Teaching statistics to non-specialists

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Teaching Statistics to Non-Specialists: Challenges and Strategies for Success

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Abstract

Training in research methods is a crucial component of the student experience in further and higher education. A common set of statistical and experimental design methods are taught across a broad range of non-mathematics disciplines, spanning STEM subjects, medicine, and the social sciences. Understanding these methods is central to students' ability to engage with their course, tutors, and the literature. It is also the key to enabling students to become not only practitioners of their chosen subject, but also statistically literate citizens, capable of understanding and evaluating everyday statistics. The first aim of this paper is to review the specific set of challenges faced by staff and students teaching and learning statistics within non-mathematics disciplines. Secondly, we review best practice and current trends in the design of motivating and effective statistics courses for non-specialists. Our findings suggest that many of the key challenges stem from negative attitudes towards statistics coupled with poor motivation to study the subject, factors which are exacerbated by statistics anxiety. Fortunately, because these challenges are so widespread, and have attracted the attention of innovative educators across broad disciplines, there is a wealth of good ideas and resources available to statistics teachers seeking ways to create effective learning experiences.

Keywords

Statistics; Statistical literacy; Research methods; Statistics anxiety; non-specialists

Word count

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Introduction

There is wide agreement that training in research methods and data analysis, and particularly statistics, is becoming increasingly important both within individual academic disciplines and in cross-disciplinary research (Garfield and Ben-Zvi 2008; Meng 2009). Thus, there is a greater demand for statistics teaching and expertise in colleges and universities than ever before. Furthermore, beyond the academic context, it is important for citizens in general to develop 'statistical literacy', the ability to understand and evaluate statistics, given their use and abuse by politicians, corporations and the mass media (Hulsizer and Woolf 2008). This understanding enables citizens to become critical consumers of information who can interpret data to evaluate the quality of research.

Unfortunately, statistics teaching in further and higher education often has a poor reputation, amongst both students and staff. Academic staff often find themselves teaching a subject in which they do not consider themselves to be experts, to an audience of students who frequently lack motivation to engage with statistics, because they do not appreciate its relevance to their studies and/or because they feel that they do not have the necessary skills or aptitude to be successful. Overcoming these challenges is critical if we are to prepare future generations of students effectively for a workplace in which research skills and statistical literacy is ever-more important (Hulsizer and Woolf 2008).

This article begins with a detailed overview of the challenges facing "non-specialist" students taking statistics courses outside mathematics and statistics disciplines. We then consider the essential ingredients of the modern statistics course, considering how the goals of statistics teaching have shifted in recent years towards the development of statistical literacy, and a focus on understanding of statistical concepts, rather than on the specifics of mathematical computations. With these goals defined, we proceed to examine effective strategies for motivating students, through addressing some of the challenges identified. Having established these foundations, the next section provides examples of effective approaches to delivering statistics lessons. We review a variety of different types of computational resources, from data analysis software, simulations, and games, to visualisation tools and mobile learning apps, finishing with a look into the future of statistics teaching. Our aim is to pull together a diverse and complex literature into an accessible format to provide both a starting-point and a motivational catalyst for educators seeking to design (or re-design) statistics courses in further and higher education.

Challenges in Statistics Education from a Student Perspective

Students across diverse disciplines are required (or choose) to take statistics courses within non-specialist degree programmes outside mathematics or statistics. These students all face a similar set of challenges, which can be divided into three categories, as summarised in **Fig. 1**. The first category relates to variation in student beliefs and attitudes towards studying statistics, and their subsequent motivation to engage (Gal and Ginsburg 1994). A positive attitude towards learning statistics is not only a fundamental starting point for motivating students to engage with the subject, but also influences the general atmosphere in class and student academic performance (Gal et al. 1997; Emmioglu and Capa-Aydin 2012). As such, numerous tools have been developed to measure student attitudes. Early tools included the Statistics Attitude Survey (SAS) (Roberts and Bilderback 1980) and the Attitudes Towards Statistics (ATS) (Wise 1985) scales. Later, the Survey of Attitudes Towards Statistics (SATS) was developed (Schau et al. 1995) and then expanded into a 6-dimensional measure with six attitudinal components (Schau 2003) as illustrated in **Fig. 1**.

There has been much research indicating widespread negative attitudes towards statistics, including disinterest in taking statistics courses and a lack of appreciation of their relevance (Mills 2004; Rajecki et al. 2005). These attitudes may not change as a result of taking introductory statistics courses, or worse, they may become even more negative (Schau and Emioglu 2012; Bateiha 2020). However, the factors influencing student attitudes likely have a complex interplay with each other and with course-specific factors, including the discipline (Griffiths 2012) and mode of course delivery, including online versus face to face teaching (deVaney 2010; Gundlach 2015; Hedges 2017; Paul and Cunningham 2017). Particularly encouraging is the evidence of more positive (and malleable) attitudes, including an appreciation of relevance and willingness to put the effort in, described by a number of recent studies (Hannigan et al. 2014; Milic et al. 2016; Leavy et al. 2019). For example, Leavy et al. (2019) reported positive attitudes towards statistics in pre-service primary school teachers, who play a crucial role in creating classroom environments that will inspire future generations to value the subject. Milic et al. (2016) found that most medical students held positive attitudes, with the cognitive competence component (**Fig. 1**) not only showing the greatest improvement as a result of taking a statistic course, but also being most strongly associated with achievement. This emphasises the importance of developing student perceptions of their own abilities during statistics courses.

Attitudes, levels of motivation and student engagement with statistics courses in a variety of disciplines may be related to a general aversion towards mathematics (Blalock 1987; Field 2010). Students may be concerned that they lack mathematical skills, which in turn will make it difficult to understand statistics, suggesting it is important to help students to appreciate the differences between the two disciplines (Hannigan et al. 2014). Such “mathematics anxiety” is distinct from, and yet is a strong predictor of, “statistics anxiety” (Onwuegbuzie et al. 1997), which is depicted in **Fig. 1** as the second major category of challenge in teaching statistics to non-specialists. Statistics anxiety is a multifaceted and widespread phenomenon. Numerous instruments have been developed to measure it, including the widely used Statistics Anxiety Rating Scale (STARS) (Cruise et al. 1985). STARS has six components as depicted in **Fig. 1**, some of which relate to internal anxiety about a student’s interaction with the subject (e.g. worth of statistics, interpretation anxiety) and some of which have more to do with external perception (e.g. fear of statistics teachers, or fear of asking for help).

The experience of statistics anxiety can produce various detrimental impacts, not only on academic performance (Onwuegbuzie and Wilson 2003), but also on mental health. Effects range from feelings of apprehension, a sense of personal inadequacy and worries about being able to understand statistics (Onwuegbuzie 2004), to the more extreme response of being terrified of statistics (Gal et al. 1997). These uncomfortable emotions, which mirror those experienced by students learning other mathematical skills, may underlie or interact with a lack of motivation or willingness to engage with statistics (**Fig. 1**). Statistics anxiety has been related to personality factors such as neuroticism (Chew and Dillon 2014), while other characteristics such as gender (DeCesare 2007; Hedges 2017) and age may also have a role to play. For example, a higher level of anxiety associated with statistics classes and assessments among older students may be related to a lack of recent mathematics or statistics practice (Baloğlu

2003).

The fears underlying mathematical and statistical anxieties may be rooted in the prior mathematical and statistical experiences of the student (Baloğlu 2003), which is the third category shown in **Fig. 1**. Experiences (or lack thereof) can lead to misguided expectations regarding course content, with some students simply not expecting to encounter quantitative methods at all, which can impact on their levels of motivation and engagement with statistics, particularly in cultures where a lack of statistical skills is deemed socially acceptable. In this respect, it is encouraging that in recent years, data science/statistics has been introduced into the curriculum in many countries, including the UK, at primary and secondary levels (e.g. Pittard 2018). This means that students entering further and higher education will already have been exposed to the subject, and these exposures will shape their attitudes towards statistics, although research is needed to establish whether the increasing prominence of data science in school curricula is leading to a general reduction in anxiety about the subject. The ability to understand the abstract nature of statistical concepts can be related not only to prior knowledge, but also to thinking and reasoning styles (not simply preferred learning style). For example, success on statistics courses can be predicted by the ability to reason at Piaget's formal operational level, involving abstract reasoning and manipulation of ideas, rather than at the concrete operational level, which involves reasoning logically about objects in the real world (Hudak and Anderson 1990).

Essential Ingredients of a Motivating Statistics Course

Statistics teaching is qualitatively different to mathematics teaching, as it focuses on data and interpreting statistical results, rather than the act of computation. Over the past two decades, the world of statistics education has changed markedly. This change has been driven in particular by an increasing demand for statistical skills in the job market, the growth of available data, and the emergence of data science, a field which sits at the intersection of maths/statistics, computer science and discipline-specific knowledge (Cobb 2015; Horton and Hardin 2015; Carmichael and Marron 2018; Wood et al. 2018).

Notable changes in statistics education have included a shift of emphasis across STEM and other disciplines away from the computational mechanics of inferential statistics. This move stems from the adoption of an approach which can be characterised metaphorically as teaching students to “know how” rather than to “know that”, which is the philosophy of the statistics education reform movement in the U.S.A., summarised by Lovett and Greenhouse (2000) as “emphasizing students’ practical use of statistical reasoning relative to their memorization of statistical formulas and procedures.” A consensus has emerged that a key goal is the development of statistical reasoning (Bradstreet 1996) and statistical literacy (Yilmaz 1996; Garfield and Ben-Zvi 2008; Meng 2009; Tishkovskaya and Lancaster 2012; Sharma 2017). Statistical reasoning has been characterised by Bradstreet (1996) as students learning how to formulate appropriate research questions, how to design a study and collect data, select and apply appropriate statistics, and to summarise and interpret the outcomes. Statistical literacy is broadly defined as the ability to understand and critically evaluate the implications of statistics in the context of everyday life (Wallman 1993). This approach may offer a common ground for teaching statistics across disciplines.

Several reports on contemporary priorities in statistics teaching have been endorsed by the American Statistical Association (ASA), most notably the 2005 Guidelines for Assessment and Instruction in Statistics Education (GAISE) College Report (College Report ASA Committee 2005) and its 2016 successor (College Report ASA Revision Committee 2016). The 2016 GAISE report advocates six recommendations for teaching introductory statistics courses and beyond, focusing on both what to teach and how to teach it. The first recommendation is to teach statistical thinking, which is broken down into teaching statistics as “an investigative process of problem-solving and decision-making,” and giving students “experience with multivariable thinking.” A similar approach is also advocated by professional bodies in the UK and USA, such as the British Psychological Society (BPS 2014) and the American Psychological Association (American Psychological Association Board of Educational Affairs Task Force on Psychology Major Competencies 2013). Students need to develop an understanding of data as being inherently multivariate, even when they are presented as univariate, which is related to the important concept of confounding, especially in the current era of ‘big data’. Appendix B of the 2016 GAISE report offers easily-implemented examples to expose students to multivariate thinking (College Report ASA Revision Committee 2016).

The second of the six GAISE recommendations for teaching (College Report ASA Revision Committee 2016) involves a focus on understanding concepts. When tutors emphasize how different concepts relate to the bigger picture, students can begin to experience statistics as a coherent whole, rather than a jumble of isolated facts (Lovett and Greenhouse 2000). It is also useful to remember that everyday understanding of technical concepts (*e.g.,* chance, probability, hypothesis and variability) may inhibit learning, particularly when students wrongly believe they already understand the concepts. One approach is to study students’ intuitive understanding of key statistical concepts, and design learning experiences that can shape those initial misconceptions into more accurate forms (Garfield 1995; Lovett and Greenhouse 2000).

Historically, lists of core statistical techniques to be included in introductory statistics courses have been compiled (Giesbrecht et al. 1997; Landrum 2005). However, the GAISE report instead provides a list of nine goals covering statistical concepts and principles that underlie statistical techniques, and are therefore most important for students to grasp (College Report ASA Revision Committee 2016). In addition, suggestions are made for topics that might be omitted or de-emphasized, not only to avoid an overwhelmingly dense syllabus but also to reflect modern statistical practice. For example, dropping the use of statistical tables in favour of apps to look up p-values, allowing the focus to be on the interpretation of p-values rather than on finding them (College Report ASA Revision Committee 2016). Collectively, the above considerations provide a useful starting point when designing a new statistics curriculum or revising an existing one.

To progress beyond consideration of curriculum goals and the broad conceptual areas to be addressed, tutors need to consider the skills that students must practice and the statistical concepts that they will engage with when undertaking course assignments (Lovett and Greenhouse 2000). Various approaches may be taken to organise statistical concepts within a course, for example categorising in terms of the kind of study to which they apply (e.g. experiment versus observation). It is also wise to consider which statistical concepts may be particularly challenging to students. Utts (2003) has emphasised the importance of seven statistical topics that are frequently misunderstood, including cause and effect, and the differences between statistical significance and practical importance, and between finding no effect and finding no *statistically significant* effect. In addition, there is also the need to find a balance between supporting students who are struggling, while also holding the attention of those who are more knowledgeable about statistics. Rock et al. (2016) found it necessary to run separate statistics classes for novice, intermediate and advanced students within the same cohort.

It is well known that students particularly struggle with applying learned statistical skills and concepts to novel situations (Allen et al. 2016). It follows that the curriculum should specifically aim to develop selection skills in students, enabling them to choose appropriate statistical procedures for a given experimental design, their hypotheses and dataset (Lovett and Greenhouse 2000; Allen et al. 2016). To achieve this, learning activities can be designed that encourage students to focus on the structural features of research scenarios; for example, identifying the independent and dependent variables and defining the relationships between them (Quilici and Mayer 2002; Yan and Lavigne 2014). This enables students to develop structural awareness, allowing them to see past the surface features of research scenarios (for example, the species or population identity of individuals in a study) and recognise that the same kinds of analyses can be applied (Quilici and Mayer 2002). This approach leads to measurable improvements in student performance (Quilici and Mayer 2002; Yan and Lavigne 2014).

Strategies for Motivating Students to Engage

There is broad agreement that effort should be focused on increasing student motivation to engage in statistics. There are two major aspects to this: reducing apprehension about the mathematical aspects of learning statistics, and building students' personal interest in the subject.

Hulsizer and Woolf (2008) suggest that maths anxiety should be taken into account during the design of statistics courses. For example, research methods training can be scheduled near the start of a course, to equip students with background knowledge to engage in statistics throughout the remainder of their course. They also suggest that tutors should assess students' self-efficacy and maths understanding at the start of a course, to identify those who need additional support. Pan and Tang (2004) showed that a range of innovative instructional strategies could be used to reduce students' anxiety about statistics. These included acknowledging and being attentive to their anxiety, offering encouragement, offering flexible and extra office hours for provision of support, and using a pass/fail system rather than grading (Pan and Tang 2004). Chiou et al. (2014) used a one-minute paper strategy, requiring students to actively consider and synthesise what they have learned and what questions they still have at the end of each class. This approach reduced statistical anxiety and improved learning outcomes by facilitating the dialogue between students and the tutor (Chiou et al. 2014). Several authors also advocate using humor as a means to reduce statistics anxiety (Schacht and Stewart 1990; Pan and Tang 2004; Field 2009; Rock et al. 2016). For example, Rock et al. (2016) outline a classroom exercise to convey the difference between reliability and validity, showing that measurements of head circumference can be reliably made using a tape measure, but this does not mean they are a valid method for estimating intelligence.

A variety of approaches have been suggested to boost engagement through building students' personal interest in statistics. Lovett and Greenhouse (2000) recommend that courses begin with learning experiences that are designed to build not only statistical skills, but also students' personal interest in solving statistical problems, prior to assigning any data analysis tasks. This can be achieved through authentic statistical reasoning activities, designed to provide the motivating experience of making an exciting new discovery (Lovett and Greenhouse 2000).

On a practical note, tutors need to clearly communicate to students the importance of statistical skills in broad contexts, such as in the research they will encounter or carry out themselves during their course (Lovett and Greenhouse 2000) or in their future careers (Snee 1990; Harkness et al. 2003). One approach is to convey to students a sense of statistics as a "set of critical thinking skills and knowledge structures" (Hulsizer and Woolf 2008) that enable them to critically understand and evaluate research. This focus could enable the relevance of statistics and research methods to be demonstrated across diverse academic disciplines. Learning activities can also be designed specifically to encourage students to reflect during their course on the importance of statistics for their future careers (Wilson 2013). However, Meng (2009) suggests that a utilitarian view of the benefits of statistical training is not enough, instead suggesting that tutors must strive to change the perception that learning statistics is difficult and boring, and to make it both easy and fun to learn. Ironically, this makes statistics hard to teach, in the sense of needing careful design, preparation and teaching, to create courses that students see as fun and worthwhile.

Meng (2009) advocates a radical approach in which two kinds of course need to be created at undergraduate level. The first are subject-oriented statistics (SOS) courses, using real research examples from specific academic disciplines. The second are so-called "happy" courses organised around real life topics, intended to inspire a more general audience to not only learn statistics, but to enjoy doing so. In an undergraduate course with the inspiring title "Real-Life Statistics: Your Chance for Happiness (or Misery)", modules were focused on bringing statistics to life, using themes such as finance (*e.g.,* the stock market) and romance (*e.g.,* the on-line dating module). In this approach, rather than organising the statistics curriculum as a hierarchy of increasing complexity, topics are covered as and when needed and may be revisited several times in different modules (Meng 2009). This approach may help students to relate to and connect with statistical concepts (Meng 2009). It may also help to avoid the mistaken perception that statistics is a catalogue of disconnected topics (Wood et al. 2018) and encourage students to see the connections between topics, and importantly, to realise that there is often more than one acceptable solution (College Report ASA Revision Committee 2016). An alternative approach requiring less investment of resources is to incorporate statistics more explicitly into non-methodological components of the course, which boosts student interest in statistics and improves the retention of statistical skills developed within focused statistics modules (Slootmaekers 2014).

Delivering Effective Statistics Lessons

Alongside the shifts in goals and content that have characterised the recent statistics reform movement, there has also been a focus on developing innovative techniques to improve the delivery of statistics teaching beyond a traditional lecture/workshop format. Four GAISE recommendations focus on how to teach statistics courses, specifically: 1) Integrating real data with a context and purpose; 2) Fostering active learning; 3) Using technology to explore concepts and analyse data; and 4) Using assessments to improve and evaluate student learning (College Report ASA Revision Committee 2016). These recommendations are accompanied by extensive appendices with examples of activities and assessments, and advice on how to apply them in diverse learning environments.

Collaborative and active learning approaches have been widely advocated and adopted since the 1990s as an effective way to engage and motivate students with statistics. Collaborative learning approaches are highly student-centred and involve students working together to share ideas, develop their understanding and accomplish shared goals in a wide variety of ways. For example, students may be carrying out hands-on research (Allen et al. 2016) or collaborating to deepen their understanding of a statistical concept by writing their own wiki page (Rock et al. 2016). This kind of approach promotes active learning and the benefits have been widely demonstrated in terms of fostering more positive attitudes towards statistics, as well as improving assessment scores (Borresen 1990; Dietz 1993; Garfield 1993; Keeler and Steinhorst 1995; Giraud 1997; Gnanadesikan et al. 1997; Magel 1998). In addition, a flipped lecture approach facilitates time for active learning in an environment where students can receive immediate feedback, boosting both student performance and attitudes towards statistics (Wilson 2013). Even when time is very limited, there are always ways to squeeze in opportunities for active learning, for example using think-pair-share discussion (College Report ASA Revision Committee 2016).

To integrate real data with a context and purpose (College Report ASA Revision Committee 2016), actively involving students in generating their own data improves motivation and understanding compared to providing existing datasets (Stedman 1993; Bradstreet 1996). Strangfield (2013) takes this approach further using research projects led by students at all stages of the process, from designing research questions of personal interest, to collection and analysis of data, and finally presentation of research findings. This kind of approach enables an authentic experience in which students develop their statistical thinking skills (College Report ASA Revision Committee 2016; Wood et al. 2018).

Ideally, where students are provided with existing datasets, real data should be used that are directly relevant to their field of interest, as this will motivate students to understand the statistical methods they are applying and to apply them correctly, knowing that their findings will have real world implications (Bradstreet 1996; Boyle 1999). The recent proliferation of open research data provides a wealth of authentic datasets, which can be selected for their relevance to particular cohorts of students in order to improve learning outcomes (Coughlan 2020). For example, Mittelmeier (2018) showed how use of open data from the World Bank that were personally relevant to students' cultural backgrounds rather than specific to the local context boosted student participation on collaborative projects. The effective use of open data is facilitated by initiatives such as the Open Stats Lab (openstatslab.com), which guides teachers and students through reproducible analyses using open data from recent research papers published in *Psychological Science*. Alternatively, artificial datasets could be provided in those circumstances where real data are not appropriate, but it is important for such datasets to be as realistic as possible to motivate students (Bradstreet 1996). Provision of real datasets provides an ideal opportunity to implement Problem-Based Learning (PBL) in statistics teaching (Boyle 1999; Jaki and Autin 2009; Marriott et al. 2009; Dierker et al. 2018a).

In a PBL approach, students work in groups to solve genuine research questions, and the tutor plays the role of facilitator. Focusing on the analysis of data from real studies provides an authentic experience in developing statistical reasoning (Bradstreet 1996) and selection skills (Allen et al. 2016), and in the critical interpretation of statistical results, which may extend to include the portrayal of those results in the media. This approach fosters a sense of independent learning and responsibility for learning, and improves students' ability to understand and apply statistics in new scenarios, for example in their own research (Boyle 1999). It can also be an effective mechanism for dealing with wide variation in ability and confidence with statistics within the student cohort (Jaki and Autin 2009). Importantly, this approach also fuels students' interest in gaining further experiences involving data analysis (Dierker et al. 2018b). A large body of free teaching resources are available to facilitate use of a PBL approach (Tishkovskaya and Lancaster 2012; Dierker et al. 2018b).

While actively working with different research scenarios and datasets has a central role to play, it is important to remember the value of "putting pen to paper". Incorporating writing skills into a statistics course is valuable in numerous ways, including deepening understanding of statistical definitions and concepts in diverse cultural groups, which can lead to improved examination performance (Whaley 2017). Low-stakes writing tasks (e.g. keeping a journal) provide an outlet for students to acknowledge and experience their own emotions as they progress through the statistics course, which may be shared with others to remind students that they are not alone, and reduce feelings of statistics anxiety (Sgoutas-Emch and Johnson 1998). Moreover, writing assignments allow students to express their creativity and can give the tutor an insight into how their students have developed their statistical reasoning, which can be used to tailor course content (Woodard, Lee and Woodard 2020).

Digital Resources for Statistics Teaching

Although traditional lectures, textbooks, and pen and paper analyses still play a large role in statistics teaching, the incorporation of a wide range of computational tools and interactive resources has long been widespread, including mobile apps, widgets, videos and games that can help support both traditional lectures and more active learning approaches.

Computational Tools

A wide variety of statistical software is available for use in teaching, including proprietary programmes (*e.g.,* GenStat, MatLab, SPSS, Stata) and open source options (*e.g.,* JASP, R/RStudio, Scilab, SOFA, PSPP). The variety available means you can choose which programme meets your students' needs in terms of ease of use, computational transparency, required functionality, and disciplinary conventions. However, the diversity of statistical software in use across, and even within disciplines, is inevitably a barrier to sharing resources and disseminating good teaching practice. Tutors from different disciplines traditionally use particular software packages. For example, Matlab and Statistica are widely used in engineering, Excel and SPSS in geography, and Minitab in business. However, the use of R (https://www.r-project.org/) is increasingly popular across diverse disciplines, and may help to alleviate this barrier (Bolker 2008; Bloomfield 2014; Wilcox 2017).

Building the use of statistical analysis software into learning activities may present a training challenge, but may also provide an opportunity to teach statistics using a practical approach. It can also be an effective route to de-emphasising the computational mechanics of statistics. This can enable attention to be focused on developing an understanding of statistical concepts (Lovett and Greenhouse 2000; Mills 2002; Hulsizer and Woolf 2008), deciding on appropriate statistical techniques, and interpreting statistical test results (Garfield et al. 2002; Chance et al. 2007). However, these benefits are not a necessary consequence of merely using the software; the integration of software usage into teaching must be carefully planned (Garfield 2002). There is always the danger that students become focused on learning to implement commands correctly in the software itself, and become blind to the bigger picture involving the underlying statistical concepts (Chance et al. 2007). A related issue is that analysis software can act like a black box of statistical tricks that obscures the computational mechanics underlying statistical tests and procedures. Consequently, students may not necessarily gain an understanding of how the statistical procedures manipulate the raw data (Chance et al. 2007; Callingham 2011). Without this understanding, they may find it difficult to interpret what the results of the data analysis mean (Callingham 2011).

One way to address these potential difficulties is to contextualise students' software use within simulated data analysis tasks (Mills 2002). Alongside the application of standard data analysis techniques, it is straightforward using software such as Microsoft Excel to generate repeated random samples from a population with defined parameters. These simulated data can be used to investigate and improve understanding of the logic underlying statistical inference and important statistical concepts, such as the distribution of the sample mean, randomisation, or the definition of a p-value (Mills 2002; Chance et al. 2007; Cobb 2007; College Report ASA Revision Committee 2016). The use of simulation and randomisation-based methods to establish the foundations of statistical inference has grown extensively in recent years, and a call has been made to implement this new approach across all undergraduate statistics courses for its efficacy in developing an intuitive understanding of statistical inference (Simon 1995; Rossman and Chance 2014a,b; Tintle 2014, 2015).

Interactive Learning Resources

Simulated data as discussed above provide a useful resource for learning statistics. Taking the idea of simulation further, the use of gaming technologies or Game Based Learning (GBL) in teaching diverse subjects including statistics has been explored since the early 2000's (Ke et al. 2009; Wouters and van Oostendorp 2013; Bhalla 2014; Novak et al. 2016). The benefits of this approach include improvements in decision-making abilities and improved motivation because of the active learning process (Novak et al. 2016).

Numerous characteristics define an online instructional programme as a game, including challenge, competition, control, adaptation, assessment, immediate feedback, storyline and rules (Wilson et al. 2009). However, the relationships between the positive outcomes of GBL and specific gaming characteristics are not well understood. For example, Novak et al. (2016) explored the effect of embedding a storyline into an instructional simulation in an undergraduate statistics course, but found no effect on statistical understanding, and indeed a negative effect on student engagement and satisfaction. It is likely that great care must be taken in the implementation of GBL. For example, in this case, the contextualised task was not truly comparable to a recreational computer game, not least because it did not adapt to the students' interactions with it, for example by deploying a different story branch depending on student decisions. It is also possible that the storyline was distracting or added an extra cognitive load to the simulated task (Novak et al. 2016). Aside from the difficulties in finding an effective way to develop GBL approaches for teaching statistics, the task presents statistics tutors with additional challenges, such as limitations in resources, and the need to address a lack of technical expertise in game development. While this is true of any computer-enhanced learning (Allen et al. 2016), attempting GBL poses far greater technical challenges than, for example, learning to use a virtual learning environment (VLE). Both host institutions and tutors themselves must consider what is needed in terms of training and support to effectively implement these more ambitious ideas (Novak et al. 2016).

Students often prefer a graphical illustration of statistical concepts to written explanations. This could take the form of videos demonstrating worked examples or more simply a basic graph. Graphs can be turned into interactive learning objects that demonstrate statistical concepts in a visual and non-mathematical way and respond dynamically to user inputs. For example, Rossman and Chance have developed an extensive collection of applets to illustrate abstract statistical concepts including sampling and power, featuring games such as guess the p-value (www.rossmanchance.com/applets). Beyond simple or dynamic graphics, animated visualisations have been used to convey the beauty of statistics and help develop an understanding of real-world statistics for a wide audience. The Gapminder project (https://www.gapminder.org/) offers a free design tool for animated visualisations of datasets, and a wealth of free resources for teaching statistics. A particularly creative example of visualisation is the exploration of statistical concepts through the medium of dance (Irving 2015). The Dancing Statistics films are designed to augment more traditional learning activities by giving students the opportunity to think about concepts in a completely different and highly memorable way (Irving 2015).

One of the most ubiquitous forms of graphical learning resource or graphical organiser is the classic decision tree commonly used to guide the choice of an appropriate statistical test. This kind of resource allows students to develop an understanding of the differences between statistical concepts or tests, as well as how they are related to each other, which facilitates the development of selection skills (Allen et al. 2016). Early decision trees were limited by the requirement to fit within only a few sheets of paper, and were later adapted for digital media. For example, an online selection tool in table format is provided by the UCLA Institute for Digital Research and Education (https://stats.idre.ucla.edu/other/mult-pkg/whatstat/). Hypertext systems consist of a series of interconnected pages and may have expanded functionality, including links to other useful resources, though there is always the problem that users can find themselves lost within the web of interconnected pages, and thereby struggle to see the bigger picture (Allen et al. 2016).

The next logical step in the evolution of statistical selection tools was to develop a mobile app to facilitate convenient statistical decision-making, free of any requirement for internet connectivity. The use of mobile applications can lead to improvements in student learning compared with pen and paper only. Allen et al. (2016) have developed StatHand, a mobile app that guides students interactively through a series of questions to enable them to identify which statistical technique to apply to their dataset. While use of the app can lead to slower decision-making, both the accuracy of those decisions and student confidence in making them are improved (Allen et al. 2019). However, the mere availability of apps does not guarantee their effective use by students. Rock et al. (2016) point out that the experience of using mobile apps may be characterised by multi-tasking, with students dividing their attention between use of the app and other activities. This emphasises the need to consider the necessary pedagogical strategies to enable the effective use of mobile apps to enhance learning, so that they are integrated into the curriculum and do not simply become a quick-fix tool leading to shallow learning (Chance et al. 2007; Allen et al. 2016).

Future Developments in Statistics Teaching

In the coming years, methods of teaching statistics will almost certainly continue to move away from lectures and paper-and-pencil analysis towards technology-driven active learning using real datasets. In the era of "big data", the scale and complexity of datasets encountered across disciplines means that the use of technology in statistical analysis, and therefore teaching, has become essential. A data-driven world demands statistical approaches (e.g. multivariate and network analyses) and skills (e.g. coding) which are not necessarily taught in traditional statistics courses. Specialist statistics and non-specialist departments alike are working hard to adjust to this new landscape. With huge amounts of data being produced constantly, the challenge is increasingly one of turning data into useful information and knowledge. The data are readily available, as is the technology to handle it, but we urgently need to train people to engage critically with big data and make sense of it (Song et al. 2015). The majority of students studying introductory statistics within non-mathematics courses may not go on to become data scientists, and we are not advocating trying to shoe-horn extensive data science training into such courses. However, it is important for students to recognise that big data are here, they require particular tools and expertise to interpret, and that they play an increasingly large role behind the scenes in everyday society through social media targeting, marketing, and more. Students now need not just statistical literacy, but big data literacy.

Of course, some students may choose to work with big data more directly in the future. Certainly within the sciences, there is concern that students are not being equipped to handle big datasets which are the new norm (Donovan 2008). By teaching introductory classes using tools that adapt well to big data, we give students an advantage for the future. For example, using R and user-friendly interfaces such as 'R Commander' and 'RStudio' for introductory statistics gives the flexibility to teach students the basics using point-and-click analysis as well as moving into coding, which becomes necessary when dealing with larger, more complex datasets. While R is just one example, the key is to use tools which can be introduced without too steep a learning curve, but which can adapt to the bigger, more complex data that students are likely to encounter in the future.

Interesting possibilities also exist for genuine inter-professional learning, which aims to prepare students for professional lives that are likely to feature boundary-crossing collaboration between professions in order to achieve optimum outcomes (Smith and Clouder 2010). We would argue that a course which aims to develop statistical literacy and critical thinking skills offers a common ground not only for teaching statistics across disciplines, but also for interprofessional learning. The rise in the use of R software across diverse academic disciplines will provide a software platform for facilitating learning in such inter-professional contexts.

Modern students have used the internet and been immersed in data all their lives. Their learning styles value use of multiple media, collective and active learning, and co-design of learning experiences (Dede 2005). They are adept at skimming huge amounts of information, but need training in critical thinking and information literacy (Barnes et al. 2007). Experienced educators are increasingly finding that giving students the chance to "do statistics" in an active way that is relevant for their studies is more effective than traditional teaching, but there is room to expand these methods of active and problem based learning further outside the classroom by incorporating social media.

The vast majority of internet users now participate in some kind of social media - a staggering 2.8 billion people worldwide (Clement 2019). Use of social media in education is on the rise as a way to extend learning beyond the classroom. It varies from informal "study group" use by students (Gray et al. 2010), to more formalised engagement and communication between lecturers and students, or between students for collaborative work (Bosch 2009; Charlton 2009; Schroeder and Greenbowe 2009; Everson 2012), or even as the primary means of administering a course (Baran 2010; Wang et al. 2012). While there are concerns around data protection and privacy with the use of social media in education, careful and creative use can manage the pitfalls while harnessing the positive potential for increasing learning and engagement. Finding ways to link the power and ubiquity of social media use with broader co-designed and active learning methods in statistics could lead to improved engagement and learning outcomes without increasing classroom time.

Conclusion

Statistics is a fundamental subject that must be taught across a wide and ever-increasing range of disciplines, from STEM subjects to business, arts, languages, and beyond. Students of these disciplines, and in turn their tutors, face a wide variety of challenges. Arguably the most notable of these is statistics anxiety, and there is now a large body of research devoted to understanding this experience, and how to design statistics courses to reduce its effects. The job of a statistics tutor is therefore a very difficult one, requiring careful planning and design to deliver statistics courses that not only address the challenges, but also make the experience of learning statistics an enjoyable one.

In this review, we have summarised current best practice for statistics tutors who want to update statistics courses or develop new ones, in light of the recent trends in statistics teaching. We have reviewed the changes in scope of the statistics curriculum that have taken place in recent decades, shifting the focus from teaching students how to compute inferential statistics, to shaping the minds of students into statistically literate citizens, capable of experiencing statistical reasoning and interpreting the meaning of statistics as they apply to real life scenarios. We also hope to have stimulated research-informed ideas on how to deliver the curriculum content to achieve these goals, for example using active approaches such as problem-based learning, or through designing interactive learning objects for visual communication of statistical concepts. The use of technology in teaching statistics has clearly progressed far beyond simply uploading material to a VLE, emphasising the need for lifelong learning in order for tutors to keep pace with rapid changes, and to integrate new technologies into their courses within a pedagogical framework.

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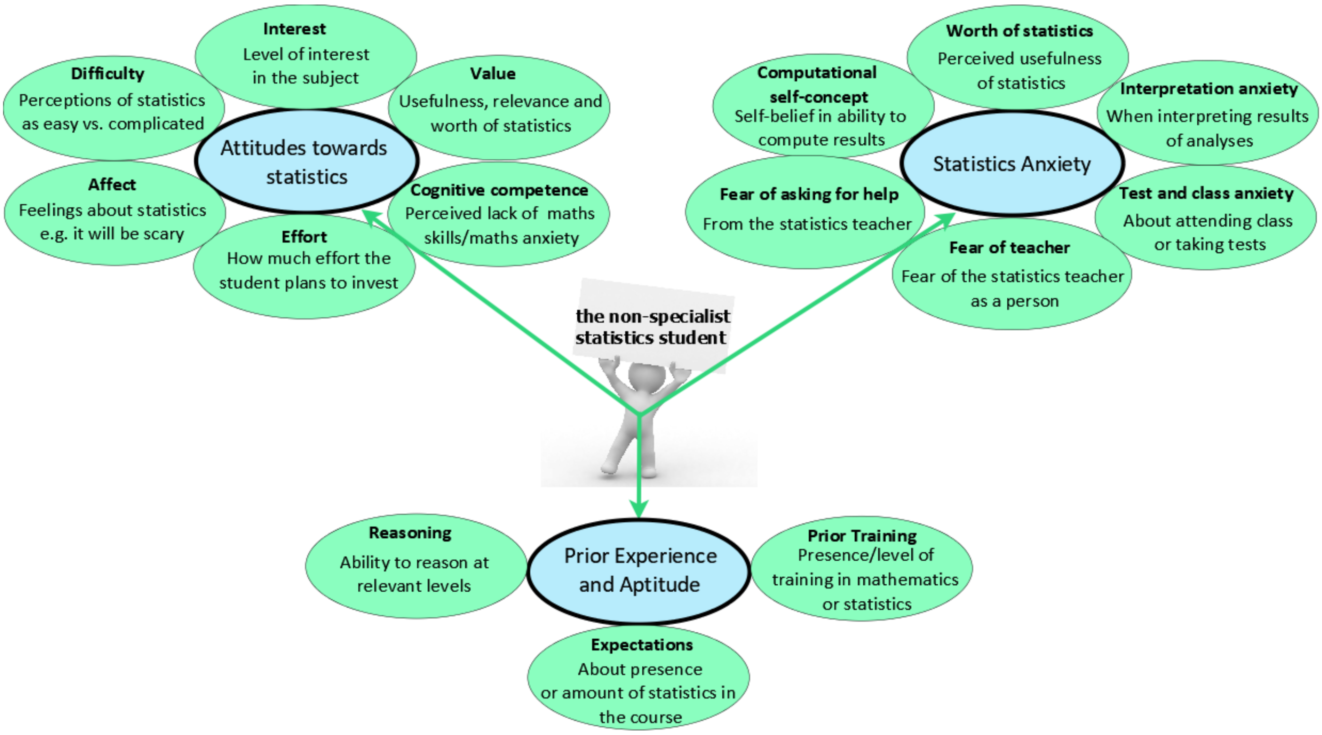
Figure Captions

Fig. 1 Interacting Student-Centred Factors Affecting the Experience of Learning Statistics.



The six components for each of the Survey of Attitudes Towards Statistics (SATS) scale and the Statistics Anxiety Rating Scale (STARs) are shown.