ICETA 2022

International Conference

20th Anniversary of IEEE International Conference on Emerging eLearning Technologies and Applications

IEEE
Czechoslovakia Section

PROCEEDINGS

Information and Communication Technologies in Learning

October 20-21, 2022
Grand Hotel Starý Smokovec, High Tatras
Slovakia

Website: http://www.iceta.sk

ISBN: 979-8-3503-2032-9
IEEE Catalog number: CFP2238M-USB
Proceedings editor: František Jakab

TABLE OF CONTENTS

Open R and Python-based Digital Tools in Statistics, Random Processes, and Metrology

J. Hanč*, M. Hančová** and A. Gajdoš**
* Pavol Jozef Šafárik University, Institute of Physics, Košice, Slovakia
** Pavol Jozef Šafárik University, Institute of Mathematics, Košice, Slovakia
jozef.hanc@upjs.sk, martina.hancova@upjs.sk, andrej.gajdos@upjs.sk,

***Abstract*— In the contribution, we present our ideas supported by almost ten years of experience successfully applying and combining pedagogy with open digital technology in teaching university courses on statistics, random processes, and metrology. Our approach relies on open R and Python data science tools and innovative teaching strategies – an interdisciplinary STEM approach with blended learning. Simultaneously, we show that the given approach helps students acquire digital and computational skills immediately applicable to actual scientific work, as demonstrated within our research.**

***Keywords*— blended learning, research, scientific work, R commander, RStudio, Jupyter**

I. Introduction

In the twenty-first century, due to enormous advances in hardware, the digital technology of scientific computing has become a core of modern science. For example, progress in the field of today's measurement science and metrology is determined not only by new mathematical, statistical, and numerical methods but also by state-of-the-art computational tools.

More than ten years ago, it was simply assumed that researchers, statisticians, engineers, teachers, and students dealing with scientific computing or statistical tasks use one of the well-known commercial digital environments — e.g., Mathematica, MATLAB, SAS, or SPSS [1]. These computational tools provide a very comfortable way to apply appropriate scientific methods or procedures. However, the situation is changing dramatically, favoring open, free data science tools based on R and Python programming languages providing everybody with very accessible ways how to gather, store, process, analyze, present, or share data in any human activity [1], [2].

In our article, we present our almost ten years long experience with open R and Python-based digital tools in statistical sciences from two closely connected perspectives – educational and scientific. Particularly, we summarize our pedagogical approach in applying mentioned digital tools in teaching university courses on statistics, random processes, and metrology.

We also demonstrate that our selection of digital tools appears crucial from the viewpoint of scientific work. Indeed, students armed with digital and computational skills gained during working with these tools can be immediately and successfully engaged in actual scientific tasks in the research frame as student research assistants or later as Ph.D. students.

II. Teaching with Digital Technology

A. *Statistical concepts across the curriculum*

Table I summarizes our statistical and data-based courses for future informaticians, mathematicians, data, computer and natural scientists, math, and science teachers. The courses are taught by us at our university with given meeting times (lectures and recitations per week — Lec/Rec) and various R and Python-based digital tools (in the next section, we explain why so many tools).

As the main educational outcome, common to these courses, students should know to apply fundamental statistical concepts in modeling and solving real practical problems in the given subject effectively using appropriate digital technology.

For example, in Physics Practical I (abbr. ZFP1) primarily based on metrology, it means to know how to apply knowledge and skills in processing, visualizing, analyzing, modeling, evaluating, and scientific presenting experimental data according to the Guide to the Expression of Uncertainty in Measurement (GUM, [3]) using Google spreadsheets and Jupyter notebooks (Python, SageMath).

Regarding pedagogy, our approach is based on modern innovative educational methods enhancing students' conceptual understanding and active learning [4]–[6]. To be more specific, we apply a pedagogical strategy called blended learning [7]–[10] — an effective and powerful fusion of face-to-face out-of-class online learning. In math and science blended learning, we focus on teaching methods supporting interactivity and interdisciplinarity, which we will shortly explain in particular pedagogical examples.

TABLE I.
OUR DATA-BASED COURSES ENHANCED WITH DIGITAL TECHNOLOGY

Course		Abbr.	Lec/Rec	Digital Tool
Statistics Metrology	Introduction to Data Analysis	UAD	1/1	Spreadsheets R Commander
	Data Analysis	ADA	1/3	Spreadsheets R Commander
	Physics Practical I	ZFP1	0/3	Spreadsheets SageMath, Python
Random Processes	Markov's processes and their applications	MPA	3/2	SageMath, Python
	Stochastic processes	NPR	3/2	RStudio (R Markdown)

In Fig. 1, we see a multiple-choice question probing students' understanding and misconceptions. After posing the question (or a problem) during a lecture by an audience response system (we use a cloud service Poll Everywhere, www.polleverywhere.com), students discuss their answers in small groups. Then students choose final decisions via their smartphones. The response system automatically displays the histogram of answers without revealing the correct answer. After that instructor opens and moderates a class-wide discussion finished by a closure activity. Typically, it is reposing the same or a related question followed by summarizing the key points by students and/or instructor.

Such teaching method is pedagogically known as *Peer Instruction* or *Question Driven Instruction* [9], [11]. Since students socially and actively learn through discussions, the closure typically leads to a significant improvement and often fixes misconceptions.

In our case (Fig. 1), we can see the actual histogram after the first voting from our course UAD, which shows students' misconception dealing with the wrong intuition about the statistical (frequency) interpretation of probability, described by the law of large numbers.

During a closure class-wide discussion, students have to realize that daily random samples in a small rural are significantly smaller than in a large urban hospital. Simultaneously, they must connect this fact with the statistical (frequency) interpretation of probability, which says that as a sample grows, the relative frequency of an event fluctuates within narrower limits around a number determining the event probability. Or in other words, only for a random sample with a very large number of child births the proportion of times when a boy or girl is born will be very close to probability 1/2. So, a small rural hospital gives a greater chance of a bigger fluctuation of boys' or girls' proportion from the expected 50% proportion. Here it is very helpful to ask and allow students to carry out real or virtual experiments (simulations) with coin tossing demonstrating and visualizing this frequency interpretation of probability. Such simulations can be easily created and realized in Jupyter notebooks which we will talk about later in sec. C.

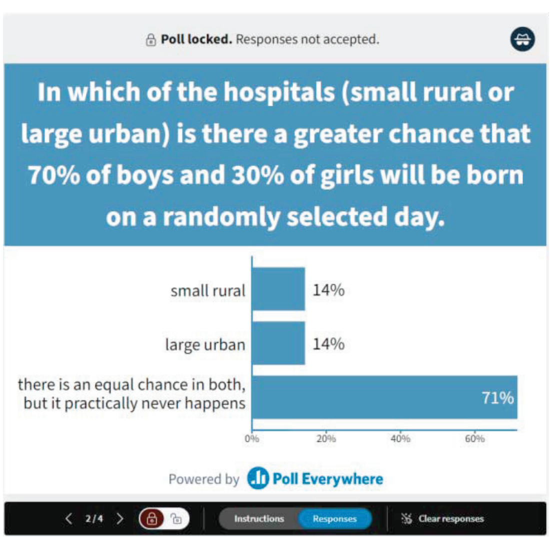

Figure 1. A conceptual multi-choice question in Poll Everywhere

Since the fundamental pedagogical principle of blended learning says [8]

> *Let the students do* ***easier things independently alone*** *in their individual space, online, asynchronously and* ***harder, more demanding things together with the teacher as a guide*** *in a common group space, face-to-face, synchronously;*

we do not lecture. Our students, typically at home, actively read a textbook (or prepared study material), watch a video lecture, listen to a podcast or do a simple structured learning activity in advance of a joint group session (typically in a class) where students in small groups with our help answer conceptual questions, solve problems, consult difficulties or do more experiments. Such a version of blended learning is also called *flipped learning* [10], [12]. One of the strong benefits of flipped learning is that during face-to-face, onsite group sessions it creates extra time for doing more complex educational activities, solving more problems, and discussing more conceptual questions like in Fig. 1.

To easily manage such an approach, we use the Google workspace ecosystem of educational apps, e.g., Google Classroom as a learning management system for posting, monitoring, and grading assignments, Google drive (or YouTube) as storage for educational materials and resources, or Google docs as collaborative media for small group works, projects or presentations.

Here it is important to use well-known distinguished study references, which promote active learning and conceptual understanding. During the last five years, we found the following textbooks fulfilling these demands:

- statistics and metrology: Utts & Heckard [13], Peck & Short [14], Cumming & Calin-Jageman [15], Ratcliffe's [16], Taylor [17]
- random processes: Brockwell & Davis [18], Shumway & Stofer [19], Ross [20], Hyndman & Athanasopoulos [21]
- Data Science in R and Python: VanderPlas [22], Wickham & Grolemund [23]

Another essential element of our blended learning is small group projects on which students work during the semester. In the end, they present and defend steps of processing, visualizing, analyzing, and modeling in solutions to their project problems. To strengthen collaboration, motivation and learning among students, such an educational method must formally respect the basic steps of *project based learning* [24].

As for project topics, we recommend STEM-oriented topics emphasizing interdisciplinary connections with real-world phenomena [25]. For example, we use very reliable authentic data about many indicators of countries around the world from Gapminder (www.gapminder.org, [26]). This tool provides and visualizes data from collections of global organizations like the UN, WHO, World Bank, UNESCO, or OECD. Students select various country indicators and explore interesting statistical relationships between these quantitative variables. It turns out that students are really creative; e.g. they analyzed and modeled % of children out of school vs. murders, distance to the north vs. % of paved roads, total forest land vs. yearly CO_2 emissions.

The work with real data is not only motivating and enriching but in some cases truly shocking since it usually disproves our global misconceptions what we think the world looks like.

B. Pedagogy vs. technology

As mentioned in the previous section, we use several R and Python-based digital tools in statistical work with data. Why? Extensive educational research has shown in many cases [7], [8], [10] that the effectiveness of digital technologies depends strongly on the pedagogical ways in which teachers use them. This research-based conclusion is formulated as another critical principle of blended learning [6], [8]:

Pedagogy ***first****, Technology* ***second****.*

This principle also means that mastering technology cannot be an educational goal but only inevitable means for achieving proper conceptual understanding and skills in applying learned concepts to thinking and problem solving. If we focus too much on technology, students tend only to memorize steps of solutions without proper understanding.

In that case, even a small change in problem context causes students to fail in its solving. Therefore, the following three successive levels of mastering digital tools worked for us (Fig.2):

1. *Visual spreadsheets* (Google or Excel)
2. *Point-and-click graphical user interfaces* (R Commander, [27]–[29])
3. *Dynamic interactive documents* (RStudio with R notebooks [30], [31] or Jupyter Notebook)

The first level is well-known spreadsheets providing clear visual storage and simple manipulations with data via the intuitive point-and-click menu. They include elementary or medium-complexity mathematical and statistical functions. At the same time, students often know spreadsheets from secondary schools.

Therefore simplicity, intuitiveness, and familiarity allow us to focus more effectively on statistical concepts and pedagogy than on the technology itself, making spreadsheets appropriate for beginners. In Fig. 2 (upper level) we demonstrate clear Google spreadsheet's visualization of measurement uncertainties from ZFP1, which helps students better understand what it does mean to experimentally prove the fundamental conservation law – conservation of momentum.

The second level or step of mastering digital tools is R commander, which is also a point-and-click graphical interface very similar to spreadsheets. However, now a user deals with R software, one of the best and major tools in data science and statistical research used in both academia and industry. Data can easily be imported from a file (e.g., dat, txt, csv, xls, xlsx). The manipulation is as simple as in the case of spreadsheets.

However, R commander offers more advanced and highly reliable statistical functions typically required for introductory and some advanced university statistics courses. After performing the individual menu item actions, the source code (R script) can also be seen, so it is possible to start learning the R programming language. This tool is therefore suitable for more advanced users. As an illustrative example in Fig. 2 (middle part), we show results of stochastic modeling from ADA via linear regression for a relationship between two quantitative variables: driver age and the maximum distance at which a

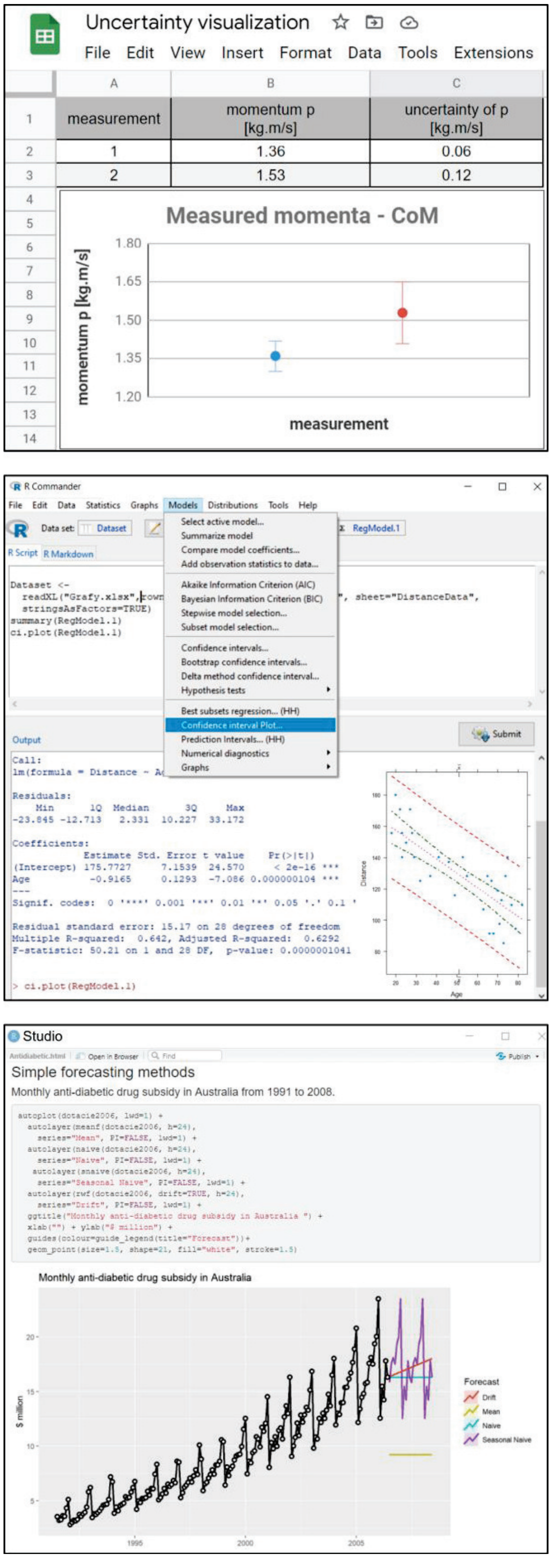

Figure 2. Three successive levels of digital tools in our courses:
(1) Spreadsheets – Google or Excel (upper part)
(2) R Commander (middle part)
(3) RStudio with markdown (lower part)

highway sign was read. This modeling allows us to decide if the driver's age really affects the view [13].

The third, final level is mastering dynamic interactive notebooks, in our case R notebooks in RStudio. These notebooks allow very accessible and interactive so-called literate scientific computing and programming — writing and easily modifying an R source code with human-readable narratives and comments (written in markdown language) clearly explaining the author's intentions, actions, and workflow.

RStudio is a multiplatform modern integrated development environment (IDE for short) with access to all state-of-the-art and highly reliable statistical functions from any R package (over 18,000 in June 2022).

Writing R commands is facilitated by a high-quality source code editor with intuitive controls and an auto-completion function, so coding is much easier than the classic R console. RStudio runs in all major operating systems (Windows, Linux, Mac). Another benefit is that the code, data, and processing remain in one place. Thanks to the mentioned advantages, RStudio enables creating new, custom libraries adapted directly to the given problem — thereby fully exploiting the potential of the R language. RStudio allows a very complex and high-quality scientific data analysis and modeling in actual research. Special attention in R notebooks can be devoted to R package *reticulate* [32] which allows using Python and R simultaneously, combining the power of both languages. To have a better idea how R notebooks look like, we present an example from NPR (lower part in Fig. 2) showing time series forecasting for the anti-diabetic drug subsidy granted in Australia (1991-2008) using elementary, simple prediction methods.

Using the previously mentioned three-level process of mastering technology with R, we naturally shallow a steep learning curve, which could not be handled by the majority of students if we started to use RStudio as the only tool.

C. Jupyter Notebooks, Virtual Experiments and Research skills

In this section, we will deal with Jupyter notebooks, which we use as a supporting alternative to R notebooks. Jupyter notebooks [33] are also an open, free web environment that runs in any modern web browser. Jupyter notebook can be easily modified like a Word document. Again, using markdown, we can insert texts, equations, graphs, annotations, images, sound recordings, videos, and simulations in the form of cells. We can see an example of such a Jupyter notebook in Fig. 3 (from our course ZFP1) about measurement uncertainties in particular problems dealing with e.g., analog devices.

Therefore, these features are used by teachers in the digital curriculum as interactive tutorials, assignments, worksheets, explanatory documents, or as online interactive e-textbooks not only in all STEM courses, but also in some humanities subjects and languages. At the same time, they are easily available, sharable and publishable. Compared to point-and-click interfaces like mentioned spreadsheets or R Commander, both R and Jupyter notebooks are much less consuming if we speak about reproducibility.

Of course, we can also put in cells a computational code [34] or programming code (not only R but more than 100

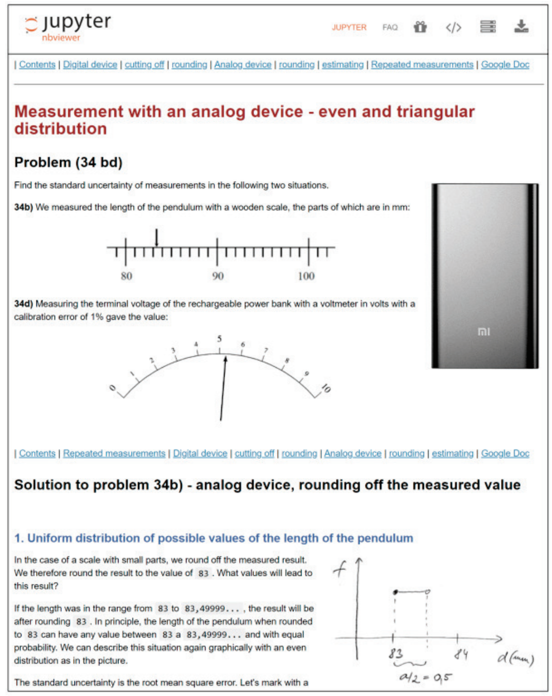

Figure 3. Excerpt from a Jupyter notebook as a study material with a narrative text, images, formulas, and plots.

computer languages), which will be executed in the given notebook, or can be easily repeated. We discuss powerful possibilities of mathematical calculations in Jupyter related to different mathematics domains in our second conference paper *Interactive Jupyter Notebooks with SageMath in Number Theory, Algebra, Calculus, and Numerical Methods.*

Finally, it is very important to say that dynamic interactive notebooks (R notebooks or Jupyter notebooks) were originally developed for research purposes, not education. Over the last five years Jupyter technology has become the most widely used scientific environment for doing actual research, open analysis, scientific computations, data processing, and scientific reporting [35]. This means that students armed with digital skills in using Jupyter or R notebooks can be immediately involved in scientific research in the frame of student scientific work or in their bachelor and diploma thesis. Such students are also very successful in applying for positions of student research assistants or later Ph.D. students.

More specifically, we describe one of the typical scenarios from our education connected to our research in statistics, data science, and metrology. In our article [36], we stochastically modeled the kidney transplant waiting list, where we investigated the influence of four main factors on the waiting time and the probability of a waiting patient's kidney transplant through a large-scale simulation study. The key steps of our simulation study follow the general scheme from Lorscheid et al. [37], which assures a systematic analysis producing valid and objective results. In this case, simulations (bootstrap and Monte Carlo) also play an important role in evaluating some steps of the study [38].

Therefore, we use Jupyter interactive simulations as virtual teaching experiments in our courses. One such example (from ADA) is depicted in Fig. 4, where students explore via bootstrap what happens with a sample mean if we repeat a random selection of a sample from original data many times. In such a way, they see not only what the Central limit theorem means but also develop their research and statistical skills. In order to get and develop the research skills of our students more successfully, we apply a pedagogical framework called *inquiry-based science education* [39] which helps us to design educational activities mimicking real scientific work effectively.

III. CONCLUSIONS

Today's education faces a challenge how to prepare future scientists and engineers, who will be working on such problems as the design of new materials, data storage of high density and access speed, new communications technologies, nanoscience and nanotechnology, alternative green energy sources, quantum computers, computational drug design, and modeling of complex systems involving extreme climatic and geophysical phenomena.

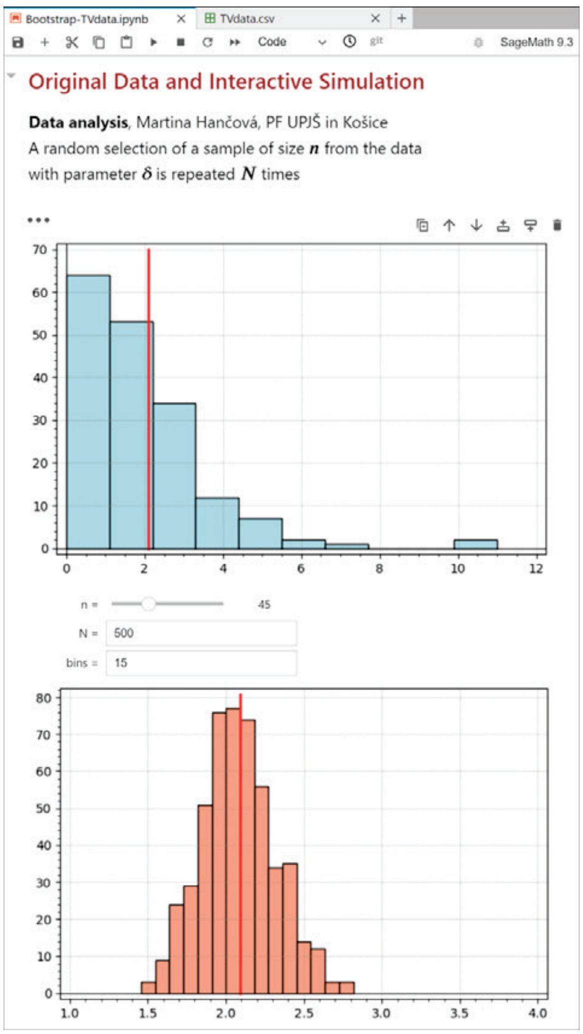

Figure 4. Virtual experimenting using a simulation based on the bootstrap of the original data (watching TV per day in hours [13])

In connection with this challenge, we presented pedagogical and technological ideas applied in our courses intended for future data scientists, computer scientists, informaticians, mathematicians, econometricians, future math teachers, and natural scientists.

By our almost ten years long experience, teaching statistics, random processes and metrology with free open R and Python digital tools can arm our students not only with necessary statistical and data science knowledge but also with key digital and research skills needed for future challenging practice.

However, it is essential to say that the effectiveness of education with digital technologies depends strongly on applied pedagogy. In our case, we have excellent experience with blended learning and STEM education as a framework incorporating active learning methods like peer instruction, inquiry-based science education, team and project based education.

From the research viewpoint, such an essential interconnection of research digital tools with sound pedagogy in education prepares students with skills allowing immediately engage them in actual scientific tasks as student research assistants or later as Ph.D. students. As for our research connected to statistics, econometry and metrology [40], [41], such perspective also leads to much broader opportunities to test and inspect the benefits and pitfalls of selected digital tools, which are also crucial in our current scientific projects *Advanced mathematical and statistical methods for measurement* (APVV-21-2016) and *Optimal decision-making and control methods in complex data* (APVV-21-0369).

ACKNOWLEDGMENT

This work is supported by the Slovak Research and Development Agency under the Contract no. APVV-21-0216 and APVV-21-0369.

REFERENCES

[1] W. W. Piegorsch, R. A. Levine, H. H. Zhang, and T. C. M. Lee, *Computational Statistics in Data Science*. Hoboken: Wiley, 2022.

[2] M. Chambers, C. Doig, and I. Stokes-Rees, *Breaking Data Science Open: How Open Data Science is Eating the World*. Boston: O'Reilly Media, 2017.

[3] BIPM *et al.*, "Evaluation of measurement data — Guide to the expression of uncertainty in measurement." Joint Committee for Guides in Metrology, JCGM 100:2008. [Online]. Available: https://www.bipm.org/documents/20126/2071204/JCGM_100_2008_E.pdf/cb0ef43f-baa5-11cf-3f85-4dcd86f77bd6

[4] S. A. Ambrose, M. W. Bridges, M. DiPietro, M. C. Lovett, and M. K. Norman, *How Learning Works: Seven Research-Based Principles for Smart Teaching*. San Francisco: John Wiley & Sons, 2010.

[5] S. Freeman *et al.*, "Active learning increases student performance in science, engineering, and mathematics," *PNAS*, vol. 111, no. 23, pp. 8410–8415, 2014, doi: 10.1073/pnas.1319030111.

[6] R. Bale and M. Seabrook, *Introduction to University Teaching*. London: SAGE, 2021.

[7] F. S. Glazer, Ed., *Blended Learning: Across the Disciplines, Across the Academy*. Sterling, VA: Stylus Publishing, 2011.

[8] C. R. Tucker, T. Wycoff, and J. T. Green, *Blended Learning in Action: A Practical Guide Toward Sustainable Change*. Thousand Oaks: Corwin Press, 2016.

[9] J. Hanč, "Application of the flipped classroom model in science and math education in Slovakia," in *HSCI 2013: Proceedings of*

the 10th International conference on Hands-on Science (1st-5th July 2013, Košice), Košice, Slovakia, 2013, pp. 229–234.
[10] R. Talbert and J. Bergmann, *Flipped Learning: A Guide for Higher Education Faculty*. Sterling, Virginia: Stylus Publishing, 2017.
[11] E. Mazur and J. Watkins, “Just-in-Time Teaching and Peer Instruction, chap. 3,” in *Just in Time Teaching: Across the Disciplines, and Across the Academy*, S. Simkins and M. Maier, Eds. Sterling: Stylus Publishing, 2009, pp. 39–62.
[12] J. Bergmann and E. S. C. Smith, *Flipped Learning 3.0: The Operating System for the Future of Talent Development*. Irvine: FL Global Publishing, 2017.
[13] J. M. Utts and R. F. Heckard, *Mind on Statistics*, 6th ed. Boston, MA: Cengage Learning, 2021.
[14] R. Peck and T. Short, *Statistics: Learning from Data*. Cengage Learning, 2018.
[15] G. Cumming and R. Calin-Jageman, *Introduction to the New Statistics: Estimation, Open Science, and Beyond*, 1st ed. New York: Routledge, 2016.
[16] C. P. Ratcliffe and B. Ratcliffe, *Doubt-Free Uncertainty In Measurement: An Introduction for Engineers and Students*. London: Springer International Publishing, 2015.
[17] J. R. Taylor, *An Introduction to Error Analysis: The Study of Uncertainties in Physical Measurements*, 3rd ed. Herndon: University Science Books, 2022.
[18] P. J. Brockwell and R. A. Davis, *Introduction to Time Series and Forecasting*, 3rd ed. New York: Springer, 2016.
[19] R. H. Shumway and D. S. Stoffer, *Time Series Analysis and Its Applications: With R Examples*, 4th ed. New York: Springer, 2017.
[20] S. M. Ross, *Introduction to Probability Models*. London: Elsevier Science, 2019.
[21] R. J. Hyndman and G. Athanasopoulos, *Forecasting: Principles and Practice*, 3rd ed. Melbourne, Australia: OTexts, 2021. Accessed: Sep. 18, 2022. [Online]. Available: https://otexts.com/fpp3/
[22] J. VanderPlas, *Python Data Science Handbook: Essential Tools for Working with Data*, 1st ed. Sebastopol, CA: O’Reilly Media, 2017.
[23] H. Wickham and G. Grolemund, *R for Data Science: Import, Tidy, Transform, Visualize, and Model Data*, 1st edition. Sebastopol, CA: O’Reilly Media, 2017.
[24] D. Jones and J. Bergmann, *Flipped 3.0 Project Based Learning: An Insanely Simple Guide*. Irvine: FL Global Publishing, 2018.
[25] T. R. Kelley and J. G. Knowles, “A conceptual framework for integrated STEM education,” *Int. J. STEM Educ.*, vol. 3, no. 1, p. 11, 2016.
[26] O. Rosling and others, *Gapminder*. Stockholm, 2005. [Online]. Available: www.gapminder.org
[27] J. Fox, *Using the R Commander: A Point-and-Click Interface for R*, 1st ed. Milton: Chapman and Hall/CRC, 2017.
[28] J. Fox, “R Commander,” 2022. https://socialsciences.mcmaster.ca/jfox/Misc/Rcmdr/ (accessed Sep. 15, 2022).
[29] R Development Core Team, “R: A language and environment for statistical computing.” R Foundation for Statistical Computing, Vienna, 2022. [Online]. Available: http://www.r-project.org/
[30] Y. Xie, *Dynamic Documents with R and knitr*. Boca Raton: Chapman and Hall/CRC Press, 2017.
[31] RStudio Team, *RStudio: Integrated Development Environment for R*. Boston, MA: RStudio, PBC., 2022. [Online]. Available: http://www.rstudio.com/
[32] K. Ushey, J. J. Allaire, and Y. Tang, *reticulate: Interface to “Python.”* 2022.
[33] T. Kluyver *et al.*, “Jupyter Notebooks-a publishing format for reproducible computational workflows,” in *Positioning and Power in Academic Publishing: Players, Agents and Agendas. Proceedings of the 20th ELPUB*, F. Loizides and B. Schmidt, Eds. Amsterdam: Ios Press, 2016, pp. 87–90.
[34] P. Zimmermann *et al.*, *Computational Mathematics with SageMath*. Philadelphia: SIAM, 2018.
[35] B. Frederickson, “Ranking Programming Languages by GitHub Users,” 2019. https://www.benfrederickson.com/ranking-programming-languages-by-github-users/ (accessed Nov. 29, 2019).
[36] K. Cechlárová, M. Hančová, D. Plačková, and T. Baltesová, “Stochastic modelling and simulation of a kidney transplant waiting list,” *Cent Eur J Oper Res*, vol. 29, no. 3, pp. 909–931, 2021, doi: 10.1007/s10100-021-00742-9.
[37] I. Lorscheid, B.-O. Heine, and M. Meyer, “Opening the ‘black box’ of simulations: increased transparency and effective communication through the systematic design of experiments,” *Comput Math Organ Theory*, vol. 18, no. 1, pp. 22–62, 2012, doi: 10.1007/s10588-011-9097-3.
[38] T. P. Morris, I. R. White, and M. J. Crowther, “Using simulation studies to evaluate statistical methods,” *Stat. Med.*, vol. 38, no. 11, pp. 2074–2102, 2019, doi: 10.1002/sim.8086.
[39] C. P. Constantinou, O. E. Tsivitanidou, and E. Rybska, “What Is Inquiry-Based Science Teaching and Learning?,” in *Professional Development for Inquiry-Based Science Teaching and Learning*, O. E. Tsivitanidou, P. Gray, E. Rybska, L. Louca, and C. P. Constantinou, Eds. Cham: Springer International Publishing, 2018, pp. 1–23. doi: 10.1007/978-3-319-91406-0_1.
[40] M. Hančová, A. Gajdoš, J. Hanč, and G. Vozáriková, “Estimating variances in time series kriging using convex optimization and empirical BLUPs,” *Stat Papers*, vol. 62, no. 4, pp. 1899–1938, 2021, doi: 10.1007/s00362-020-01165-5.
[41] M. Hančová, A. Gajdoš, and J. Hanč, “A practical, effective calculation of gamma difference distributions with open data science tools,” *Journal of Statistical Computation and Simulation*, vol. 92, no. 11, pp. 2205–2232, 2022, doi: 10.1080/00949655.2021.2023873.