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COMMENTARY

The Use of Statistics in Health Sciences: Situation Analysis and Perspective

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Abstract Statistics plays a crucial role in research, planning and decision-making in the health sciences. Progress in technologies and continued research in computational statistics has enabled us to implement sophisticated mathematical models within software that are handled by non-statistician researchers. As a result, over the last decades, medical journals have published a host of papers that use some novel statistical method. The aim of this paper is to present a review on how the statistical methods are being applied in the construction of scientific knowledge in health sciences, as well as, to propose some improvement actions. From the early twentieth century, there has been a remarkable surge in scientific evidence alerting on the errors that many non-statistician researchers were making in applying statistical methods. Today, several studies continue showing that a large percentage of articles published in high-impact factor journals contain errors in data analysis or interpretation of results, with the ensuing repercussions on the validity and efficiency of the research conducted. Scientific community should reflect on the causes that have led to this situation, the consequences to the advancement of scientific knowledge and the solutions to this problem.

Keywords Statistics · Health Sciences · Medical research · Statistical methods · Statistical errors

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1 Background

Statistics is a branch of mathematics that studies random events. Opposite to factual sciences, where the knowledge is based on observation and experimentation, Statistics is a formal science that studies abstract structures and obtains new knowledge through logic reasoning [51]. This formal science is under continuous development, and provides a knowledge which is essential in factual sciences for decision-making in uncertain settings. In particular, Statistics plays a crucial role in research, planning and decision-making in health sciences, by providing essential information about the random structure of health phenomena [42,69]. Progress in technologies and continued research in computational statistics has enabled us to implement sophisticated mathematical models within software that are easily handled by non-specialists [12]. Such accessibility has undoubtedly made a major contribution towards the dissemination and transfer of mathematical know-how to other disciplines and, in particular, towards practical applications within health research. As a result, over the last decades biomedical journals have published a host of papers that use some novel statistical method or other. However, the application of statistical techniques and the interpretation of results are often inappropriate. The aim of this paper is to present a review on how the statistical methods are being applied in health research, as well as, to propose some improvement actions.

2 The Beginnings of a Scandal

The foundations of statistical inference and modern statistics, as we know it today, were laid down in the early twentieth century by great contemporary mathematicians. Almost immediately, these statistical methods were built into health research and just a few years later the mathematicians themselves who had developed these techniques began to issue warnings about errors in their application [23].

During the second half of the twentieth century, there was a remarkable surge in scientific evidence alerting to the errors that many researchers were making in applying basic statistical methods [21,36,46,61,67]. Indeed, this issue became so serious that Douglas Altman, Director of the Centre for Statistics in Medicine in Oxford, qualified inappropriate use of statistical techniques in biomedical research as a scandal, in one of the most striking articles for the scientific community published in the 1990s [2]. Given that many medical decisions, including disease diagnosis and choice of appropriate treatment, were based on statistical tests, this situation took on a very serious note.

3 The Eternal Problem

Considering that these first warnings came over 50 years ago and that we have now entered a new century, we might think that there have been major improvements in the use of statistics and the quality of research in the health sciences. However, this is far from the truth.

I carried out a bibliographic search in PubMed database to find the papers published between January 1950 and July 2015 which title and content were related directly to

Table 1 PubMed query on statistical errors in health sciences research (January 1950–July 2015)

Building block	Field	Search term	Boolean logic operator
1	Title	Statistical	OR
		Statistics	OR
		Design	OR
		Designs	
			AND
2	Title	Mistake	OR
		Error	OR
		Pitfall	OR
		Misconception	OR
		Misinterpretation	OR
		Misunderstanding	OR
		Misreported	OR
		Failure	OR
		Use	OR
		Abuse	OR
		Misuse	OR
		Mistakes	OR
		Errors	OR
		Pitfalls	OR
		Misconceptions	OR
		Misinterpretations	OR
		Misunderstandings	OR
		Failures	OR
		Uses	OR
		Abuses	OR
		Misuses	OR

statistical errors in health sciences research. The search was systematised in a PubMed query (Table 1), which execution gave 1451 papers. However, after reading the abstract, only 229 papers were related to the search's objective. Then the full read of these papers confirmed their inclusion in the final Zotero repository for analytical purposes. The frequency distribution by year of these 229 documents shows that, since 1950, the annual number of papers reporting statistical errors in health sciences research has increased progressively (Fig. 1). Half papers were published after 2000, i.e. during the last 15 years of a period composed by 65 years (1950–2015).

In addition to this finding, during the first decade of the twenty-first century other scientific works showed that a large percentage of articles published in high-impact factor medical journals contained errors in data analysis or interpretation of results, with the ensuing repercussions on the validity and efficiency of the research conducted [6,8,19,25,43]. Assessments conducted over the past few years are still showing misuse of statistical methods by non-specialised professionals and point to science's failure to tackle this malpractise. The authors of these reviews criticise widespread misuse

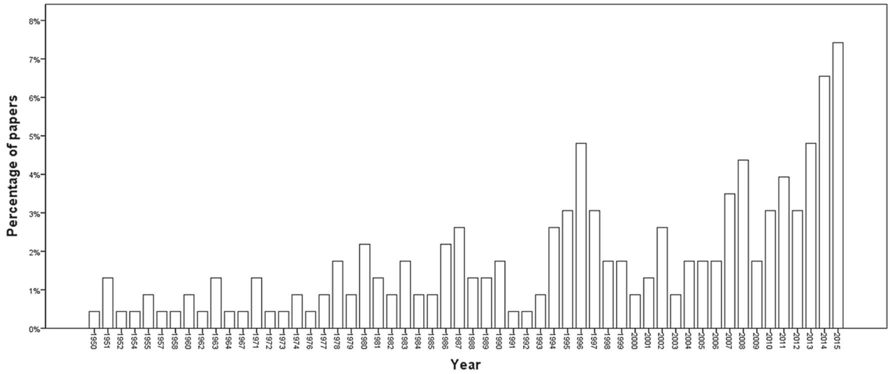

Fig. 1 Frequency distribution of 229 scientific papers that were recorded in PubMed between January 1950 and July 2015 and their content was related to statistical errors in health sciences research

of statistical methods in health and bring into question the validity of the conclusions published in some papers of the most prestigious journals of the day [18,44,47,54]. Statisticians are still alerting to this situation which does not appear to be improving over time and which can be summarised by this quote from Horace F. Judson, from his book *The great betrayal, fraud in Science*: "In any taxonomy of fraud, classical or recent, statistical anomalies are among the most frequent signs of trouble" [33].

Inappropriate use of statistical methods poses a serious problem affecting both the quality of publications and the advancement of scientific knowledge [63]. Journal editors are not unaware of this issue. Some editors even acknowledge that many studies published today have serious methodological flaws that lead to unfounded conclusions [30,38,56]. The scant critical discussion on this kind of study has also meant that new research hypotheses, health policy implementations and the risks conveyed to the population are based on spurious conclusions arising from ecological fallacies and other methodological mistakes [40]. Often, the proliferation of this practise has led to inefficient decision-making, social alarm and scientific frustration as well as to political, economic and social deterioration that evidently all have a negative impact on the advancement of scientific knowledge and the implementation of appropriate health policies [55].

Table 2 summarises the most frequent statistical errors found in the published papers. These errors are related to the planning of the analysis, the analysis of the data and the interpretation of results, and most of them have been recognised as common problems by the editors of the medical journals with the highest impact factor in the Journal Citation Report [22].

4 The Causes of the Problem

4.1 Health Researchers Lacking Appropriate Training in Statistics

All too often, the medical and other health sciences researchers using statistical methods lack training and understanding in the field of mathematics but have been

Table 2 Common statistical mistakes in health sciences' journals

Planning of the analysis	Statistical analysis	Interpretation of results
Confusing the concepts *unit of analysis*, *characteristic of the unit of analysis* (variable) and *sample size*	Ignoring the sampling design in the statistical analysis of survey-based studies, as well as the weighing of the observations	Type III error: Provide the right answer to the wrong question
Confusing the independent and dependent variables	Ignoring the clustering of the data in the statistical analysis when this structure is present	Highlight the small *P*-value of a dummy variable belonging to a qualitative variable that is not statistically significant as a whole
Choosing a wrong experimental design to contrast the research hypothesis	Using the incorrect parametric or non-parametric statistical tests to contrast the hypothesis of interest	Interpreting non statistically significant results as *evidence of absence* rather than *absence of evidence*, especially in studies with low statistical power
Planning ecological data analysis to contrast hypothesis about individuals	Performing multiple comparison of groups using *t*-Student test	Confusing correlation with causality
Absence of sampling framework or insufficient justification of the sample size	Using a specific parametric statistical test or a particular regression model when the data do not meet the essential assumptions	Confusing standard deviation and standard error
Calculating type II error or power after the statistical data analysis rather than being taken into account to calculate the sample size into the sampling design	Using automatic procedures to select independent variables in regression models, such as backward, forward and stepwise regression, which introduces bias into parameter estimates	Wrong interpretation of statistical measures, with special mention to the odds ratio, the standardised incidence ratio (SIR) and the standardised mortality ratio (SMR)
Selecting a non random sample	Introducing into a multivariate regression model only those independent variables that showed statistical significance in the bivariate analysis	Interpreting the results of a non-parametric test as if a parametric test had been used
Categorise quantitative variables without ensuring equal behaviour within each category respect to the dependent variable	Validating the estimated regression model using the training set rather than the test set data	Confusing *P*-value with Type I error

Table 2 continued

Planning of the analysis	Statistical analysis	Interpretation of results
Lack of planning confusion and interaction between independent variables, based on the theoretical framework and the hypothesis of the study	Using single imputation methods, which can bias the estimates and understate the variance	Use of the *P*-value as demonstration of association between variables
No describing the method that will be used to carry out the statistical analysis of the data	Deleting outliers from the database	Emphasise statistical significance and forgetting practical relevance
	Calculating standardised rates without previous assessment of specific rates	Reporting results between groups for grouped data without mentioning the results within-groups
	P-hacking: Perform multiple statistical analyses until non significant results become significant	Interpreting or discussing inadequately problems related to interaction, confusion, missing data and outliers
	Performing arithmetic and calculation errors	Ecological fallacy: Inferences about the health status of individuals are deduced from the statistical analysis of the group to which those individuals belong

encouraged to use statistics freely by the ease of access to the latest generation IT programmes. Despite their usefulness in conducting any kind of analysis, these cannot offer multi-purpose recipes, nor are they able to replace the know-how of a statistician. Among the most common errors seen in research conducted by non-statisticians, we find inappropriate models, non-compliance with the rules for application and incorrect interpretation of the results. As a result, the findings only contribute further to spreading false conclusions. People without qualified training in statistics who read these articles, in turn, copy a given method for similar research efforts in their own work centres, assuming that the method is appropriate merely in light of its publication, which only fosters further methodological errors [4].

4.2 Unqualified Reviewers to Evaluate Statistical Methods in Health Research

It is part of the remit for reviewers of a manuscript to pinpoint such anomalies before the paper submitted to the scientific journal is published. However, most publishers do not have a team of statisticians to conduct such an appraisal. For this purpose, the editor usually calls on two or more researchers who have published papers on topics similar to that addressed in the manuscript submitted. These researchers tend to be healthcare specialists but are not statisticians. As a result, the lack of knowledge that led them to publish statistical errors in their own research papers will also make them unable to recognise methodological flaws in colleagues' work [3,64].

Concerning this subject, the editorial team of the renowned *British Medical Journal* conducted a curious experiment. They selected 607 professionals who were regular reviewers for the journal from their database. They all received an article for appraisal in line with the usual procedure. However, they were unaware that the editorial team had deliberately included nine serious and five lesser methodological errors. On average, each of the reviewers detected less than three of the serious errors and only one slight error, leading the editors to conclude: "Editors should not assume that reviewers will detect most major errors, particularly those concerned with the context of study" [50].

4.3 The Seductive Nature of Complex Statistical Methods

The editors of medical journals and reviewers of scientific articles who are not specialised in statistics are often fascinated by the mathematical language used by authors, placing greater value on the method used than on the research problem itself [48]. Today's researchers in the health sciences are aware that their papers are more likely to be published if they use complex statistical models in vogue in healthcare, even though they know these are unnecessary to meet the aim of their research [9,27]. This fascination for sophisticated mathematical models applied by unskilled professionals, assessed by non-statistician reviewers and published in journals outside the field of statistics have all led to the widespread dissemination of errors and scientific fraud even in the most respected journals. Some of these frauds, like the Sokal hoax, have been deliberately carried out, and later confessed, by the authors to bring into question the scientific review process on mathematical issues [59]. Others have been caught by the editorial team and removed from publication, even though such efforts do not always lead to the desired result. Recent studies show that the percentage of articles withdrawn by health sciences journals on the basis of scientific fraud has multiplied tenfold since 1975. Of all articles withdrawn, 67.4% are due to scientific misconduct (fraud, suspected fraud, duplicate publications and plagiarism) while 21.3% are due to errors [20]. The journals with the highest impact factor receive the greatest number of fraudulent articles or papers with methodological errors. However, the number of papers they manage to withdraw on the grounds of fraud is well below the real number of fraudulent papers [20].

5 Social Repercussions of the Problem

Most health research requires statistical methods to reach conclusions. The detection of risk factors for health, comparisons of treatments or diagnosing disease are, amongst others, common studies based on statistical data analysis. Inappropriate use of these techniques not only leads to false conclusions and distorts the advancement of scientific knowledge but also, as a result, hinders the most suitable decision being taken to improve people's health status. Also, unfounded conclusions caused by applying the wrong statistical method or incorrect interpretation of the results and then disseminated in the media also cause unwarranted social alarm and scientific frustration in the absence of consistent explanations. All this leads to political, scientific, economic and social erosion which could be avoided [55].

The ethical guidelines for statistics drawn up by the American Statistical Association give a clear warning: “The use of statistics in medical diagnoses and biomedical research may affect whether individuals live or die […] Because society depends on sound statistical practise, all practitioners of statistics, whatever their training and occupation, have social obligations to perform their work in a professional, competent, and ethical manner” [15].

6 Proposal of Solutions

6.1 Basic Training in Statistics for Health Researchers

The skills any given person requires in statistics will depend on the level of knowledge he/she needs to be able to engage actively in the scientific and social debate. We can set three sequential levels of knowledge, namely, Literate, User and Specialist.

According to the OECD, a person literate in mathematics is able to identify and understand the role that mathematics plays in the world, to make well-founded judgments and to use mathematics to meet their own needs as a constructive, committed and reflective citizen [45]. Anyone literate in statistics will also be able to interpret and provide critical judgment on basic statistical information displayed in numbers or graphs [24].

On the second level, the statistics user is a person who, without formal qualifications in statistics, occasionally applies the most common statistical techniques for their work or for research in factual sciences, including health sciences.

Lastly, the specialist in statistics (statistician) has an university degree in statistics, with a solid grounding in mathematics, or mathematics, with a specialisation in statistics, has up-to-date in-depth knowledge in his/her field, applies complex statistical techniques to data analysis and is capable of developing new mathematical models to resolve theoretical or applied problems. Usually, a senior professional statistician also possesses a Master’s degree or a PhD in statistics. Some individuals with a degree in another field have become specialist in statistics and have achieved recognition from statistical associations in terms of training, experience and contribution to statistics along their life. However, this is not the rule but the exception among health practitioners.

It is quite clear that it is essential for researchers in the health sciences to understand the basis of statistics so they may undertake critical appraisal of papers published by colleagues, as well as interpret statistical information correctly and perform basic data analyses appropriately [28]. The skills such users should acquire are included in the second level, i.e. statistics users.

Such skills and know-how entail not only understanding the right statistical procedure to apply for the research aims. The health sciences professionals that wish to do basic statistical analysis also need to understand and learn how to use statisti-

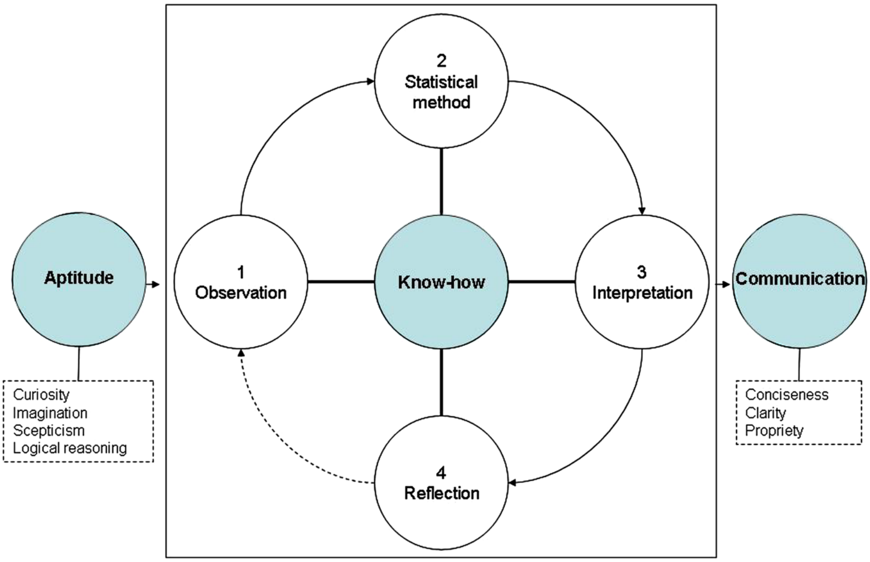

Fig. 2 The basic pillars of statistical thinking

cal thinking overall, acquiring all-round training in the three basic pillars: Aptitude, Know-how and Communication (Fig. 2) [58,68].

Aptitude is a dimension of statistical thinking that brings together the essential features a person devoted to statistical data analysis must have. Amongst these features are curiosity, imagination, scepticism and logical reasoning.

Know-how refers to the whole statistical process that enables appropriate analysis of the information. This process starts with observing the data, followed by the choice of the most suitable statistical technique, correct interpretation of the results and reflection on the conclusions drawn. This process is a closed cycle that will be complete only when reflection leads to conclusions that are both logical and consistent with the theoretical research framework and prior know-how acquired.

Finally, communication is the dimension that brings together the skills needed to be able to convey the results and conclusions reached from the statistical analysis appropriately. This dimension is the last stage in statistical thinking and can only be attained once sound aptitude and know-how have been developed.

Managers and politicians responsible for promoting such training must be aware that it is a lengthy process for a professional in the health sciences to acquire the know-how, skills and attitudes required to tackle the various aspects of statistical information analysis successfully and independently. Just as it would be unthinkable for someone outside the medical profession to perform a heart transplant after a 30-h training course, it is equally impossible for a health science professional to acquire the know-how required to perform and correctly interpret basic statistical analyses after a similar number of hours' training [31].

6.2 Professionalising Statistics

6.2.1 Only Statisticians Can Provide Quality Training in Statistics

As can be deduced from the above, a high degree of preparation is required to pass statistical skills and know-how on to professionals from other fields, even if these are basics. Only a specialist in statistics with long-standing experience in teaching is capable of doing so. It is commonly believed that anyone who knows and applies statistical techniques is capable of teaching Statistics to others. It is not uncommon to find statistics users (often merely people with numeracy skills) responsible for devising training schemes and post-graduate teaching programmes on statistics within health sciences departments, public health schools or biomedical research institutions, with no qualifications in this field, yet trusting they have the right skills. However, teaching is not merely a question of showing what you know. The statistics teacher should not only be a specialist with up-to-date, in-depth understanding of the area of knowledge he/she is teaching but who understands and can inter-relate the content involved. Also, it should be someone with the necessary teaching and educational skills to convey and disseminate such know-how, making it readily understandable for others [17, 53]. Conveying such knowledge is particularly complex in mathematics, in general, and in statistics, in particular. As a result, it should be graduates in statistics with a broad knowledge base and widespread teaching experience in training healthcare professionals who take on this task.

6.2.2 Only Statisticians Can Ensure Quality in Statistical Data Analysis into Research Teams

Health research teams should be multidisciplinary and statisticians should be incorporated into them. As in other areas of knowledge, statistics is a constantly evolving science that continues to provide new methods, philosophies and analytical techniques. As a result, it is essential that qualified statisticians join the research team on a given research project right from the very beginning. They should be involved in or take responsibility for study design, setting up the information systems, analysing complex data, supervising basic analyses, interpreting results and drawing conclusions [5].

All researchers involved in health research are assigned particular tasks. The statistician has certain, specific responsibilities that should be stated and duly acknowledged in the authorship of scientific reports and papers [37]. Among such responsibilities are: statistical analysis of the information, supervision of basic data analyses performed by non-statisticians and signing of all statistical reports generated during the research effort, ensuring quality throughout the procedures in use and complying with ethical principles of sound statistical practises [15,34]. Additionally, the statistician should be fully conversant with the scientific area of application and should participate fully in all the research process, including the formulation of the scientific question, study design, data collection, statistical analysis, interpretation and discussion of results and final conclusions from the research. Statisticians also must be assertive in countering bad research. The ethical conduct of their work demands that they speak out forcefully when they see inappropriate conclusions being drawn [32].

Sequencing the human genome has opened a new research field in biomedical science. Genomics, proteomics and other new technologies, referred to as *omics*, need bioinformatics, data management, analysis of very large datasets and the use of rigorous statistical methods for research. Complexity of this kind of research suggests that the misuse of statistics could be increased in the future, so we should call attention to another important role for the statistician, as director of data management. The need of statisticians and statistical thinking in *omics* research was referred in the recent report of the Institute of Medicine of the National Academies, USA, in response to the scandal at Duke University regarding premature use of gene expression data to select particular drug treatments for cancer patients [39].

6.2.3 Only Statisticians Can Assess Quality of Statistical Methods Used in Scientific Articles

Along the same lines, editorial teams in scientific journals should rely on a stable group of statisticians with broad experience in applied research to perform a systematic evaluation of all papers submitted so as to guarantee that all published papers are accurate from the methodological standpoint. Some journals make check lists available to reviewers to facilitate the evaluation of the statistical methods used in the paper [3,26]. However, these lists will not yield the desired result if they are being used by people who are not specialists in this area of knowledge for them to be able to give the researchers guidance on the best way to correct the errors pinpointed and choose the statistical method that best suits their study's aims. In the current context, the peer-review system should seriously consider including a specialist with degree in statistics who is experienced in applying statistical methods in health sciences research. Perhaps moving towards the open publishing system, currently being adopted by many journals where the reviewers', editor's and authors' comments are made public throughout the review process, may contribute to enhancing the current review process [57].

Apart from contributing towards improved scientific publications, bringing statisticians into a journal's editorial team may also help to detect scientific fraud by using statistic procedures and computerised controls that have proven their worth over the years [13].

6.3 Setting up Statistics Units within Health Schools and Health Research Centres

Centres or institutions that often use statistical methods need to set up statistics departments, areas or units comprising statisticians able to devise, systematise and analyse information from research projects requiring such methods. A team of just a few specialised, co-ordinated professionals would then be able to guarantee sound use of traditional methods and to devise new methods that can impact on quality research. This kind of unit would also enable even more specialised know-how to be shared among professionals in the same field and would facilitate the spreading of this know-how to other professionals who are not specialised in statistics [14].

Even though this proposal was built into health policies in the 1960s [65,66], many public health schools and biomedical research centres in developed countries still have no statistics units or departments to support their research efforts, to evaluate the methodological quality of studies and to enhance the efficiency of any research conducted.

In 1992, the Report of the Ad Hoc Committee of the International Statistical Institute warned that, due to the relatively small numbers of people compared to other professional groups, statisticians find themselves outvoted in the making of important policy decisions [41]. However, they are essential to evidence-based management, and are uniquely positioned to contribute significantly in addressing and solving the complex problems the humanity faces. For this reason, their role and importance should be appropriately recognised. Today, governments all over the world have a challenge. They should increase the appreciation of the importance of statisticians to achieve a statistically advanced country, where experts in the production and the analysis of data are co-ordinated in statistical units or statistical centres, all research teams include statisticians as partners, and politic decisions are based in statistical data analysis carried out by statisticians of excellence [1,29].

7 Conclusions

Despite efforts made by editors, errors in applying and interpreting statistical methods remain common in scientific papers published in both high-impact factor and less prestigious journals. In part, this problem stems from the professional deskilling this particular area of knowledge suffers from, where health science professionals devise training programmes in statistics, teach statistics, conduct statistical data analysis and review statistical procedures without appropriate qualifications. Unfortunately, there is no legislation or regulation for professionalising of statistics in most countries, unlike other professions such as medicine, pharmacy, psychology, law, engineering or architecture. Professional bodies in statistics, scientific societies for statistics, research managers, editors, reviewers and researchers all need to pool their efforts and devise strategic plans to improve this situation which is hindering the advancement of scientific knowledge and indeed seems to be getting worse over time.

On the other hand, fraud and scientific misconduct have grown enormously over the last decade, together with major statistical errors. As a result, the number of papers withdrawn from high-impact factor journals has also increased. There is no single cause for this trend. Some authors distinguish between intrinsic and extrinsic causes. Intrinsic causes are linked to the researcher's attitude and personal vanity, while extrinsic causes are related to the working environment and institutional pressure exerted on scientists, where economic incentives are linked to the number of publications and the value of bibliometric indicators, such as the impact factor [11]. The higher the number of papers published in renowned journals, the greater the possibility that the research in question will be qualified as excellent, leading to greater funding options for the research group and institution involved. In fact, research published in peer-reviewed

Table 3 Analysis of situation and perspective of the use of statistics in health sciences

Key point	Description
What is statistics?	Statistics is a branch of mathematics that studies random events. As a formal science, statistics obtains new knowledge through logic reasoning, opposite to factual sciences, where the knowledge is based on observation and experimentation.
Who is a statistician?	The statistician is a professional that has an university degree in statistics, with a solid grounding in mathematics, or mathematics, with a specialisation in statistics, has up-to-date in-depth knowledge in his/her field, applies complex statistical techniques to data analysis and is capable of developing new mathematical models to resolve theoretical or applied problems. Usually, a senior professional statistician also possesses a Master's degree or a PhD in statistics.
Who is a user of statistics?	A statistics user is a person without formal qualifications in statistics who occasionally applies the most common statistical techniques for their work or for research in factual sciences, including health sciences.
The eternal problem	A large number of papers published in health journals contains errors in statistical analysis
	Inappropriate use of statistics affects the validity of the conclusions and the advancement of scientific knowledge
	The problem was detected in the second half of the twentieth century and persists today
	Journal editors are not unaware of this issue and acknowledge that many studies published today have serious statistical flaws that lead to unfounded conclusions
The causes of the problem	Health researchers lacking appropriate training in statistics
	Unqualified reviewers to evaluate statistical methods in health research
	The seductive nature of complex statistical methods which often fascinates non-statistician health researchers
	The pressure exerted on scientists to publish, where the scientific excellence are linked to quantity (such as the number of publications and high-impact factor) rather to quality
Social repercussions of the problem	Wrong scientific knowledge, based on spurious conclusions
	Inefficient decision-making
	Negative impact on the implementation of appropriate health policies
	Unwarranted social alarm, produced by spurious risk factors for health

Table 3 continued

Key point	Description
Proposal of solutions	Basic training in statistics for health researchers performed by statisticians with long-standing experience in teaching
	Professionalising statistics: all the statistical tasks should be carried out by statisticians. In other case, statisticians should supervise the statistical analysis performed by the users of statistics. Only statisticians can provide quality training in statistics, ensure quality of the statistical analysis into health research teams, and assess quality of statistical methods used in scientific papers.
	Setting up Statistics Units within Health Schools and Health Research Centres
	Promoting leisurely research, where the scientific excellence is not defined by quantity, but by quality

or high-impact factor journals is still called research of excellence and the results are often cited. However, there is enough scientific evidence available to deduce that the peer-review system, a journal's impact factor and the number of citations a paper has cannot guarantee the quality of the published research, and, consequently, neither can it endorse its excellence [10,35,52,60].

It is clear that scientific culture is changing. The impartial search for the truth is being left to one side while a mercantile philosophy is increasingly gaining ground [16,62]. Being competitive, publishing in prestigious journals, directing a large number of projects, securing patents and attracting major funders are all issues that rank too high in our priorities. As a result, traditional scientific values, originality and reflection are all being relegated, leading to negative repercussions for the quality of research and the advancement of scientific knowledge [7,49].

Both the scientific community and society at large should reflect on this mad race that started several years ago, on the achievements that are being made and on the legacy being left to future generations of researchers. Perhaps now is the time to think of alternative strategies capable of promoting excellence in research that focuses more on quality than on quantity, where statistical procedures are devised, taught, applied and evaluated by experienced and duly qualified specialists (Table 3).

In the twenty-first century, the challenge for science and governments all over the world is now achieving professionalisation of the statistical practise and getting statistically advanced societies to improve decision-making based on adequate evidences.

References

1. Ahmed M (2011) Meeting report: ISOSS Lahore conference. IMS Bull 40(5):11
2. Altman DG (1994) The scandal of poor medical research. Br Med J 308:283–284
3. Altman DG (1998) Statistical reviewing for medical journals. Stat Med 17:2661–2674
4. Altman DG (2002) Poor-quality medical research: what can journals do? J Am Med Assoc 287:2765–2767
5. Altman DG, Goodman SN, Schroter S (2002) How statistical expertise is used in medical research. J Am Med Assoc 287(21):2817–2820

6. Armitage P, Berry G, Matthews JNS (2002) Statistical methods in medical research, 4th edn. Blackwell Scientific, Oxford
7. Azoulay P, Zivin JSG, Manso G (2011) Incentives and creativity: evidence from the academic life sciences. RAND J Econ 42(3):527–554
8. Basskin L (2003) Statistical interpretation can also bias research evidence. Br Med J 327(7417):752
9. Block WM, Morrison ML (2007) Tread lightly or carry a big stick? J Wildl Manage 71(2):301–302
10. Bornmann L, Daniel HD (2008) What do citation counts measure? A review of studies on citing behaviour. J Doc 64(1):45–80
11. Breen KJ (2003) Misconduct in medical research: whose responsibility? Intern Med J 33:186–191
12. Buchan IE (2000) StatsDirect-statistical software for medical research in the 21st century. Br Med J 321:7275
13. Buyse M, George SL, Evans S, Geller NL, Ranstam J, Scherrer B et al (1999) The role of biostatistics in the prevention, detection and treatment of fraud in clinical trials. Stat Med 18:3435–3451
14. Cartera RL, Scheafferb RL, Marksa RG (1986) The role of consulting units in statistics departments. Am Stat 40(4):260–264
15. Committee on Professional Ethics (1999) Ethical guidelines for statistical practice. American Statistical Association. www.amstat.org/about/ethicalguidelines.cfm. Accessed 17 Dec 2015
16. De Jonge B, Louwaars N (2009) Valorizing science: whose values? EMBO Rep 10(6):535–539
17. Dormolen JV (1991) Metaphors mediating the teaching and understanding of mathematics. In: Bishop AJ, Mellin-Olsen S, Dormolen JV (eds) Mathematical knowledge: its growts through teaching. Kluwer Academic Publishers, The Netherlands, pp 89–106
18. Dufault B, Klar N (2011) The quality of modern cross-sectional ecologic studies: a bibliometric review. Am J Epidemiol 174(10):1101–1107
19. Ercan I, Yazıcı B, Yang Y, Özkaya G, Cangur S, Ediz B, Kan I (2007) Misusage of statistics in medical research. Eur J Gen Med 4(3):128–134
20. Fang FC, Steen RG, Casadevall A (2012) Misconduct accounts for the majority of retracted scientific publications. Proc Natl Acad Sci USA 109(42):17028–17033
21. Felson DT, Cupples LA, Meenan RF (1984) Misuse of statistical methods in arthritis and rheumatism. Arthritis Rheum 27(9):1018–1022
22. Fernandes-Taylor S, Hyun JK, Reeder RN, Harris AHS (2011) Common statistical and research design problems in manuscripts submitted to high-impact medical journals. BMC Res Notes 4:304
23. Fisher R (1955) Statistical methods and scientific induction. J R Stat Soc B 17(1):69–78
24. Gal I (2002) Adults' statistical literacy: meanings, components, responsibilities. Int Stat Rev 70(1):1–51
25. García E, Alcaraz C (2004) Incongruence between test statistics and P values in medical papers. BMC Med Res Methodol 4:13
26. Gardner MJ, Machin D, Campbell MJ (1986) Use of check lists in assessing the statistical content of medical studies. Br Med J 292(22):810–812
27. Gelles RJ (1993) From yellow pads, to typewriters, to wordprocessors: confessions of a. writer?, author?, scholar? Marriage Fam Rev 18(1–2):81–92
28. Gigerenzer G, Gaissmaier W, Kurz-Milcke E, Schwartz LM, Woloshin S (2007) Helping doctors and patients make sense of health statistics. Psychol Sci Public Interest 8(2):53–96
29. Hall HR, Roussel LA (2012) Evidence-based practice: an integrative approach to research, administration and practice. Jones & Bartlett Learning, Burlington
30. Health & Medicine Week (2004) Published research contains high level of statistical errors. 21 June, p 887
31. Herman A, Notzer N, Libman Z, Braunstein R, Steinberg DM (2007) Statistical education for medical students: concepts are what remain when the details are forgotten. Stat Med 26(23):4344–4351
32. ISI Council (2010) Declaration on professional ethics. International Statistical Institute, Reykjavik
33. Judson HF (2004) The great betrayal: fraud in science. Harcourt, New York
34. Lewis JA (1999) Statistical principles for clinical trials (ICH E9): an introductory note on an international guideline. Stat Med 18:1903–1904
35. Lipworth WL, Kerridge IH, Carter SM, Little M (2011) Journal peer review in context: a qualitative study of the social and subjective dimensions of manuscript review in biomedical publishing. Soc Sci Med 72:1056–1063
36. Marks RG, Dawson-Saunders EK, Bailar JC, Dan BB, Verran JA (1988) Interactions between statisticians and biomedical journal editors. Stat Med 7(10):1003–1011

37. Matcham J, Julious S, Pyke S, O'Kelly M, Todd S, Seldrup J, Day S (2011) Proposed best practice for statisticians in the reporting and publication of pharmaceutical industry-sponsored clinical trials. Pharm Stat 10:70–73
38. Michel MC (2014) How significant are your data? The need for a culture shift. Naunyn Schmiedebergs Arch Pharmakol 387:1015–1016
39. Micheel CM, Nass SJ, Omenn GS (eds) (2012) Evolution of translational omics: lessons learned and the path forward. The National Acadamies Press, Washington, DC
40. Monmonier M (1996) How to lie with maps, 2nd edn. University of Chicago Press, London
41. Moriguti S, Diggle PJ, Gower JC, Wallman KK, Ren WS (1992) The role of statisticians: report of the Ad Hoc Committee. Int Stat Rev 60(3):227–246
42. Nicholls D (1999) Statistics into the 21st century (with discussion). Aust N Z J Stat 41(2):127
43. Ocaña-Riola R (2007) The misuse of count data aggregated over time for disease mapping. Stat Med 26(24):4489–4504
44. Ocaña-Riola R (2010) Common errors in disease mapping. Geospat Health 4(2):139–154
45. OECD (2010) PISA 2009 assessment framework: key competencies in reading, mathematics and science. OECD, Paris
46. Pike MC, Berstein L (1985) Statistical errors invalidate conclusions in "caffeine and unsaturated fat diet significantly promotes DMBA-induced breast cancer in rats". Cancer 55(8):1855–1857
47. Russell L (2011) The spread of evidence-poor medicine via flawed social-network analysis. Stat Politics Policy 2(1)
48. Salsburg DS (1985) The religion of statistics as practiced in medical journals. Am Stat 39(3):220–223
49. Schafer A (2004) Biomedical conflicts of interest: a defence of the sequestration thesis learning from the cases of Nancy Olivieri and David Healy. J Med Ethics 30:8–24
50. Schroter S, Black N, Evans S, Godlee F, Osorio L, Smith R (2008) What errors do peer reviewers detect, and does training improve their ability to detect them? J R Soc Med 101:507–514
51. Schurz G (2014) Philosophy of science: a unified approach. Routledge, New York
52. Shatz D (2004) Peer review: a critical inquiry. Rowman & Littlefield Publishers, Maryland
53. Shulman LS (1986) Those who understand: knowledge growth in teaching. Educ Res 15:4–14
54. Siegfried T (2010) Odds are, it's wrong: science fails to face the shortcomings of statistics. Sci News 177(7):1–13
55. Smith D, Neutra RR (1993) Approaches to disease cluster investigations in a state health department. Stat Med 12:1757–1762
56. Smith R (2001) Medical editor lambasts journals and editors. Br Med J 323:651
57. Smith RW (2009) In search of an optimal peer review system. J Particip Med 1(1):e13
58. Snee R (1990) Statistical thinking and its contribution to quality. Am Stat 44:116–121
59. Sokal A, Bricmont J (1997) Impostures intellectuelles. Odile Jacob, Paris
60. Starbuck WH (2005) How much better are the most-prestigious journals? The statistics of academic publication. Organ Sci 16(2):180–200
61. Stephen LG (1985) Statistics in medical journals: a survey of current policies and proposals for editors. Med Pediatr Oncol 13(2):109–112
62. Stuart TE, Ding WW (2006) When do scientists become entrepreneurs? The social structural antecedents of commercial activity in the academic life sciences. Am J Sociol 112(1):97–144
63. Wang Q, Zhang B (1998) Research design and statistical methods in Chinese medical journals. J Am Med Assoc 280(3):283–285
64. Ware JH (2005) Statistical review for medical journals. In: Armitage P, Colton T (eds) Encyclopedia of biostatistics. Harvard School of Public Health, Boston
65. White KL (1967) Improved medical care statistics and the health services system. Public Health Rep 82(10):847–854
66. White KL (1973) Priorities for health services information. Health Serv Rep 88(2):106–112
67. White SJ (1979) Statistical errors in papers in the British Journal of Psychiatry. Br J Psychiatry 135:336–342
68. Wild CJ, Pfannkuch M (1999) Statistical thinking in empirical enquiry. Int Stat Rev 67(3):223–265
69. Zeger SL, Diggle PJ, Liang KY (2004) A Cox model for biostatistics of the future [Department of Biostatistics working paper]. Johns Hopkins University, Berkeley