (e.g., conferences, journals, and press releases) for disseminating information. As an activity governed by norms that define acceptable practices, science institutes the gate-keeping or quality control mechanism of peer review to ensure the work is sound. As a career, science requires ways to grant recognition for contributions to communal knowledge. As a commercial enterprise, research often generates intellectual property with restrictions on its dissemination. Thus, this section takes up the issues of: (a) peer review; (b) authorship and allocation of credit; and (c) intellectual property.

Peer review

In the seventeenth century, Newton and many other natural philosophers would keep new findings secret so that others could not claim the results