

THE SUBJECT OF STATISTICS IN NATURAL SCIENCE CURRICULA: A CASE STUDY

Aneta Hybšová¹, Jimmie Leppink²

¹Charles University in Prague, ²Maastricht University

Highlights

- Undertake curriculum and course design in a multidisciplinary team
- Spidergrams can provide a useful tool in curriculum and course design
- Course design should minimize extraneous cognitive load and optimize intrinsic cognitive load

Abstract

Statistics is considered to be an indispensable part of a wide range of curricula across the globe, natural science curricula included. Teachers and curriculum developers are typically confronted with four questions with regard to the role and position of statistics in a curriculum: (1) how to integrate statistics in the curriculum; (2) which topics to cover and in what detail; (3) how much time to allocate to statistics in a curriculum; and (4) how to organize a course and which study materials to select. This paper addresses these four questions through a case study: four curricula at Charles University, Prague, Czech Republic, are compared in terms of how they address these four questions. Placing this comparison in a framework of cognitive load theory and two decades of research inspired by this theory, this paper concludes with a number of guidelines for addressing the aforementioned four questions when designing a curriculum.

Keywords

Statistics education, course analysis, curriculum development, cognitive load theory

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Introduction

An enormous growth of data and information load has contributed to the fact that statistics is considered an indispensable part of a wide range of curricula across the globe, natural science curricula included. Students are taught to make sense of the multitude of quantitative data and learn to engage in quantitative thinking and reasoning.

Problem of Research

Teachers and curriculum developers typically have to answer four interrelated questions with regard to the role and position of statistics in a curriculum. Firstly, in natural science, statistics generally serves as a means for doing research; it is not a goal in itself. In this context, statistics is one of a series of subjects to be integrated in a curriculum. To provide students with opportunities to practice with statistical content and to illustrate that statistics can provide them with tools to address questions and challenges in their field, the subject of statistics needs to be properly integrated in the curriculum at hand (Leppink, 2012). The first question to be addressed by curriculum developers and teachers is therefore how to integrate statistics in their curriculum.

Secondly, each curriculum has different needs and attracts different populations of students. Prior knowledge of statistics may vary considerably among students who enter a statistics course in a given curriculum. It is of crucial importance to consider this variation in prior knowledge, as this has crucial implications for instructional design of a course. Various studies in statistics education have demonstrated a so-called expertise reversal effect in statistics education (Leppink, Broers, Imbos et

al, 2012a, 2012b, 2014). Succinctly put, instructional methods that are effective for students who have little prior knowledge tend to lose their effectiveness and may even affect learning negatively among their more knowledgeable peers (Kalyuga, Ayres, Chandler et al, 2003; Kalyuga, Chandler, Tuovinen et al, 2001). This robust finding from educational research and the specific needs of a given curriculum give rise to second question, namely which topics to cover and in what detail.

Thirdly, sufficient time should be allocated to the subject of statistics to avoid that most students develop an only superficial understanding of the content covered. Frequently, part of the time allocated to the subject is used to make students familiar with statistical software. Moreover, a proper understanding of core concepts appears to require at least a basic understanding of formulae and mathematical relations. Many students entering natural science or other (e.g., social and health science) curricula in which statistics is a tool but not a goal in itself lack such an understanding, meaning that some time should be reserved for increasing that understanding. However, there is a tradeoff. On the one hand, the aforementioned factors require that a sufficient amount of time be reserved for the subject. On the other hand, statistics is but one in a chain of many subjects forming a curriculum. This tradeoff typically requires curriculum developers and teachers to come to a practical compromise on a third question, namely that of the amount of time to allocate to the subject given the function and position of the subject in the curriculum at hand.

Fourthly, the three questions addressed until here – how to

integrate statistics in the curriculum, which topics to cover and in what detail, and how much time to allocate to the subject in the curriculum – naturally lead to a fourth question: how to organize a statistics course and which study materials to select. The aforementioned expertise reversal effect is of crucial importance here and is one of the merits of well-designed experimental research inspired by cognitive load theory (Sweller, 2010; Sweller, Ayres and Kalyuga, 2011). In cognitive load theory, learning is defined as the process in which new information elements are related to knowledge available in long-term memory, resulting in more elaborated cognitive schemata. However, whether learning takes place depends on the intrinsic complexity of the new information as well as on the way in which that information is presented. The more working memory capacity is needed for dealing with the way in which information is presented (i.e., extraneous cognitive load), the less working memory capacity remains available for dealing with the intrinsic complexity of the information (i.e., intrinsic cognitive load). For instance, if a distributional concept that should be presented graphically is presented textually, this is likely to impose a relatively high extraneous cognitive load on students, meaning they have fewer resources available to actually learn what the distributional concept is about. Likewise, instructional methods that require students with limited prior knowledge to engage in problem-solving search activity impose an extraneous cognitive load that may disable them to deal with the actual content (Kalyuga et al, 2001, 2003; Leppink et al, 2012a, 2012b). Simultaneously, however, instructional guidance that can greatly reduce extraneous cognitive load among novices (through a reduced appeal on problem-solving search activity) may require more knowledgeable students to process information they no longer need and as such increase extraneous cognitive load.

Research Focus

No matter where or in what curriculum statistics is taught, the aforementioned four questions arise naturally. A cross-country comparison or a comparison of universities in a country could yield interesting insights with regard to how different universities address these particular questions. However, an advantage of a case study is that it enables one to zoom in on key choices and discuss these key choices from an educational theory and research perspective. Whether it is about curriculum design at the University of South Bohemia, the University of Veterinary and Pharmaceutical Sciences in Brno, another university in Europe or a university elsewhere, the same four questions have to be addressed. Therefore, this paper does not provide a cross-university comparative review, but addresses these questions through a case study to discuss key choices more in depth.

Four curricula at Charles University, Prague, Czech Republic, for prospective teachers of biological topics are compared in terms of how they address these four questions. Placing this comparison in a framework of cognitive load theory and two decades of research inspired by this theory, this paper concludes with a number of guidelines for addressing the four questions every curriculum developer and teacher has to address when designing a curriculum or course within a curriculum. These guidelines can also provide a useful framework for cross-university comparisons of how the four key questions are addressed.

Methodology of Research

General Background of Research

Through content analysis, the following four curricula are compared: (1) the Bachelor of Biology, Geology, and Environmental Science (FEBGES), (2) the Master of General Education Subjects for Elementary and Secondary Schools (Biology), (3) the Bachelor of Biology, and (4) the Master of Biology Education for Secondary Schools. The first two curricula are organized by the Faculty of Education (henceforth: FE Bachelor and FE Master, respectively), while the latter two curricula are part of the Faculty of Natural Sciences (henceforth: FNS Bachelor and FNS Master). The two Master's curricula are potential follow-ups of the two Bachelor's curricula. All four curricula focus on preparing students for a practice of teaching biological topics.

The FE Bachelor involves neither compulsory nor optional courses with statistical topics, whereas FE Master's students must complete a biostatistics course. FNS Bachelor's students are given the option to take an elementary biostatistics course, and the FNS Master includes a mandatory course on research methods in natural science education. A concise overview of the four curricula in terms of statistics coursework is presented in Table 1.

Curriculum	Course and link to syllabus
FE Bachelor	None
FE Master	Biostatistics (ON2302052, mandatory)
FNS Bachelor	Elementary biostatistics (MS710P09, optional)
FNS Master	Research methods in natural science education (MB180C41, mandatory)

Table 1. Overview of the four curricula compared in this paper

Content Analysis

The three statistics courses were analyzed with regard to the aforementioned four key questions: (1) how to integrate statistics in the curriculum, (2) which topics to cover and in what detail, (3) how much time to allocate to the subject in the curriculum, and (4) how to organize a statistics course and which study materials to select.

With regard to the second question, coverage of ten statistical topics that have countless applications in biological research was evaluated: (a) introduction to statistical methods, (b) probability theory, (c) random event and its probability, (d) sampling and descriptive statistics, (e) hypothesis testing, (f) two-sample comparison, (g) non-parametrical methods, (h) categorical data analysis, (i) time series, and (j) measuring statistical dependence (correlation and regression). The courses were compared in terms of level of implementation or detail. Spidergrams were used since these enable one to contrast various ordinal variables. Following standard content of complex statistical textbooks (Pagano and Gauvreau 2000), the following 0-5 assessment was made for each of the ten topics (a-j): the topic does not occur in the syllabus (0); the topic is mentioned in the syllabus but remains unspecified (1); the topic is included in the syllabus along with a brief outline of its essence (2); the topic is described in the syllabus with the omission of some subtopics (3); the syllabus presents an elaborate description of the topic but without mathematical details (4); the syllabus comprises a detailed presentation of the topic including the mathematics underlying the topic (5).

The use of spidergrams is in line with Vondra and Vltavská (2014), who used spidergrams to analyze study plans and to

compare the structure of subjects and their relevance according to the opinions of students and academic staff.

Results of Research

FE Master's course in biostatistics

In two seminars of 90 minutes each, the mandatory FE Master's course in biostatistics introduces students to elementary statistical terminology, the potential of analysis and statistical data presentation, elements of inductive thinking along with the most frequently used statistical methods, the conditions of their usage as well as their potential and shortcomings. Besides, there is attention for the interpretation of outcomes of biological and pedagogical studies. Figure 1 presents the spidergram for the FE Master's course in biostatistics.

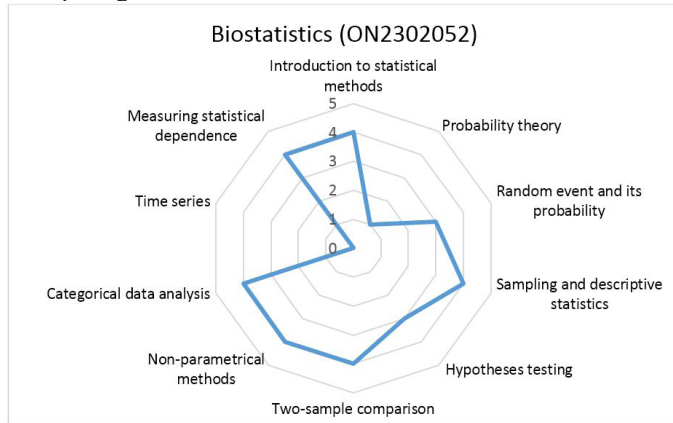


Figure 1: Spidergram for the FE Master's course in biostatistics.

Figure 1 illustrates a clear emphasis of the course on the introduction to statistical methodology, sample and descriptive statistics, two-sample comparison, categorical data analysis, and non-parametrical methods.

The course highlights the significance of biostatistics in biology and teaching and covers graphical and numerical tools for one-dimensional as well as multidimensional data (Hybšová, 2013). Hypothesis testing in biostatistics is covered through a presentation of the following tests: t -test, F -test, Mann-Whitney test, Wilcoxon test, sign test. Further, correlation (Pearson's and Spearman's coefficient), contingency table analysis, and simple and multiple regression are covered.

The course is completely free of mathematical proofs and mathematical essence of the methods presented. The course aims at acquainting students with the potential of statistics. If students are interested, they are given a sufficient ground for deeper study. Recommended study materials include textbooks written by Chráska (2010) and Gavora (2010) who attempted to adapt their explanation to a reader with secondary school knowledge of mathematics.

FNS Bachelor's course in biostatistics

The optional FNS Bachelor's course in biostatistics includes a wide range of topics: (1) descriptive statistics; (2) relative frequency and probability, independence, and Bayes' theorem; (3) random variables and their distributions and features; (4) sampling theory, parameter estimation, and the hypothesis testing principle; (5) parametric and non-parametric tests for single and paired samples, (6) tests for two independent samples, (7) spread-analysis principle, (8) correlation and regression, (9) contingency tables and (10) measuring statistical dependence (Zvára, 2014). Figure 2 presents the spidergram for the FNS Bachelor's course in biostatistics.

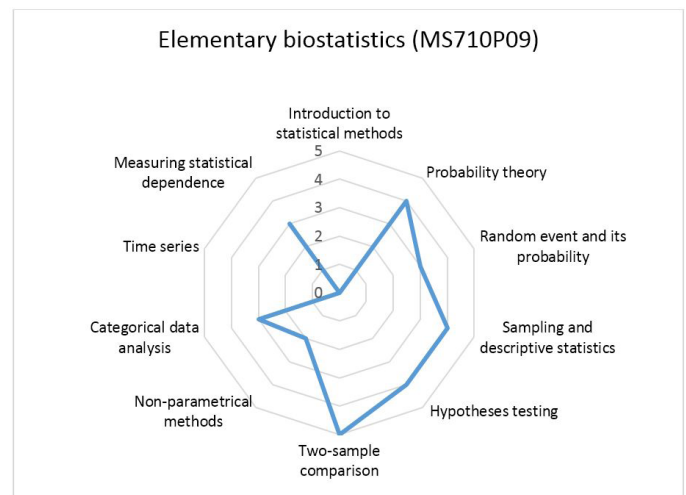


Figure 2: Spidergram for the FNS Bachelor's course in biostatistics.

The most thoroughly covered topic is that of two-sample comparison. Course seminars take place in computer laboratories and use R as statistical software. Students learn to use common statistical procedures, using their own real data. In more complicated cases, students are encouraged to ask for qualified assistance.

The compulsory reading list includes more mathematically-oriented textbooks by Zvára (2001, 2013, 2014) and Havránek (1993) that require advanced, university-level knowledge of mathematics. Although the combination of lectures (two times 90 minutes) and seminars (two times 90 minutes) adds to the strength of this course, the use of R does require some programming skills and can make the course challenging.

FNS Master's course in research methods

The FNS Master's course in research methods consists of only two seminars of 90 minutes each and focuses on quantitative and qualitative methods of pedagogical research in methodology of natural sciences with an emphasis on biology. In fact, students are presented with tools for writing their thesis. Students learn about research planning, generating testable hypotheses, and basic data collection methods. The introduction to types of variables and basics of statistical data analysis and evaluation constitutes an integral part of the course. Figure 3 presents the spidergram for the FNS Master's course in research methods.

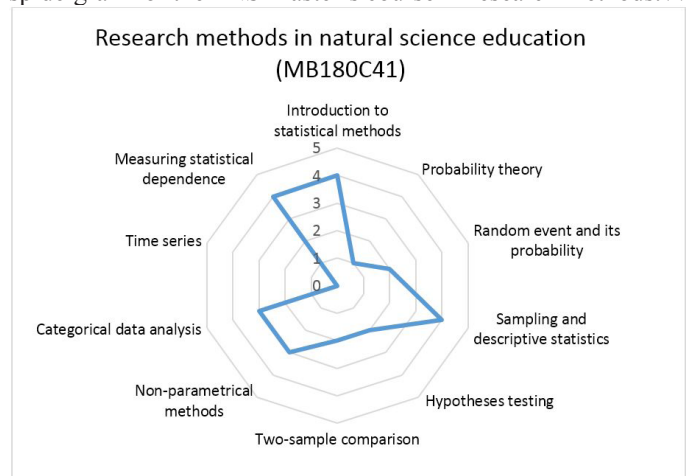


Figure 3: Spidergram for the FNS Master's course in research methods.

Students receive a detailed overview of the introduction to statistical methodology, sample and descriptive statistics, and dependence of quantitative data. Non-parametric methods and

categorical data analysis are covered with less detail and the syllabus completely omits other areas, such as time series.

The compulsory course literature comprises Chráska (2010) and Gavora (2010) for the quantitative part and Švaříček and Šedřová (2007) for the qualitative part. These textbooks appear much more suitable for the needs of teachers than the books used in FNS Bachelor's course in biostatistics; the explanations are much more gradual, with no mathematical elaboration, and therefore easier to grasp by students who have a non-mathematical background.

Discussion

Cross-curricular comparison of topic coverage and consequences for students' learning

The FE Bachelor does not include any course that covers statistical content. A potential advantage of this approach is that more time remains available for biological content, communication and teaching skills, and other knowledge and skills that can make a good teacher. However, having had no statistical coursework at all leaves students unprepared for research and research-oriented Master's curricula.

Meanwhile, given that in many Master's curricula – the ones discussed in this paper are exemplar for non-mathematical Master's curricula across the globe in this respect – include at most one course that addresses a selected set of topics in a limited period of time, students graduating from a Bachelor's curriculum that includes no statistical coursework may not have the necessary groundwork for developing a proper understanding of the statistical content covered in the Master's course.

The effectiveness of statistical coursework in Master's programs is generally built on the premise that students have an at least basic understanding of core statistical concepts. In the light of the aforementioned expertise reversal effect, this is problematic, as instructional methods that work for students who have a certain knowledge tend to be less effective for students who lack that knowledge. Thus, including at least one mandatory statistics course in a Bachelor's curriculum appears desirable.

A major strength of the FNS Bachelor's course in biostatistics relative to the other two courses discussed in this paper is that dedicates a substantial amount of time to probability theory. In the light of commonly encountered and persistent misconceptions about conditional probabilities like the p-value in null hypothesis significance testing (Fidler and Cumming, 2010), covering probability in sufficient detail in a statistics course appears a wise choice.

However, two main challenges for students taking the FNS Bachelor's course in biostatistics are the use of a statistical package that requires programming skills and the mathematical presentation of topics that should be presented in a more conceptual manner to students who have a non-mathematical background. From a cognitive load theory perspective, all resources students have to allocate to dealing with programming difficulties are simply not available for dealing with the intrinsic complexity of the actual statistical content. Since programming skills are in essence extraneous to purely statistical content, any mental effort to be invested in learning how to use a program is extraneous to learning; it does not contribute to the actual goal of the course, if that goal is to learn statistical content.

A similar reasoning holds for a mathematical presentation of statistical concepts. What students in non-mathematical curricula typically need, to become researchers or professionals,

is a conceptual understanding of statistics (Leppink, 2012). Any mathematical presentation that is not necessary for such a conceptual understanding is – from that perspective – extraneous to learning and as such imposes an extraneous cognitive load on students that limits their ability to develop a conceptual understanding that is needed to do research or to assess the merits of an empirical study in a practical context. This holds even more when introductory concepts of statistical methodology are not even covered, as is the case in the FNS Bachelor's course in biostatistics. In this respect, the other two courses have an advantage.

As holds for the vast majority of natural, social, and health science curricula, none of the courses compared in this paper covers time series analysis. Although time series analysis is of great use in biology (as it is in for instance econometrics), students need to have mastered quite a number of more basic concepts to start their journey through time series analysis. Given that statistics is only one of many topics in a curriculum, and part of the time for a statistics course needs to be spent on software, only a limited number of topics can be covered in a course in such a way that students can digest most of the content.

Therefore, it appears wise to leave time series analysis for curricula that attract PhD candidates who need time series analysis in their research. Of course, the latter recommendation is built on the assumption that the PhD candidates' knowledge of more basic statistical concepts be sufficient to get started with this course; otherwise, candidates should be encouraged to go through more basic coursework first.

Finally, the FE Master's course – more than the other two courses – pays attention to non-parametric methods. Considering the fact that data may violate conditions for the use of parametric methods, including non-parametric methods in the course appears a wise choice, even if this comes at the cost of covering more advanced parametric tools which require the student to have mastered more basic concepts anyway.

Guidelines for curriculum and course design

Students frequently develop an only superficial understanding of statistics because they take a course for which they have not been prepared or a course that presents the content in a way that is of at best limited practical use (Kvasz, 1997; Leppink, 2012). This constitutes two arguments against a predominantly mathematical presentation of statistical content in a non-mathematical curriculum.

Firstly, students enrolled in a non-mathematical curriculum generally do not have the mathematical background that is needed to understand mathematical formulae and relations underlying statistical concepts.

Secondly, much of the mathematics encountered in mathematical statistics literature is not necessary for doing and understanding the outcomes of empirical research; a proper conceptual understanding of statistics may well do in this context.

For instance, if researchers understand the difference between a standard deviation around a sample mean and a standard error (i.e., the standard deviation of a sampling distribution) and that a way to decrease the standard error – which is part of confidence intervals and statistical significance tests – is to use larger samples, they do not need further formulae to understand that non-statistically significant results and excessively wide confidence intervals are much more likely in a sample of $N = 10$ than in a sample of $N = 100$. Reading a research paper that reports a non-statistically significant correlation in a sample of $N = 10$, they realize that a correlation of the same size would be

statistically significant in a sample of sufficient size, and that the reported non-statistically significant outcome should not be interpreted as evidence in favor of the null hypothesis of zero correlation. No mathematical equations enter the argument here.

The most fundamental guideline for curriculum and course design is to undertake this enterprise with a multidisciplinary team. Statisticians know better than anyone else what definitions and arguments are correct and what is incorrect. Unfortunately, the subject of statistics is not rarely taught by non-statisticians who have a limited understanding of key statistical concepts themselves. Persistent misconceptions about the p-value (Fidler and Cumming, 2010) constitute just one example of this. Teaching core statistical concepts incorrectly has negative implications on the short run (i.e., flawed understanding of these concepts among students) as well as on the long run (e.g., continued misuse of p-values and other statistical concepts in empirical research across domains). Having a statistician in the team is therefore recommended.

However, in their enthusiasm about their subject, statisticians typically feel the desire to cover either many topics or specific topics in extensive detail but are frequently also not really aware of how to present these topics to students with a non-mathematical background. This is why including an educationalist in the team is a very good choice.

Finally, one needs to include content experts, for instance biologists in the case of a biology curriculum. The simple reason for this is that that content experts can assess better than anyone else what knowledge and skills define a good researcher or professional in the domain.

Therefore, with a multidisciplinary team that includes at least one statistician, at least one educationalist, and at least one content expert, one optimally increases chances to (1) achieve a good integration of statistics in the curriculum, (2) make appropriate decisions with regard to which topics to cover and in what detail, (3) find a good balance between time allocated to statistics and time available for other knowledge and skills, and (4) organize a course and select study materials such that learning is stimulated to an optimal extent.

The spidergrams used to compare existing courses in this paper can also serve as starting point for curriculum and course development. A careful analysis of the domain and of aims of a curriculum can help a team of curriculum developers and teachers to construct a spidergram detailing what topics should be part of a statistics course in that program, in what detail these topics should be covered given the aims of the curriculum, how much time should be reserved for activities in that course, and eventually how specific topics can reoccur in the form of a practical application in one or more later courses. The spidergrams can also be used to facilitate comparisons of curricula and courses in different universities in a country or in different countries.

Course-specific guidelines

One of the key observations this paper started with is the expertise reversal effect and how this robust phenomenon can be explained in a cognitive load theory framework. This paper concludes with a set of guidelines that can facilitate decision-making with regard to how to learning task complexity and the degree of instructional support provided to students. The basic principle underlying these guidelines is that a course should be designed such that extraneous cognitive load is minimized and students are stimulated to optimally allocate their available resources to dealing with the intrinsic cognitive load arising

from the intrinsic complexity of information.

One way of reducing extraneous cognitive load is scaffolding, that is: to provide sufficient instructional support to students with limited prior knowledge (e.g., partially or fully worked examples; Leppink et al, 2012a, 2012b) and to gradually fade that guidance for tasks of a given complexity level as students advance.

A second way of reducing extraneous cognitive load is to present content in a single integrated source of information rather than in multiple sources that are distributed in either space or time (Sweller, 2010). The latter requires students to split their attention between sources and hold information from one source in their working memory while attempting to process information from another source. For instance, providing students with instructions for how to use a particular hypothesis test way before instead of right when students need to apply it requires students to hold information about that hypothesis test during a time interval in which students may also need to process other information.

Modality plays an important role in the effectiveness of instruction. Concepts like a cube, for instance, should be presented visually not verbally. Providing verbal descriptions of a cube, students in the end may or may not realize that it is a cube and not some other object the teacher is describing, but it takes an unnecessary effort to digest information that is not needed when presenting the cube visually. Likewise, verbal descriptions of that cube are redundant when presented along with the cube in visual form; students understand without any additional explanation that the object they see is a cube. Similarly, concepts like shape, center, and variation are often more easily understood when presented visually than when presented in textual form.

Keeping extraneous cognitive load to a minimum is a necessary but not sufficient condition for students to optimally allocate their resources to dealing with intrinsic cognitive load. Firstly, the intrinsic cognitive load needs to be at an optimum. A task of a given complexity level can be expected to impose a higher cognitive load on a novice student than on a more knowledgeable student, because the latter already has more elaborate cognitive schemata of the content in long-term memory than the former. The complexity of learning materials must align with students' prior knowledge of the content for learning to take place. Too easy materials may simply bore students (Young and Stanton, 2002), whereas materials of too high complexity are likely to hamper learning (Ayres, 2001). Therefore, it is important to have learning materials match students' prior knowledge from the start, and attempt to gradually increase complexity as the course advances.

Additional to aligning task complexity to students' prior knowledge, teachers really need to be aware of the extent to which assessment can drive learning. Even if instruction throughout a course is aimed at stimulating students to invest effort in dealing with the complexity of learning materials, if students have the impression that the exam at the end of the course assesses knowledge in a fairly superficial manner, students may mainly feel stimulated to engage in superficial learning (Laffleur, Côté and Leppink, 2015). A somewhat more challenging assessment in combination with a well-designed course that is well integrated in the broader curriculum can stimulate students to invest an optimal effort in learning from the course.

Finally, recent studies have provided self-report measures of intrinsic and extraneous cognitive load experienced by students

when processing information (Leppink, Paas, Van der Vleuten et al, 2013; Leppink, Paas, Van Gog et al, 2014). Teachers could start to include these measures in their course to monitor intrinsic and extraneous cognitive load experienced by their students across course activities and to further align task complexity and instructions to students' needs.

The guidelines in eight bullet points

These guidelines can facilitate curriculum and course design and drive future research that involves cross-university comparisons of curricula and coursework:

- Undertake curriculum or course design with a multidisciplinary team
- Spidergrams can provide a useful tool in curriculum and course design
- To reduce extraneous cognitive load, keep the mathematics limited to what is needed to facilitate the conceptual understanding students are expected to develop
- Instructional support should decrease while complexity of learning tasks should increase as students advance in a particular topic
- When introducing a new topic, avoid situations in which students have to split their attention between different sources of information when a single source can be sufficient
- When introducing concepts that are best understood if presented visually, textual descriptions may complement but not replace visual presentations
- Instruction and assessment are two sides of the same coin; learning can be stimulated when the two are appropriately aligned and the course is well integrated in the broader curriculum
- Consider keeping track of intrinsic and extraneous cognitive load experienced by students throughout a course to further optimize course design.

Conclusion

Through a case study, this paper has presented guidelines for curriculum and course design to stimulate students' learning through (1) a good integration of statistics in the curriculum, (2) appropriate decisions with regard to which topics to cover and in what detail, (3) a good balance between time allocated to statistics and time available for other knowledge and skills, and (4) a proper course organization and appropriate selection of learning materials. These guidelines are aimed at minimizing effort needed for processes that do not actually contribute to learning and optimizing the effort invested in dealing with an optimum of intrinsic complexity of content. Task complexity and instructional support must be aligned to students' knowledge and needs throughout the course, and the way in which knowledge is assessed at the end of a course must be such that it stimulates learning. The guidelines provided in this paper can facilitate curriculum and course design and drive future research that involves cross-university comparisons of curricula and coursework.

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