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Scientific ignorance: Probing the limits of scientific research and knowledge production

(La ignorancia científica: una indagación sobre los límites de la investigación científica y la producción del conocimiento)

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ABSTRACT: The aim of the paper is to clarify the concept of *scientific ignorance*: what is it, what are its sources, and when is it epistemically detrimental to science. While some sources of scientific ignorance come inevitably with the process of knowledge acquisition, others are deliberately created. The former includes selection processes, inductive reasoning, and cognitive biases, while the latter includes scientific fraud. Another important source of scientific ignorance appears when scientists introduce methodological biases through micro-decisions in the research process. I provide three examples from medical research to illustrate this point. I argue further that methodological biases present a challenge, in so far as they are no easily classifiable as deliberate: they might also be the result of entrenched research practices within a scientific community. Strategies to identify and prevent methodological biases in research should take into account such difference.

KEYWORDS: scientific ignorance, agnotology, cognitive biases, selective ignorance, medical research, methodological biases.

RESUMEN: El objetivo del artículo es aclarar el concepto de *ignorancia científica*: qué es, cuáles son sus fuentes y cuándo es epistémicamente perjudicial para la ciencia. Mientras que algunas fuentes de ignorancia científica vienen dadas inevitablemente con el proceso de adquisición de conocimiento, otras se crean deliberadamente. Las primeras incluyen los procesos de selección, razonamiento inductivo y sesgos cognitivos, mientras que las segundas incluyen el fraude científico. Otra fuente importante de ignorancia científica aparece cuando los científicos introducen sesgos metodológicos a través de micro-decisiones en el proceso de investigación. Proporciono tres ejemplos de investigación médica para ilustrar este punto. Además, sostengo que los sesgos metodológicos representan un desafío, en la medida en que no son fácilmente clasificables como deliberados: también podrían ser el resultado de prácticas de investigación arraigadas dentro de una comunidad científica. Las estrategias para identificar y prevenir los sesgos metodológicos en la investigación deben tener en cuenta dicha diferencia.

PALABRAS CLAVE: ignorancia científica, agnotología, sesgos cognitivos, ignorancia selectiva, investigación médica, sesgos metodológicos.

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1. *Introduction*

The pursuit of knowledge is one of the main reasons scientific research exists. However, science not always serves the most epistemically fruitful goals. As the emerging field of agnotology, or the epistemology of ignorance, illustrates, scientific research also contributes to the production of ignorance (Proctor & Schiebinger 2008; Sullivan & Tuana 2007). On the one hand, this is inevitable. Given science's limited resources, research must focus on understanding certain phenomena, while leaving others aside. In this sense, the more scientists know about the phenomena they research, the more ignorant they become about the phenomena left aside. On the other hand, scientific research can miss the understanding of epistemically or socially significant phenomena, if research is targeting distracting aims. This happened for decades with research on the genetic causes of lung cancer, which actively ignored the health hazards of tobacco smoking (Proctor 2012). Distinguishing between cases in which scientific ignorance emerges as an inevitable counterpart of scientific knowledge and cases in which ignorance is the product of research interests that go against epistemic or social aims is fundamental to identifying preventive measures for detrimental cases of scientific ignorance.

Accordingly, the aim of the paper is to provide a philosophical analysis of *scientific ignorance*: what is it, what are its sources, and when is it epistemically detrimental to the scientific enterprise. First, I provide a brief introduction to the social studies of ignorance and its relation to science. Second, I offer a working definition of scientific ignorance as non-knowledge resulting from processes of scientific knowledge production. Third, I propose a taxonomy of sources of scientific ignorance, distinguishing between inevitable sources of scientific ignorance that emerge from the constraints attached to the production of scientific knowledge, on the one hand, and deliberate sources of scientific ignorance, which are related to the way scientific research is sometimes inadequately set up to deliver certain results and not others, on the other hand. I also present methodological biases as another significant source of scientific ignorance, and I provide three examples from medical research to illustrate that different decisions in the research process can end up compromising the reliability of scientific results, producing ignorance instead of knowledge. I argue further that methodological biases present a challenge, in so far as they are no easily classifiable as deliberate: they might also be the result of entrenched research practices within a scientific community. Strategies to identify and prevent methodological biases in research should take into account such difference.

2. *Agnotology and the social studies of ignorance*

Our human desire to know the world around us goes hand in hand with the extension of our ignorance. We seek knowledge because we are ignorant and, as we accumulate more and more knowledge of our surroundings, we hope to be less and less ignorant. Scholars interested in the study of ignorance have challenged this traditional conception of ignorance as a natural vacuum that ought to be filled with knowledge, introducing a broader conception that includes ignorance as the product of social forces (Mills 1997; Proctor 2008; Smithson 1989). For instance, in addition to the traditional conception of ignorance as *native state*, ignorance can also be the product of the social conditions in which science is produced, i.e., the inevitable *lost realm* of scientific knowledge, or even the deliberate product or *strategic ploy* of partisan interests (Proctor 2008, 6). These distinctions will become clear in the following sections but notice for now that in both cases ignorance is no longer a natural state, but a social construction, i.e., the result of social processes.

Agnotology, or the epistemology of ignorance, has recently emerged as a subfield interested in these social dimensions of ignorance. The term *agnotology* was originally coined by Proctor with the help of linguist Iain Boal, and the volume *Agnotology: The Making and Unmaking of Ignorance* (Proctor & Schiebinger 2008) put it on the academic map. Agnotology has served as a tool for scholars to uncover cases in which research done for the private interest has led to the obstruction of scientific knowledge and its public dissemination (Elliott 2011; Markowitz & Rosner 2013; McGarity & Wagner 2008; Michaels 2008; Oreskes & Conway 2010; Proctor 2012). Such studies have certainly illuminated the limitations of industry-funded research, including research funded by the tobacco industry, the petro-chemical industry, and the pharmaceutical industry, among others. However, many of these works on agnotology also presuppose a normative distinction between knowledge and ignorance, which still needs important philosophical input.

As I have argued elsewhere in detail (Fernández Pinto 2015), most contributions to agnotology make broad claims regarding what counts as proper scientific knowledge and should be protected, and what counts as scientific ignorance, and should be prevented, without proper justification or without considering relevant exceptions.[1] Instead of presupposing that scientific ignorance is detrimental to science, this paper aims to contribute to this discussion by clarifying what scientific ignorance is, identifying different sources of scientific ignorance, and examining in which cases scientific ignorance can be considered detrimental to the goals of research. In this way, the argument of the paper offers a more philosophically complex and nuanced view of scientific ignorance.

One should also notice that other social studies scholars who do not agree with the framework of agnotology, but still work on the social studies of ignorance, have advocated for a more descriptive and sociological approach to the study of ignorance in science (e.g., Frickel *et al.* 2010; Gross & McGoey 2015). While acknowledging these important contributions, my aim in this paper is to enrich the philosophical discussion of the study of ignorance, maintaining its normative dimension.

3. *What is scientific ignorance?*

To start, let me clarify what I understand by *scientific ignorance*. An important distinction for the present argument, which is not commonly acknowledged in the social studies of ignorance, is the distinction between the *conception* of ignorance and the *sources* of ignorance. Sociologists of science have argued convincingly that scientific knowledge is the product of social processes that lead scientists to certain beliefs, identified as knowledge by the scientific community (Bloor 1976; Latour & Woolgar 1979; Shapin & Shaffer 1985). More recent studies have made a similar point with respect to the production of ignorance

[1] For a similar critique, see the introduction to Gross and McGoey (2015). For a discussion about the positive aspects of ignorance, see Wehling (2015).

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(Croissant 2014; Frickel 2014; Frickel *et al.* 2010; Gross & McGoey 2015). Meanwhile, philosophers of science have provided different epistemological accounts of scientific knowledge that try to incorporate its social dimensions (Longino 2002; Kitcher 2001; Solomon 2001; Kourany 2010). This social epistemology of science aims at providing a *social conception* of scientific knowledge, i.e., a philosophical account of what scientific knowledge is, where scientific knowledge is understood at the same time as the product of social forces. Within this framework, one can still make a conceptual distinction between what we currently understand as scientific knowledge, or in this case, ignorance, i.e., a working definition or conception of ignorance, and the different processes or factors leading to it. For the sake of the argument, I will first establish a working definition of scientific ignorance, and then I will proceed to examine its sources.

In the paper, I follow what epistemologists call *the standard view* of ignorance, according to which ignorance is the lack or absence of knowledge, encompassing states of false belief, unjustified true beliefs, and non-belief (Le Morvan & Peels 2016). This is certainly not the only available epistemological conception of ignorance. The current debate in the epistemology of ignorance contrasts the standard view with what has been called *the new view*, according to which ignorance is just the lack or absence of true belief, and not the absence of knowledge as the standard view states.[2] The views differ, among other things, in their treatment of unjustified true belief, which would be considered a case of ignorance in the standard view, but not in the case of the new view. I follow the traditional definition for the sake of argumentative clarity, and because I consider it fits better with our evaluation of cases of methodological biases, as will become clear in section five. Moreover, given that works on agnotology are not clear about their conception of ignorance (Fernández Pinto 2015), I start with the standard definition to see how far it takes us; further limitations and challenges to this standard conception will be left for later. Perhaps a parallel analysis to the one proposed in this paper can be made following the new view of ignorance, or other alternative conceptions.

The working conception of knowledge is contextual and intersubjective, depending on the beliefs, standards, and self-regulatory processes of scientific communities (Longino 2002). Thus, this conception of knowledge (or ignorance) is historically and geographically located, following the different times and places in which scientific disciplines develop. Identifying cases of scientific ignorance, accordingly, depends on what scientific communities sanction as knowledge, i.e., beliefs that result from following the standardized processes of knowledge production. Following the standard view, beliefs that do not meet such requirements, i.e., beliefs whose production has failed to meet the standards, are not considered knowledge, but ignorance.

To clarify, endorsing the standard view of ignorance is not synonymous with endorsing the traditional understanding of ignorance as *native state*. The standard view is only providing an analytic definition of ignorance, without saying anything about the origins of such ignorance, whereas the conception of ignorance as native state emphasizes the fact that ignorance is natural or given. In this sense, the standard definition serves as a tool for identifying cases of scientific ignorance, e.g., when people are misguided about certain scientific beliefs, independently of the factors that led to such beliefs.

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[2] For a summary of the main arguments on both sides, see Le Morvan and Peels (2016).

While holding the idea of ignorance as non-knowledge, my interest in this paper is to identify different ways in which the actors involved in the epistemic practice of scientific research—mainly scientists, but also policy-makers, funders, and the like—can become ignorant. In this sense, the paper follows an understanding of ignorance as a social product and aims to identify the factors leading to states of ignorance. Finally, I am not interested in the production of ignorance in general, but specifically in the production of ignorance that emerges from scientific research. Thus, when I talk about *scientific ignorance*, I am referring to a state of non-knowledge resulting from scientific research. I will now turn to characterize the different ways in which scientific ignorance can come about.

4. Sources of scientific ignorance

The production of scientific ignorance, as Proctor has highlighted, has at least two sources. On the one hand, ignorance emerges as an inevitable by-product of the search for knowledge. On the other hand, ignorance can also be deliberately created and maintained. Starting with this broad distinction, this section examines in more detail the types of inevitable and deliberate sources of scientific ignorance, as well as sources that are not so easily classifiable in these two groups.

4.1. Knowledge and ignorance two sides of the same coin

The production of scientific knowledge goes hand in hand with the production of scientific ignorance or, to put it another way, scientific ignorance is, in a sense, a counterpart to scientific knowledge. As science renders better knowledge about the world we live in, it inevitably leads to new states of non-knowledge or ignorance. This happens in at least three ways: first, given the fact that scientists have to make different decisions during the research process; second, given the fallibility of research results; and third, given the limitations of human cognition. All of these sources of ignorance are inseparable from empirical inquiry, and hence inevitable, as will become clear in what follows.

A first inevitable source of scientific ignorance is related to the decision process in science, or what Proctor called, *selective ignorance* (2008, 3). Due to limited time and resources, scientists cannot explore every possible line of research. Accordingly, some lines of research, and some research questions need to be chosen on top of others. The more we know about certain things, the further apart and the less likely to know about others. Ian Hacking made this point using weapons research as an example: "When so much knowledge is created by and for weaponry, it is not only our actual facts and the content of knowledge, that are affected. The possible facts, the nature of the (ideal) world in which we live become determined" (Hacking 1999, 167). In a way, Kuhn (1962) made a similar point when suggesting that paradigms determine the scope and type of questions to be answered by researchers. In this way, current scientific research limits future research.

In addition to choosing certain lines of research over others, scientific ignorance also emerges through the selection of different paths within the research process. As Kevin Elliott (2013, 2015) identifies, selective ignorance also stems from choices about how to study a complex topic in some way rather than others, what sort of information to collect, and how to disseminate such information (see also, Cosgrove *et al.* 2016; Holman & Bruner 2015; Sismondo 2009). In this sense, selecting a line of research over others is just one decision in the scientific process among many, inevitably contributing to the production of scientific ignorance.

In addition to its inevitability, selective ignorance has also a positive side, since new research also illuminates the boundaries of what we are ignorant about, but capable of knowing. Robert Merton called it *specified ignorance*:

> In anything but a paradoxical sense, newly acquired knowledge produces newly acquired ignorance. For the growth of knowledge and understanding within a field of inquiry brings with it the growth of specifiable and specified ignorance: a new awareness of what is not yet known or understood and a rationale for its being worth the knowing. (Merton 1987, 8)

Karl Popper made a similar point: "The more we learn about the world, and the deeper our learning, the more conscious, specific, and articulate will be our knowledge of what we do not know, our knowledge of our ignorance" (1963, 38). Thus, the selection processes leading the advancement of science also help scientists specify their ignorance, or in other words, determine what they do not know, but should get to know if they concentrate their efforts in that direction. In fact, specified ignorance has been considered a fundamental motor of scientific research, driving scientists toward achievable epistemic goals (Firestein 2012; Kerwin 1993; Kuhn 1962). Specified ignorance emerges hand in hand with scientific knowledge, and also bolsters the acquisition of new knowledge. It is thus an epistemically valuable aspect of selective ignorance.

Selective ignorance however can also be socially detrimental, even when epistemically adequate. Although making choices during the research process is inevitable, and so is the scientific ignorance that emerges, what choices are made is a matter of controversy. To choose might be inevitable, but surely we must have good reasons to prefer certain options over others. As David Hess (2015) argues, scientific knowledge is not indifferent to the unequal distribution of power in society, and thus, scientists make choices that systematically benefit those who are in positions of economic privilege and power, undermining those who are not. The resulting *undone science*, i.e., the ignorance about the issues that mostly affect the poor and socially marginalized, could be the result of scientists making unjust decisions when facing some of the decisions previously identified—what to research, how to research it, how to communicate results, and so on. It could also be the result of current financial schemes, in which research mainly targets industrial interests (Carrier 2008). In both cases, selective ignorance can be, and certainly has been, in many cases, socially inappropriate.

A second and equally inevitable source of scientific ignorance, different from selective ignorance, stems from the intrinsic fallibility of scientific results, also known as scientific uncertainty. As the history of science clearly shows, results of scientific research very often turn out to be false in the long run. Even the most well-regarded theories, Newtonian mechanics being the paradigmatic example, have been eventually replaced by more accurate or even completely different scientific theories. Statements that the old theory considered true, turn out to be false under the new theory. This is an old problem for philosophers of science, who have dedicated many pages to the study of fallibility and uncertainty in scientific reasoning. The empiricist philosopher David Hume famously examined this issue in terms of *the problem of induction*, or the inescapable uncertainty intrinsic to the inductive reasoning proper of studying natural phenomena from experience (Hume 1748 [1999], 115). Given the lack of demonstrative reasoning to prove matters of fact, scientists appeal to inductive reasoning, together with the idea that past experiences of cause and effect will still hold in the future. But this idea is fallible. Or in other words, the results of scientific inquiry can only render probable results, never certainty.

The uncertainty of scientific findings is not only inescapable, but also, in a sense, valuable. After all, the fallibility of research results is what makes science revisable and non-dogmatic. Hence, the problem of induction makes scientific inquiry at the same time empirically accurate, i.e., based on the best available evidence, and prone to error, i.e., without warrant that results will hold in the future. Here again, the production of scientific knowledge goes hand in hand with the production of scientific ignorance: as scientists seek better explanations of the phenomena, their findings can always be wrong.

A third possible source of inevitable ignorance in science comes from human cognitive limitations. The same cognitive system that allows us to understand and explain the world around us, also sets limits to the possibilities of our knowing. Research in behavioral psychology has shown how cognitive biases affect human behavior (Tversky and Kahneman 1974; Nisbett and Ross 1980), making us less rational than expected. Human cognitive capacities have been adapted to make optimal decisions under environmental pressures, using different heuristics and biases. While these mechanisms seem to work well most of the time—we are efficient decision-makers—they can easily be misapplied (Lilienfeld *et al.* 2009), leading us to unwarranted and sometimes blatantly wrong conclusions. A good example of this is confirmation bias: the tendency to seek evidence that supports our beliefs, while dismissing or reinterpreting evidence that goes against them. While this mechanism might prove useful in some circumstances, e.g., when meeting a complete stranger and trying to assess whether her testimony is true or not, it can easily backfire if no evidence can make us question our beliefs.

As a human endeavor, science is no different. Cognitive biases affect scientific research in different ways. For instance, scientists are prone to *asymmetric attention bias*—double-checking unexpected results, while giving a free-pass to expected ones—and to *hypothesis myopia*—looking for evidence to support their hypothesis, while ignoring evidence against it (Nuzzo 2015). Cognitive biases can be a source of scientific ignorance in so far as they lead scientists to wrong or unjustified conclusions. They are also difficult to identify and counteract, since we are not aware of them. In fact, cognitive biases appear as intuitive evolutionary responses most of the time (Croskerry *et al.* 2013). However, they can also be actively counteracted through a series of debiasing techniques, such as explicitly considering alternative hypothesis or inviting others to double-check your results (Nuzzo 2015). Although debiasing mechanisms require constant vigilance of one's behavior as well as reflection and critical thinking (Crosskerry 2015), which makes them costly and unlikely to work under pressure and time constraints, they can be effective under the appropriate circumstances (Lilienfeld *et al.* 2009). Accordingly, while cognitive biases might present important limitations to the production of scientific knowledge, they are not completely unavoidable. They are inevitable in so far as they are part of our cognitive capacities, and they might be considered an inevitable source of ignorance, insofar as we cannot keep them in check all the time. However, they can be controlled, at least to certain extent, through debiasing techniques.

4.2. Deliberate ignorance

Ignorance is the unavoidable result of the quest for knowledge. Ignorance, however, also emerges deliberately from the way scientific research is sometimes conducted to deliver certain results and not others. While this may happen in a variety of ways, perhaps the clearest case of deliberate ignorance is the case of blatant scientific fraud through fabrication or falsification of data, i.e., when scientists make up data or alter research results. Cases of scientific fraud are broadly repudiated in science: when a case of blatant fraud is demonstrated, scientists can quickly lose their jobs and reputation, which normally means the end of their career.

Consider, for example, infamous cases of fraud, such as Andrew Wakefield's and Hwang Woo-suk's. Wakefield was the physician who published an article in *The Lancet* arguing for a connection between vaccines and autism (Wakefield *et al.* 1998), while Woo-suk was the South Korean researcher whose publications in *Science* made him at the time one of the world-leading expert in creating human embryonic stem cells through cloning (Woo-suk *et al.* 2004, 2005). In both of these cases, allegations of fraud led to in-depth investigations of the research behind these publications, the scientists involved were accused of fabricating data, and the papers were retracted.

Although blatant cases of scientific fraud receive clear disapproval from the scientific community, the evidence unfortunately suggests that fraud might be more frequent than expected, and that there are many gray-zones in the research process, where scientific misconduct might be lurking (Fanelli 2009). In any case, the fabrication and falsification of data is an important source of scientific ignorance, in which scientists purposely mislead their peers towards false or unjustified belief. Contrary to the inevitable sources of ignorance previously described, there is no necessity and no inherent value (social or epistemic) in scientific fraud. Without controversy, fraud is a detrimental practice in scientific research.

4.3. Less transparent cases

Scientific fraud is a transparent case of ignorance production, leading the scientific community, policy makers, and even the public at large to accept results that are wrong or not properly justified. It is also clearly deliberate. Regardless the motivations, fraud cases require scientists to actively alter the standard procedures of data collection and interpretation. Other cases of ignorance production are less transparent. Research requires scientists to make a number of decisions and methodological choices at different stages, decisions underdetermined by the available evidence, in which scientists have to appeal to other criteria for choice.

For instance, scientists decide how to pose the main research question, which outcomes to measure, how to present data for publication, how to interpret the results from available data, etc. Such decisions are proper of the research process, and all scientists make them at some point. Normally, they appeal to the epistemic standards of their disciplines or to their scientific intuition (their scientific *bon sens,* in Duhem's words) to make the most appropriate decisions for obtaining reliable results. However, it is also possible for scientists to follow other criteria in making such choices, the sum of which can predetermine research results. Such biased methodological decisions can shape research results in order to obtain expected results. This is a fifth way in which scientific ignorance emerges: scientists are not properly justified to believe results following the introduction of methodological biases.

A more detailed examination of methodological biases will follow in the next section. For now, notice that methodological biases are not easily classifiable as inevitable or deliberate sources of ignorance. On the one hand, introducing biases through methodological decisions can be a deliberate process, one in which scientists clearly understand how a minor decision in experimental design, for example, can shape the results of research, moving them closer to expected outcomes. On the other hand, methodological biases can be tied to entrenched practices within a scientific community, where individual scientists do not understand that some standardized methodological decisions are actually biasing research results. Accordingly, scientific ignorance emerging from methodological biases can be in some cases the result of deliberate decisions, and in other cases the result of entrenched scientific practices not necessarily understood as biased.

In sum, there are different sources of ignorance in science. Some of them are inevitable, for they come together with the process of knowledge production. Ignorance emerges given that research results are fallible even when reliable, given that scientists ought to choose some lines of research over others, and also given our human cognitive limitations. In such cases, knowledge and ignorance seem two sides of the same coin. Other sources of ignorance are, however, deliberate and thus avoidable. The clearest case is scientific fraud: when scientists purposely misrepresent results leading the scientific community to false or unjustified beliefs. Finally, some sources of ignorance are not so clearly classifiable as inevitable or deliberate. Methodological biases are one example, in which scientists make micro-decisions in the research process that predetermine desired results. Such conduct might be considered deliberate in some cases, and thus closer to scientific fraud, while in other cases, scientists are just following entrenched practices in their disciplines without acknowledging that they are biasing their research results, making these cases similar to cognitive biases. Ignorance results in both cases, given that we lack proper justification for believing scientific findings from such biased inquiries. However, notice that the moral responsibility of the individual scientist seems very different: we would be hesitant to blame the scientist acting according to disciplinary standards of scientific misconduct, but we would presumably be less charitable towards the scientist who introduces methodological biases deliberately. In order to understand better in which way the introduction of methodological biases is detrimental to scientific research and how to prevent it, a more detailed analysis is needed.

5. *The problems, illustrated by clinical research*

The last section introduced different sources of scientific ignorance. Among them, methodological biases seemed particularly difficult to categorize: they can be both deliberately introduced by individual scientists or automatically followed by the community without notice. This section examines with more detail the introduction of methodological biases in research. The aim is to better understand how biasing micro-decisions in the research process are introduced, and how they lead to scientific ignorance. Having a better grasp of methodological biases can also help to create better strategies to mitigate and prevent them.

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Taking clinical research as an example, I present three ways in which methodological biases are introduced in the research process leading to epistemically detrimental results: (i) by using placebos or inaccurate doses of the best alternative treatments for the control group in clinical trials, (ii) by selecting or changing the primary outcome post hoc, and (iii) by presenting results in favorable but inappropriate ways.

5.1. Comparison groups and doses

In clinical research, investigators have a number of methodological decisions to make during the research process, such as choosing the specific question the trial aims to answer, choosing the specific patient population for the trial, choosing the comparison group against which the new treatment is tried, determining the dosage for both the control and the treatment groups, picking a specific outcome or endpoint to measure, deciding how to interpret and present results, deciding whether to publish the results or not, and so forth. Each of these decisions has a spectrum of epistemically legitimate choices. Methodological biases appear precisely when making decisions beyond the spectrum of what is epistemically (or methodologically, if you prefer) appropriate, jeopardizing the reliability of the results.

Methodological biases can be introduced, for instance, when choosing comparison groups and doses. In clinical trials, new treatments can be compared against a control group taking placebo or a control group taking an effective available treatment. Although placebo controlled groups are in many cases necessary for determining the effectiveness of the new treatment (Bero & Rennie 1996, 216), a number of ethical issues have been raised regarding placebo controlled trials. One major issue has to do with denying patients in the control group, who are suffering from the medical condition being studied, an effective available treatment (WHO 2013, §32).

Beyond the ethical reasons for avoiding placebo controlled trials, there are also compelling epistemic reasons. Placebo controlled trials might be telling us whether a drug is better than nothing, but if other effective treatments are already available, this is far from sufficient. What we really want to know, what would be significant in terms of advancing current knowledge, is whether the new treatment is better than the best available one. Despite these good ethical and epistemic reasons, around one third of phase 3 clinical trials with alternative treatments available are still designed as only placebo-controlled trials (Goldberg *et al.* 2011). Results of a good number of clinical trials are not relevant for patients currently suffering for the medical condition being studied due to the way investigators set the comparison groups.

A similar issue arises when researchers choose to compare the new treatment against too small a dose of the alternative treatment, making the drug seem ineffective, or against too high a dose of the alternative treatment, making the secondary effects much worse (Bero & Rennie 1996; Smith 2005). Using doses outside the standard range has proved successful in establishing either the efficacy or the benefits of new treatments compared to available alternatives. Clinical trials on new antipsychotic medication for the treatment of schizophrenia are good examples, where old treatments, such as haloperidol or risperidone, were given at higher doses than normally used, almost ensuring the experience of uncomfortable side effects, which in turn led to favorable results for the new treatment (Safer 2002; Goldacre 2012). Here again, a (small) decision in the experimental design can easily lead to the favorable outcome.

5.2. Post hoc endpoints

Another way in which methodological biases lead to scientific ignorance in clinical research is related to picking the endpoints or outcomes to be measured during the trial. According to protocol, researchers should specify the primary outcome to be measured, i.e., the most significant outcome to be examined during the study, before the trial starts. One powerful epistemic reason for establishing the primary outcome before the trial is to reduce multiple analyses that might render false-positive results. If one measures many outcomes in the same trial, some are likely to show statistically significant results just due to chance. Hence, picking only one primary outcome reduces the risk of randomly obtaining significant results (Andrade 2015). After all, the goal is to determine whether the new treatment provides real benefits, and not just randomly generated results. In this way, transparency with respect to the primary outcome measure of a clinical trial contributes to its internal validity.

Starting clinical trials with multiple outcomes is, however, a common way of ensuring that the new treatment is comparatively superior. If instead of identifying one primary outcome, researchers work with a number of them, say ten, while using a per-comparison error rate, then they can expect to find a statistically significant result at least in one of these outcomes. The probability of obtaining at least one significant result increases at the cost of increasing risk of false positives. The problem emerges again: researchers can predetermine favorable trial results by measuring a number of outcomes and then establishing the primary outcome, or changing the original primary outcome with an alternative outcome, once they have identified which outcome has positive results. Although many have questioned such practice (Bero & Rennie 1996; Goldacre 2012; Safer 2002; Smith 2005; Srinivas 2015), also known as *post hoc analysis* or *data dredging*, researchers have found it to be fairly common (Chan *et al.* 2004; Gøtzsche 1989; Vedula *et al.* 2009). So here is a second way in which a decision made during the research process can lead to desired results.

5.3. Risk reduction measures

Scientists can also introduce methodological biases at the end of the research process, when deciding how tho present research results. For instance, let's say that a clinical trial showed that the new treatment was effective in reducing the risk of developing a certain medical condition. There are at least two ways of presenting this risk reduction: showing an *absolute risk reduction* measure—i.e., the difference between the probability of the outcome in the treatment group and the probability of the outcome in the control group—or showing a *relative risk reduction* measure—i.e., the percentage of risk reduction of the treatment group compared to the control group. Goldacre illustrates this point as follows:

> Let's say your chances of a heart attack in the next year are high: forty people out of 1,000 like you will have a heart attack in the next year, or if you prefer, 4 per cent of people like you. Let's say those people are treated with a statin, and their risk is reduced, so only twenty of them will have a heart attack, or 2 per cent. We could say this is 'a 50 per cent reduction in the risk of heart attack', because it's gone from 4 per cent to 2 per cent [...]. But we could also express the same change in risk as the 'absolute risk reduction', the change from 4 per cent to 2 per cent, which makes a change of 2 per cent, or 'a 2 per cent reduction in the risk of heart attack'. (Goldacre 2012, 217)

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Although both risk reduction measures stem from the same facts, they convey different information. Absolute risk reduction expresses risk reduction in terms of how much the treatment has reduced the risk of developing the condition (or in other words the percentage of patients who will not develop the condition thanks to the treatment), which tends to render small percentages; while relative risk reduction expresses how much the treatment reduced the risk of developing the condition compared to the control group where no treatment was given, which tends to render big percentages. In the example above, while the relative risk reduction was 50%, the absolute risk reduction was 2%. Studies have shown that presenting research results in terms of relative risk reduction leads to overestimating the effectiveness of the treatment and, in turn, to a higher number of prescriptions (Covey 2007). Given that both measures are just giving different information about the same facts, the discrepancy shouldn't exist, which leads us to think that doctors are misunderstanding relative risk reduction measures and probably overestimating the effectiveness of the intervention. Indeed, such misunderstanding can be explained by the reference class fallacy, according to which relative risk reduction measures are mistakenly taken for absolute risk reduction measures. Following the previous example, the fallacy occurs when the statement "a 50% reduction in heart attack risk" is mistakenly taken to mean that a patient taking the treatment will be 50% less likely to develop the condition (Sprenger & Stegenga 2017; Stegenga 2015). Accordingly, it would be questionable to present research outcomes in terms of relative risk reduction measures.

As usual, the devil is in the details. Although both absolute and relative risk reduction measures stem from the same facts, doctors and patients interpret this information very differently. Moreover, for calculating the risk for an individual patient, only the absolute risk reduction measure is relevant (Sprenger & Stegenga 2017). Accordingly, if investigators choose to present results only in terms of a relative risk reduction measure, they are promoting the misunderstanding of the results in favor of the new treatment. As the example shows, scientists decide which measure of risk reduction to present. The methodologically sound decision is to present an absolute risk reduction measure, and the methodologically biased decision is to present a relative risk reduction measure, which in turn misleads others.

5.4. Discussion

In sum, decisions during the scientific research process can end up shaping research outcomes in epistemically inappropriate ways, fomenting ignorance through establishing false or unjustified beliefs as proper scientific knowledge. As the example of antipsychotic medications shows, the trials did not really prove that the new drugs had fewer side effects, but they appear to do so given the results. Thus, the belief that the new treatments are better in this respect is unjustified, or even false (something we cannot know until trials with proper doses are conducted). And these are only some instances in which biased methodological decisions lead to ignorance, instead of knowledge, within the scientific process. Several different strategies such as these have been identified in medical research (Bero & Rennie 1996; Safer 2002; Smith 2005).

Methodological biases can create a detrimental epistemic gap. In this section, I have shown how biased micro-decisions during the research process can inadequately predetermine research results, disseminating ignorance in science, as well as opening a gap between what we could and should know, and what we actually know and don't know. I consider this a detrimental epistemic gap given that the scientific community is perfectly capable of obtaining relevant and reliable results, but the process is obstructed by epistemically inappropriate decisions. The gap is epistemic, given that it impedes the production and dissemination of scientific knowledge, but it has both epistemic and ethical consequences. Actors involved in the scientific process know less than they could and should know, and this lack of knowledge ends up causing unnecessary suffering. This becomes particularly clear in the case of medical research, where false or unjustified beliefs about medical treatments can easily compromise patients' health and their families' well-being or, in Kerwin's words, "medical ignorance hurts" (1993, 175).

As previously noted, methodological biases present a further challenge, given that they are not easily understood as deliberate or not. It is clear that scientists introduce methodological biases while making decisions in the research process, but it is not clear whether these decisions are deliberate, i.e., scientists know they are biasing the process to obtain expected results, or just result from following entrenched methodological standards, i.e., scientists are not aware of the biases they are introducing.

To illustrate the former, consider the use of "spins" or distorted presentation of results in research papers. A study of a representative sample of randomized controlled trials with uncontested non-significant results (Bourton *et al.* 2010) found that 49 of the 72 abstracts had a spin on the results, and 28 had no numerical results for the primary outcome of the trial at all reported in the paper. In other words, a decision had been made to conceal the main results of the trial. Given that not reporting the main results of a trial cannot conceivably become standardized practice, we have good reasons to believe that the lack of reporting in this case is deliberate.

To illustrate the latter, consider the case of "p-hacking" and the reproducibility crisis in psychology, as well as neuroscience and other life sciences. The publication of the Open Science Collaboration study "Estimating the reproducibility of psychological science" (2015) gave proof of a suspected major methodological issue in psychology research: the fact that several experimental and correlational psychology studies could not be replicated despite having obtained significant results with a 95% confidence interval in the original studies. Among other methodological biases, the unexpected irreproducibility of results was attributed to "p-hacking" or the selection of data or statistical analyses until significant results ($p < 0.05$) are obtained (Head *et al.* 2015). The point here being that methodological biases were common practice among researchers (John, *et al.* 2012; Simmons, *et al.* 2011), and their methodological appropriateness was not questioned. In fact, methodological biases have been so common in many life sciences that the possibility that most published scientific findings might be false has been considered (Ioannidis 2005). In this sense, presumably many researchers were trained in p-hacking techniques, without realizing these were actually biasing their results.

Although many cases of methodological bias might not be easily discernible as either deliberate decision or normalized practice, the distinction is crucial for creating mitigation and prevention strategies. On the one hand, normalized practices that introduce methodological biases ought to be identified and transformed. This is precisely what is happening with the reproducibility crisis in psychology and neuroscience today, where many are advocating for blind data analysis, pre-registration for studies, where methods and analyses are established before data collection, as well as encouraging replication

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studies and their publication (Chambers *et al.* 2014; Head *et al.* 2015). On the other hand, deliberate introduction of methodological biases in research might be difficult to prove, but when possible, we have good reasons to approach it as a case of scientific fraud or misconduct. After all, scientists are deliberately biasing research to obtain a desired result, which not only compromises the epistemic reliability of the findings, but also presents potential health or environmental hazards. In other words, this deliberate production of scientific ignorance can also have negative social consequences. In this sense, individual scientists are also morally responsible for the social consequences of their epistemic shortcomings.

6. Conclusion

The aim of this paper was to provide a philosophical analysis of scientific ignorance. After providing a tentative definition of scientific ignorance as a state of non-knowledge resulting from scientific research, I examined different sources of scientific ignorance. While some sources of scientific ignorance come inevitably with the process of knowledge acquisition, others are deliberately created. The former includes selection processes, inductive reasoning, and cognitive biases, while the latter includes scientific fraud. Another important source of scientific ignorance appears when scientists introduce methodological biases through micro-decisions in the research process. Such biases can lead scientists, policymakers, and the general public to hold unjustified or even false beliefs. In addition to this epistemic flaw, such ignorance can also have significant social consequences in terms of environmental and human health. In this sense, methodological biases ought to be properly identified and prevented. I have argued, however, that this might not be as easy, given that methodological biases can be the result of deliberate decisions of individual scientists or just the result of entrenched practices within a discipline, and discerning between these options might not be obvious. When able to identify whether a case of methodological bias is deliberate or not, I have argued that deliberate cases should be regarded as cases of scientific fraud, while cases of entrenched biased practices should be followed by concerted efforts to acknowledge and transform these practices.

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