Looking forward: Reflecting on the present, envisioning the future of statistics and data science education

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In the spirit of the conference emphasis on the critical role of statistics and data science in shaping education across all STEAM disciplines and all educational levels, the conference concluded with a panel session encouraging and eliciting reflection, discussion and prompting views of current and future challenges and opportunities. Three invited panellists, representing a range of international and statistical contexts, were asked to give presentations reflecting their individual experiences and expertises with reference to a theme, followed by comments guided by questions put to them before the conference.

INTRODUCTION

The 2025 IASE Satellite concluded with a panel session by Karsten Lübke [KL], Robert Gould [RG] and Helen MacGillivray [HM]. They were asked to each give a short presentation addressing the theme of *Looking Forward: Reflecting on the Present, Envisioning the Future of Statistics and Data Science Education*. It was suggested that they could then hold a discussion guided by the following questions.

- Defining the field: If everyone claims to be doing data science, does the term risk becoming meaningless? What should the statistics education community insist on including (or excluding) when defining it?
- Balancing foundations and innovation: Are we in danger of teaching students flashy tools without deep understanding, or clinging too tightly to traditional statistics at the expense of relevance? Where should the line be drawn?
- Interdisciplinary integration: Is integrating statistics and data science into STEAM genuinely transformative, or does it risk diluting disciplinary integrity? How can educators avoid tokenistic uses of "data" across subjects?
- Looking ahead: Should the future of statistics and data science education focus more on technical mastery or on ethical and critical engagement with data? If we can't do both equally well, which should take priority?

At the conference, the three speakers met with the chair, Aisling Leavy. It was suggested to focus the discussion on the last three questions above, and the order of the prepared presentations and subsequent commentary were also arranged. This article presents overviews of the three presentations as given, and, in the absence of a transcript of the session, the comments guided by the above questions are summarized to the best of the panellists' memories. We have kept to the actual session as closely as possible and have not removed any redundancies or overlaps in the presentations or comments as these serve in emphasizing key points.

PRESENTATIONS

[KL]: But test everything; hold fast what is good

This quote from 1 Thessalonians 5.21 is a good motto for reflecting the present and envisioning the future of statistics and data science education. This conference once again shows that the body of knowledge is ever growing by research and scholarship. Technology innovations in interactivity, animations, reproducibility and assessment together with textbooks, courses, open educational resources and open data are available from pre-school to post-secondary statistics and data science education. Topics like responsibility, diversity, equity and inclusiveness are integrated and guidelines like a new German position paper (Berger et al., 2026) and teacher training are offered. So there is a lot of change and progress. And data sonification as well as statistical image analysis are examples for integrating statistics in the arts according to the conference theme *Statistics and data science education in STEAM*.

In: Birk, L., Loth, G., Jotzo, L., Binder, K., & Frischemeier, D. (Eds.) (2026). *Statistics and Data Science Education in STEAM. Proceedings of the Satellite Conference of the International Association for Statistical Education (IASE), September/October 2025, Münster, Germany*. © ISI/IASE.

The talks given at this conference also show the increasing importance of Machine Learning (ML) and Artificial Intelligence (AI). In a survey of convenience sample at the start of the presentation 91% would associate Machine Learning with the abbreviation ML – and only 6% with Maximum Likelihood ($n = 33$). (The rest with milliliter.) But as argued by a working group of the German Consortium in Statistics (DAGStat) and approved by the members:

As a core element of AI, statistics is the natural partner for other disciplines in teaching, research and practice. Therefore, it is advisable to incorporate statistical aspects into AI teaching and to bridge the gap between the two disciplines. (Friedrich et al., 2022)

Statistics and data science education are therefore still or even more important than ever. This is even more true since the ubiquitous rise of Large Language Models (LLM). The core statistical concepts of Generative AI can be discussed as well e.g. ethical aspects. Even if LLMs are not part of the subject matter of a course, they still have an impact on teaching.

Generative AI has already transformed education, by undermining the processes of reading and writing as core elements of teaching and learning. The bar is high if LLMs are going to provide a net positive impact on education (Bergstrom and West, 2025).

As mentioned, e.g., in the keynote Civic Statistical Literacy for Democratic Education by Joachim Engel, there is unfortunately a lot of misinformation and ignorance threatening our way of life. Centola et al. (2018) show by social tipping point analysis that minority groups (e.g., 25%) could be sufficient to overturn established norms. Of course, we cannot enlighten everyone, but are we reaching enough students? The problem can be illustrated by classroom experience in an intro course for nonmajors. At the beginning of the inference students are given the question: When tossing a fair coin $n = 8$ times, what number of heads is more likely?

a) 4 times head.
b) 8 times head.
c) 4 heads and 8 heads are equally likely.
d) No answer possible.

Due to the equiprobability bias initially around 50% will answer C or D. But even after collecting and analyzing the data still maybe 15% will stick with C or D. And this in a situation unlike, e.g., climate change without any particular emotions or strong opinions. Of course, this is only anecdotal evidence but the question remains: how can we help more students to recognize and appreciate the value of trustworthy statistics? Maybe we can explicitly address prior uncertainty about hypotheses, how to rationally update uncertainty based on evidence to aim for a consensus – as in Bayesian inference as this can support science learners to make sense of uncertainty (Rosenberg et al., 2022). But we need more research and evidence on this.

The problem of limited resources and time arises again and again in statistics and data science education. In a second survey at the end of the presentation a majority (63%) would prioritize teaching handling (messy) data compared to classical/ frequentist statistics (23%), machine learning or Bayesian statistics (both 7%, $n = 30$).

Genuine curiosity about the answer to a question (see, e.g., https://xkcd.com/3101/) should be the driver for conceptual understanding, critical thinking as well as the ability to use modern tools and technology.

[HM] To envision the future, we need to understand the present

As always in statistics, to understand, we need to have information and analysis, and I have been asked to incorporate features and comments relevant to the theme, based on the past eleven years as Editor-in-Chief of the journal *Teaching Statistics* (TS). As these years also included my terms as President of the International Statistical Institute (ISI) and inaugural Chair of the United Nations (UN) Global Network of Institutions for Statistical Training (GIST), my comments are also influenced by what I observed while in those roles.

Like IASE, *Teaching Statistics* has its origins in ISI's Education Committee, 1948-1992, which set up the Teaching Statistics Trust (TST) and commenced publishing the journal in 1979. Since 1885, ISI's span of the broad global tent of the statistical and data sciences is unique, encompassing their development, usage, education, communication and linkages across disciplines, government, business and society. The charter for TST stated its aim of "*furthering for the public benefit the study and* *research in statistical education*" and to establish a Journal "*devoted to the dissemination of educative information about statistics and on the teaching of statistics*".

The journal has grown and developed considerably in the last decade, and its aims and scope have been updated to reflect authors' submissions, reviewers' feedback and reader metrics. Special issues were published in 2021, 2023 with another to appear soon, and editorial pieces from 2014 on a variety of topics prompted by TS articles or topical issues drew notice from a variety of international sources. Another innovation of invited papers with discussants and response has also attracted attention.

Summarising what TS reviewers praise is a challenge with risks of generalisation, but below are some oft-seen comments.

Issues need to be identified and well-described without exaggeration; relevant to current statistical and statistics education issues; statistically correct and meaningful; and demonstrate knowledge of both statistics and statistics education, with only pertinent well-chosen references.

Contexts must be clearly identified and well-described with respect to teaching, student cohorts, curricula, and the international context. Without context information, nothing is useful.

Data sources and/or collection relevant to educational outcomes must be fully described. What was done? What did the students do? Can the reader make full use of strategies, materials and results? Is there demonstrated understanding of limitations with respect to populations in educational contexts and educational data?

Whether **data and/or information** is qualitative or quantitative or both, good visualisation and understanding of nature and types of data and their limitations are musts.

Formal analysis should use only methods appropriate within the context and data limitations, demonstrating understanding of assumptions, and use of diagnostics. Fashionable or over-exotic (and often inappropriate) methods should be avoided, as should excessive and fragmented formal analysis.

Commentary within context should be insightful with discussion of limitations, and avoidance of generalised statements.

The above do indeed have significant similarities with the statistical investigation and problem-solving process, giving rise to the question "*Is the traditional experimental science 'research' template emphasizing methods and results inhibiting, or even damaging, to good writing (and hence researching) on the teaching of statistics?*"

In teaching the statistical and data sciences, both the beauty and the challenges arise from their universality and pervasiveness, their intricate interrelationships with other disciplines, and the human desire for answers and causes. The concepts, approaches to thinking, problem-solving and modelling with their underlying constructs are transferable but complex; a missed core message of Wild and Pfannkuch (1999) is that statistical thinking does not have one description, nor be defined by cliches or mnenomics. Contexts are core to statistical thinking and work, but must not dominate the learning. If statistics is submerged in another discipline, it loses its identity and becomes a mere tool. More than 40 years ago an engineering student told me "*we don't need statistics, we just need more data*", and there is still a misbelief that big data increase certainty. The human dislike of uncertainty tends to encourage statistical paradigms that can inhibit statistical thinking, producing stultifying frameworks which can become ensconced, reducing to formulaic beliefs what statistics is, how to use and teach it, and how to research its teaching.

The *teaching* of statistics at all levels and to all is of the highest importance, and needs to be recognised as large, complex and core to the entire breadth of statistics and data science. Teaching statistics in other disciplines is as important as training statisticians and data scientists. Working with other disciplines has similar characteristics to professional statistical practice, as does leadership in teaching statistics (MacGillivray, 2025). Ongoing problems include *penetration, implementation, sustenance*, and *maintenance of good practice*, as well as *attenuation*, in that greater progress can lead to longer tails in the first four. Fundamental problems at school level persist and can have serious and long-term adverse effects into university and into research, including types of variables and the subjects of data. Examples include: the word 'numeric' is too broad and vague; assigning numbers does not change a categorical variable to 'numeric'; complete misuse of frequency due to no, or incorrect, understanding of subjects and variables.

Andee Rubin commented during question time that she had found "*understanding of the idea of 'case' to be a slippery concept for youth*"; Hollylynne Lee added agreement that these difficulties are still there at university level.

What can the whole statistical, data science and statistical education community do? More (scholarly) writing on the *teaching* of statistics is needed, as is more referencing and quoting of presentations in speeches and conferences, noting that deeply analytical commentary based on profound analysis and expertise is one type of scholastic writing, as in Wild and Pfannkuch (1999). There needs to be more emphasis in statistics and data science degrees on learning to teach.

A standing committee of representatives from the national statistical society and relevant statistical and statistical education societies could provide collaboration across the whole statistical and data science community to assist in a number of ways, including insistence that there be significant input into school curricula *and* subsequent revisions, and providing professional recognition and high-level advocacy and support of good practice and expertise in teaching and fostering of leadership in teaching.

Such a mechanism could be adapted internationally, but whatever is chosen should provide leadership to achieve high-level synthesis and collaboration based on collective knowledge and awareness, in order to develop policies, advocacies and to oversee their implementation.

[RG] Considering the Past, Regarding the Present, and Looking to the Future

In the past, statistics education struggled to define itself in the context of mathematics education, and usually did so by way of contrast. For example, learning statistics means learning concepts and ideas that aren't (traditionally) part of the mathematics curriculum, such as learning about different data collection methods and learning to embrace uncertainty. Currently, many of us are engaged in understanding how and whether "statistics" differs from "data science". For the future, it looks like we have twin challenges: understanding how generative AI will and should change our discipline and engaging with the threat caused by a lack of trust in official statistics and the systems that generate these statistics.

When I and my colleagues developed the Introduction to Data Science (IDS) curriculum in 2014 (https://idsucla.org/), we designed it to provide students with a "modern" statistics class, by which we meant that we would teach students the fundamentals of statistics in the context of data from a wide variety of types (not just numbers, but also words and images) collected from a variety of data collection methods (including non-random methods). In this course, students use R to inspect, wrangle, and analyze data. In short, the course is designed to bring students closer to statistics as it is currently practiced. But we did not call it "Introduction to Modern Statistics", in part because the course development team included both computer scientists and statisticians, and also because we felt that, to the public, "data science" connotated a challenging, interesting field that looked to the future, rather than to the past.

Labeling the course as "data science" provided us with many advantages, and I would argue that thinking of modern statistics education in general as data science education provides those same advantages, albeit with two important caveats, which I'll return to later. One advantage is that "data science" seems to appeal to a broader community than does "statistics". For better or worse, and despite the best efforts of the statistics education community, the reputation for school-level statistics among many of those in science and computer science education, at least in the U.S., is that it provides a narrow-focus on a small handful of inferential procedures. (A view almost everyone who attended this Satellite has fought but one that still, alas, remains widespread. My own experience is in the U.S., but I strongly suspect the problem is more widespread.) The label "data science" gives us permission to include non-random samples, to encourage students to think more broadly about generalizability (and its limitations), and to welcome interdisciplinary interactions throughout the K-12 curriculum. Thus, as we've seen from many of these talks at this Satellite, we now have rich data science curricula incorporating engineering, climate science, politics, and, of course, computer science.

The first caveat to jumping on the data science bandwagon is that we must not forget the past. The statistics education community has learned that providing a formula is no substitute for understanding methodology (and, in fact, in some cases may impede understanding). Students also need to understand statistical procedures within a broad context that includes consideration of data, the limitations of the procedure, the conditions required for application of the formula to be meaningful and must be given the ability to interpret the results. Algorithms are no different. Executing an algorithm is no substitute for understanding, and we should be wary of curricula that move too fast in order to introduce "cool" techniques to students who have not been provided the scaffolding necessary to understand these algorithms and their consequences.

The second caveat is that, with few exceptions, we live in a statistically illiterate world. While it is true that the world culture has embraced, in many ways, "big data" and "AI", but it has sometimes done so without the necessary understanding of the statistical implications. This is true not just of the general public, but also of at least some scientists and developers of AI. Only relatively recently have biologists warned each other of the dangers of relying on non-random, "citizen-science" data for estimating species prevalence (for example Boyd et al., 2023). Many problems with at-scale AI tools, such as the prejudicial biases demonstrated by AI or the inability to make reliable classifications for sub-groups of populations, could have been foretold by statisticians, who know that the scope of inference extends no further than the universe from which your data were acquired.

This statistical illiteracy is all the more alarming as we see governments dismantle the infrastructure of official statistics, belittle those who interpret these statistics, and discredit the scientific process that seeks to protect our health and economic well-being. At the moment, this trend is perhaps most prominent in the U.S., but throughout much of the world people are more reluctant to respond to surveys and polls, leaving those responsible for collecting official statistics with difficult challenges.

What, then, for the future of statistics education? I think our future is to double-down on the fundamental of statistics. We must find ways to ensure that all children (and adults) learn how data can provide a better understanding of the world and help us obtain real knowledge. We must recognize that statistics education now encompasses more than formulas, numbers, and random samples, and must embrace algorithms, complex data types, and sensors. And, as we move into the future, we must discover how to use generative AI to achieve these ends. This IASE Satellite provided me personally with great hope, as I saw evidence of this in every session I attended, and I'm confident that we can meet these challenges ahead.

DISCUSSION

Several questions were suggested as guides to the panel in advance, and each panelist was asked to comment in turn.

Balancing foundations and innovation: Are we in danger of teaching students flashy tools without deep understanding, or clinging too tightly to traditional statistics at the expense of relevance? Where should the line be drawn?

[HM] For any course/program/module, it must be very clear what the objectives, curricula, purposes of learning activities, assessment etc. are. So, whatever the aim, the ‘story’ must be clear, consistent, cohesive and fit for the stated purpose and role – for both students and all involved in the overall student programmes. This is true whether we are talking about statistics and data science majors or teaching into other disciplines. If the objectives and parameters for implementation of the cohesive ‘story’ are well-described, identified and defensible, everyone involved in the course, but especially students and teaching staff, can work collaboratively and purposefully towards the clear, cohesive and consistent learning outcomes.

[RG]: The temptation to provide students with flashy tools is not new. In prior decades, it was considered sufficient in some circles to provide students with formulas without understanding. The only difference is, I think, the "flash". I am convinced we can and should teach understanding of these "flashy" tools, and that doing so is not "clinging too tightly" to traditional statistics but, instead, highlights the importance of traditional statistics. There is real opportunity here to help students see why "traditional" statistics is also "flashy".

[KL]: Conceptual understanding of the core elements of statistical thinking is still mandatory. Computer and technology innovations can sometimes enable a better understanding of these concepts like random variation. Of course, some topics that we used to teach are no longer as relevant as they used to be and can be omitted or de-emphasized. As data and data analysis is everywhere, foundations seem to be more relevant than ever. Depending on the course and the desired learning outcomes, the ability to use tools is often only a means to an end—to better understand the world with the help of data—and not an end in itself.

Interdisciplinary integration: Is integrating statistics and data science into STEAM genuinely transformative, or does it risk diluting disciplinary integrity? How can educators avoid tokenistic uses of "data" across subjects?

[KL]: As data is in STEAM and everywhere integrating statistics and data science is transformative and can be beneficial for all. But even basic concepts and principles of statistics can be controversial and difficult to understand and are often misunderstood and applied or interpreted incorrectly. I have been studying statistics for over 25 years now and am still learn something new. As De Veaux and Vellemen (2008) said: "The challenge for the student (and teacher) of introductory statistics is that, as literature and art, navigating through and making sense of it requires not just rules and axioms, but life experience and 'common sense.'" (p. 55)

Maybe this is too much to ask from a teacher from a different subject. Teacher education can help and there are many great ideas but mathematically we have a constraint optimization problem with limited time and resources. I think collaboration and team-teaching are promising ideas, but we should be aware that there are no unicorns – unfortunately.

[RG]: An important message of statistics education is that our tools are widely and generally applicable regardless of context. A linear model can be as useful in physics as in sports analytics, assuming the model is sound. Students need to work with data in different contexts in order to learn this, and interdisciplinary integration offers to do this. But I think that this integration is no substitute for a dedicated, systematic, and thorough statistics curriculum. I think of it as a welcome enhancement.

[HM] There will always be challenges in the views of statistics from other disciplines, and what statistics and data science and their thinking are, must always be clearly articulated and pursued in any work with other disciplines. Integration must not mean subjugation. Working with other disciplines in teaching and teaching leadership has much in common with professional statistical practice. It is no accident that descriptions in statistical education of the statistical investigation process have their origins in descriptions by statisticians about statistical professional practice. An example of the parallels between teaching statistics and professional statistical practice is how to design a curriculum for another discipline, or groups of disciplines such as all engineering or all sciences. Listen carefully to what the other discipline say they want; research some more about the other discipline(s) and their students, including the diversity of students (backgrounds etc); work out what the students themselves will need for their immediate and future learning; take account of external (institutional, staffing etc) conditions; design an effective and efficient learning and assessment package with clear objectives and story; and sell it to the other discipline(s) as an ongoing & exciting developmental program for their students in their discipline(s) in which the statistics teaching staff will work collaboratively with the other discipline(s).

Looking ahead: Should the future of statistics and data science education focus more on technical mastery or on ethical and critical engagement with data? If we can't do both equally well, which should take priority?

[RG]: I often reach for musical metaphors when thinking about statistics education. I think the musical education equivalent of this is "Should students learn to become technically proficient musicians or to make beautiful music?" Phrased this way, I think it is clear that this is a false dichotomy. Technical proficiency must include ethical and critical engagement with the data. We should not consider the most brilliant, versatile generative AI algorithm as an example of "technical mastery" if it does not serve our society well, is built on non-representative or biased data, or causes harm. Good ethical practice requires strong technical mastery.

CONCLUSION

The topics for the conference within the overall theme of *Statistics and Data Science Education in STEAM* were written around action and future-looking words such as *"harnessing", "enhancing", "advancing", "re-defining", "innovating and expanding",* and *"fostering"*. The presentations and discussions, both formal and informal, ranged widely over these topics, incorporating and reporting on outcomes of exciting innovations, and discussing and analysing current and potential challenges. As always in statistics education, looking to the future requires considering and evaluating the present and lessons from the past. Hence the panel session reported here provided a fitting conclusion to the conference but also marked the start of continuation into ongoing discussion, collaboration and future work invigorated by the rich and varied programme of all the conference papers.

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