Students' Perceptions of their Professors' Integration of Computation in their Probability and Statistics Courses

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Technology has become an integral part of undergraduate mathematics, particularly the use of technology to solve problems (i.e., the use of computation). In probability and statistics, this push has resulted in several projects designing and assessing tools that are conjectured to be advantageous to students and their learning. Despite this trend, minimal research exists on how students perceive the use of computational tools in their courses. As such, we designed a brief survey for students enrolled in introductory probability and statistics at a university in the Northeastern United States. Using thematic analysis, we qualitatively analyzed these survey responses to explore their perceptions of the integration of computation into their courses. Three themes were identified, relating to features of tools, augmentation of actions, and long-term benefits. This exploration of students' perceptions allows us to better understand their views on computation and the need for professors to make instructional goals explicit.

Keywords: Computation, Probability and Statistics Education, Student perceptions

There have long been pushes for the further integration of technology into educational settings (e.g., Bray & Tangney, 2017). While technology has been implemented in education in several ways (e.g., instructional videos), we are focused on computation (i.e., technology as a tool for solving problems) and computational tools (i.e., devices with computational capabilities). To that end, we follow diSessa's (2018) framing of the use of computation, as a form of literacy (i.e., computational literacy), shaping communities' activities.

According to diSessa (2018), mathematics is particularly well positioned to incorporate the use of computation. Indeed, there have been a number of studies probing the use of computation in mathematical contexts (Chan et al., 2023). These studies have identified a growing interest in the use of computation (Weintrop et al., 2016) and a range of tools being used within mathematics education (e.g., Scratch, MATLAB; Chan et al., 2023). This is further evidenced in the context of probability and statistics through calls to promote the inclusion of computation as a means of exploring and visualizing concepts (e.g., Carver et al., 2016).

Despite the growth in the use of technology and computation, specifically, in mathematics education, a question emerges as to students' perceptions of their use of computation. Namely, past research has identified the positive effects of using computation on learning statistics (Wilensky, 1995), features that computational tools should include (e.g., interactive capabilities; Johnson & Berenson, 2019), and a breadth of reasons for using computation (e.g., career preparedness; Nolan & Temple Lang, 2010), but it is not clear what students think about their professor's decision to use computation in their courses. In this study, we were guided by the following research question: *What are undergraduate mathematics students' perceptions of their professor's reasons for integrating computation and specific computational tools into their probability and statistics course?*

Literature Review

The origins of the value of modern computation in mathematics trace back to the work of Papert (1980) and the creation of Logo, a programming language that has been argued to offer unique perspectives and learning opportunities in mathematics. Since Papert, many new computational tools have been designed and the positive potential of computation in mathematics has been demonstrated (Bray & Tangney, 2017).

For example, Wilensky (1995) presented a study where computation led their students to understand an apparent mathematical paradox. Specifically, Wilensky had students use the computational tool of Starlogo, a programming language. The paradox explored in this study arises when tasked to find the probability that a chord of a circle, chosen at random, is longer than the radius of the circle. Mathematically, one's method for picking a random chord determines the solution and there are at least four valid methods (i.e., the answers to this question include ½, 2/3, ¾, and $\sqrt{3}/2$). In the study, after a student produced a solution (e.g., by constructing a chord through a process of fixing a point on the circle and letting the chord's endpoint vary), the researchers presented a different method for selecting a random chord and the resultant solution. After wrestling with the apparent paradox (i.e., two different, mathematically correct, solutions to the problem), the students were prompted to use programming to simulate the problem context. Through the process of writing the program, the students came to a crossroads about how to construct the chord. For many students, this process of programming resulted in the realization that one's decision on how to construct a random chord was the determining factor in the probability you derived. Wilensky argued that the use of programming was fundamental to this discovery and allowed students to gain new insights.

In another study, Basturk (2005) identified a difference in learning outcomes in a study that compared the performance of graduate students enrolled in an introductory statistics course with a computation lab to students who took the same course without a lab. In the treatment, the SPSS statistical software was used by students who met for an extra 40 minutes a week to work on computer exercises and use real data sets to apply concepts learned in lecture. Researchers found that students who used computation scored statistically higher on midterms and final exams than control students. Basturk concluded that SPSS was a useful tool for introductory statistics.

Beyond students' mathematical performance and thinking, the integration of technology has been conceptualized as an influential part of probability and statistics instruction (Nolan & Temple Lang, 2010). Nolan and Temple Lang (2010) argued that the use of computation is an important aspect of preparing students for their future careers because practicing statisticians are continually using and being influenced by advances in computation. As such, it is important for students to learn statistical content using computation and learn broader computational skills (e.g., data structures, debugging) that allow them to adapt to future tools. Despite the influence computation can have on students, it is unclear whether students or even instructors are aware of these advantages to using computation in introductory statistics courses.

Several studies have assumed the importance of computation in introductory statistics courses and sought to identify what tool best serves students. For example, Johnson and Berenson (2019) designed a study which ranked seven different computational tools along 11 different categories. The goal of this project was to identify specific aspects that made certain tools better for teaching and learning statistics. Three of the categories were classified as utility related (e.g., availability in the workplace, cost) and the remaining eight were classified as performance related (e.g., simplicity of access and downloading, user friendliness). Johnson and Berenson concluded that JMP, a menu-driven statistical software, served these criteria the best and was a strong option for introduction to statistics. While some professors may have a similar list of considerations when choosing a computational tool for their courses, it is unlikely that these considerations are made explicit and that students are aware of the benefits of a given tool.

While several projects have identified reasons supporting the use of computation, it is possible that students do not perceive these affordances. For example, Povey and Ransom (2000) analyzed their undergraduates' journals kept over the course of a semester using computational tools like graphing calculators, Logo, and Excel and identified several surprising perceptions their students held about computation. Within these journals, "tales of resistance" (p. 48) toward these tools were identified. Specifically, students expressed concerns about being overly reliant on the tools, a lack of motivation in mathematics stemming from the use of the tools, and a lack of reflection produced by the speed and black-box nature of tools. While this study is from over two decades ago, it is reasonable for a disconnect to be present between the instructional goals of the use of computation and how students perceive the goals of computation as a whole.

Indeed, students' perceptions of their professors' goals do not always align with professors' goals. Lew et al. (2016) conducted a study comparing real analysis students' perceptions of the key points of a lecture to their professor's intended key points. Lew and colleagues reported a disconnect between what the professors of the study intended for their students to attend to and what students made note of as important. Similarly, this disconnect between objectives and students' perceptions has been identified in the use of instructional videos (Weinberg & Thomas, 2018). As such, inquiry into students' perceptions of why their professors integrated computation into their course is a needed lens for the use of computation in mathematics education.

Methods

Participants and Survey Design

To understand student perceptions of instructor goals for integration of computation into their probability and statistics course, we designed and administered a survey to students in an introductory probability and statistics course at a large, private, university in the Northeastern United States. This course was selected because the official course description mentions the use of computation. Each semester, this course is taught by five to eight different professors and serves over 400 students. Professors are given full authority to decide which computational tool they will use and how they will use it. A recruitment email was sent to eight professors who were teaching or recently taught the course, asking them to send out the survey to their students.

In the survey, students were provided a definition of computational tools, which we described as "a piece of technology used to solve problems and draw conclusions," and then they were asked who their professor was, to describe their background experience using computation, and to list the computational tools that were used in their class. Finally, two open-ended questions were posed: (a) "Why do you think your professor incorporated computation, **generally**, in your course?" and (b) "Why do you think your professor had you use that **specific** tool in your course?". We refer to these as the general and tool specific questions, respectively.

We received 106 responses from students from six different professors' classes. While no computation was required as a prerequisite, most students reported some background experience with Excel or Python. All students reported using at least one of three computational tools in their course: Minitab, R, or Python. Minitab is a menu-driven software built for statistics. R is a programming language used for statistical computation and visualization. Similar to R, Python is a programming language frequently taught in introductory computer science courses.

Thematic Analysis

As described by Braun and Clarke (2006), the six phases of thematic analysis were used to identify patterns in our students' responses. Phase 1 began by reviewing student responses and summarizing each response into short low inferential phrases. For instance, one student said, “[computation was used] in order to help visualize certain concepts through digital means.” We captured this as *tools can be used to visualize concepts/graphs/data*. During this phase, several responses were omitted because the students did not respond to the question posed. For example, some students took the survey as an opportunity to complain about their professor. For the general question, 13 total responses were omitted, and two responses were omitted from the specific tool question. In Phase 2, initial codes were induced. To do this, the brief summaries from Phase 1 were grouped in Lucidchart according to patterns of meaning. After these groupings were established, initial code names and definitions were determined. Next, all survey responses were coded. Importantly, codes were non-exclusive and multiple codes were applied when survey responses contained multiple perceptions. To ensure inter-rater reliability, Phase 2 culminated with all data being coded by two of the authors. Any discrepancies were discussed and negotiated. Phase 3 and Phase 4 consisted of rounds of thematic mapping of the induced codes, which allowed us to identify themes present in the data. Themes were then defined in Phase 5. This entire process was iterative, with the authors refining definitions, changing code names, and re-clustering themes to ensure an accurate description of student responses.

Results

Through our thematic analysis, three themes and 14 codes were induced (Table 1). In this section, we define our identified themes, outline each of the codes within the respective themes, and provide characteristic student responses for each code. Codes are italicized for clarity.

Table 1. Themes and codes inducted from students’ perceptions

Themes	Codes	
Consideration of a Tool’s Features	Preference of Professor Student Background Ease of Access Ease of Use	Built for Statistics Availability of Resources Versatility
Actions Augmented Using Computation	Ease of Calculation Exploration of Parameters and Data	Use for Visualization Collaboration
Longer-Term Benefits of Using Computation	Conceptual Understanding Use for Applications	Career Readiness

Consideration of a Tool’s Features

Consideration of a tool’s features captures the perception that computation and computational tools were used because of the affordance of the attributes related to computation, generally, or of a specific tool. Most occurrences of this theme came in responses to the specific tool question (71% of responses to the specific tool question contained at least one of the codes for this theme, compared to just 9% of the general question responses). In total, this theme has seven codes (see Table 1).

The first two codes of this theme, *preference of professor* and *student background*, relate to users' previous experiences with computation. *Preference of professor* captures students' perception that the tool used was preferred by or familiar to the professor. For example, one student said, "[Python] might just be the tool the professor likes working with." Similarly, *student background* captures students' perception that their or their peers' previous experiences with computation influenced the integration of computation. For instance, several students felt their professor was aware that many students were computer science majors. One student claimed, "a significant portion of us have experience working in Python through our majors."

Our next two codes focus on the perception that their professor chose computational tools that were easy to get ahold of and use. *Ease of access* captures the perception that computation or a specific tool was used because it was easy to find online, freely available through the university, or conveniently integrated into specific types of notebooks (e.g. Google Colab). For example, one student stated, "R was used in the Google [Colab] application, which …[made] it accessible to all students." Alternatively, *ease of use* captures the perception that a tool was easy to learn, approachable, and intuitive. One student said, "Minitab is relatively simple and easy to understand even in your first session." 47% of students evidenced *ease of use* in their responses to the tool specific question, which was the most common perception evidenced in our data. Furthermore, 67% of the responses coded as *ease of use* were from Minitab users.

The final three codes of this theme center on attributes of the design of a specific computational tool. The code *built for statistics* captures the perception that a tool was used because it had features which made it particularly suitable for a probability and statistics course (e.g., having built in statistical functions). For instance, a student said, "R is built for statistical analysis and computation… R just has the functions already built in". Similarly, *versatility* captures the perception that a tool was adaptable to other contexts (e.g., other problems, classes, academic settings). One student claimed, "[Python] is a very versatile tool and can be adapted for usage far outside of this course." For this student, the use of Python was a strategic one, which we interpreted as being a part of teaching students a tool that has a breadth of uses. The last code of this theme, *availability of resources*, captures the perception that a tool was selected because information for its use was online. For example, a student said, "R had many features as well that were easily researchable." This suggested the perception that professors care about the students' ability to locate information and learn how to best use a tool through out-of-class resources.

Actions Augmented Using Computation

Actions augmented using computation captures the perception that computation and computational tools were used because of the tasks that can be completed and processes that can be improved upon with computation. The student responses that evidenced this perception documented actions made possible and easier through computation and specific tools. This theme was identified more frequently in response to the general question (55%) than the tool specific question (34%). In total, this theme has four codes (see Table 1).

The first code, *ease of calculation*, captures the perception that computation allowed for efficient and accurate analysis, particularly in comparison to doing calculations by hand. *Ease of calculation* was the most common perception evidenced in the general question (cited by 34% of students). One student said, "[Computation is] useful for solving stats problems quicker and more accurately than solving by hand." Going a step further, many students who evidenced a perception that *ease of calculation* was a part of their professors' motivation, appreciated this benefit. For example, a student stated, "Computation is a very useful and efficient tool for statistics and statistical analysis. Not including [computation] would prove a detriment."

Beyond calculations, computation's use was perceived to be motivated by the augmentation of exploration, visualization, and collaboration. *Exploration of parameters and data* captures the perception that computation allowed for quantitative manipulation of data and experimentation with varying parameters. For example, a student claimed, "Computation was used to demonstrate how different variables impact distributions. This can easily be done with computation." *Use for visualization* captures the perception that computation allowed for the creation of graphs and figures which allowed students to qualitatively see something important. One student said, "[R helped] with visualizing distributions through plotting data." The final code of this theme, *collaboration*, captures the perception that the ability to work together and easily share or export data, was also a factor in their professors' consideration. One such student stated, "R is…easy to setup & collaborate on through notebooks, which makes it ideal for a group project."

Longer-Term Benefits of Computation

Longer-term benefits of using computation captures the perception that computation and computational tools were used as a mechanism for delving deeper into the material or as a steppingstone for something students may need later in life. We use "longer-term" in the sense that the perceived reasons for using computation have an impact that extends beyond its immediate application (i.e., one assignment). Once again, this theme was more common in responses to the general question (77%) than the tool specific question (40%). In total, this theme has three codes (see Table 1).

Our first code, *conceptual understanding*, captures the perception that computation allows for better comprehension of course concepts. One student said, "[Computation] allows for greater understanding and practice of the material." Analogously, another student said, "[computation] allows us to think more broadly about the concepts." For these students, computation was perceived to be a part of how their professor was improving their teaching. As such, computation's use in their course was perceived to be motivated by the longer-term benefit of computation's influence on learning and understanding of the course's content. For the general question, Minitab users' responses were most frequently coded for *conceptual understanding* (50%), and R users were the least frequent (18%).

Use for applications captures the perception that computation allows students to gain authentic experience with statistical problems and see the applications of their learning. For these students, computation allowed them to use pre-existing data sets or generate data for applying statistical concepts in an authentic way. In one instance, a student claimed, "[Computation was used] to assist us in applying what we learn to real world examples of raw data." For students who expressed this perception, computation was a way for their professors to give them "real" experience using statistics.

Finally, *career readiness* captures the perception that exposure to computation was useful for preparing students for future academic or professional settings. Students who evidenced this code focused on the idea that computation will be used in their careers, rather than focusing on the general benefit of computation in their current course. One student said, "in real life computation is more likely to be used in the statistics field so by giving us experience with it we are more prepared." Another student's response, to the tool specific question, was coded for *career readiness* because they claimed, "[R was used] to help us when modeling statistical information in our careers and in academic pursuits." These responses shared a perception that their professors were focused on the use of computation in the field of mathematics or statistics and, generally, that computational skills will be needed later in life. Compared to the Minitab/Python users (31%), the R users most frequently evidenced this perception (51%).

Conclusions

In this study, we identified 14 perceptions our students held about their professors' implementation of computation and computational tools in their undergraduate mathematics course. While there are several reasons why a professor may use computation or a specific tool, this work explores the different perceptions students hold of their professors' goals. The 14 perceptions were further clustered into three main themes. The first theme, consideration of a tool's features, centered on the affordances of different attributes of computation or of a specific computational tool. Several codes in this theme align with the criteria used by the statistics instructors in Johnson and Berenson (2019) to identify the best computational tool for introductory statistics courses. For example, Johnson and Berenson considered the criteria of the availability of the tool and the cost. Similarly, our students perceived *ease of access* as a part of their professor's decision to use computation or specific computational tools. Furthermore, Johnson and Berenson's criteria included whether a tool was user friendly and had features that were simple to use (e.g., simplicity in data importing). Likewise, our students expressed the perception that *ease of use* was a part of their professor's implementation of specific tools.

The second theme we identified, actions augmented using computation, centered on the tasks that can be completed with the use of computation. Again, this theme appears to align with real considerations when integrating computation into mathematics courses. For example, Bray and Tangney (2017) categorized the use of technology in mathematics education research as either transforming or enhancing a professor's course. In our theme, the codes of *ease of calculation* and *use for visualization* capture ways in which our students perceived computation to be about enhancing their work. Similarly, *exploration of parameters and data* described students' perceptions of activities that might not be possible without computation and, thus, were transformed by its inclusion in their course.

The last theme, longer-term benefits of computation, focused on the affordances of using computation that temporally extends beyond its in-the-moment use. Once again, this perception can be supported by the field's conceptualization of computation. The first code we identified, *conceptual understanding*, is grounded both by the influence computation has on students' mathematical thinking (Wilensky, 1995) and the learning gains associated with the use of computation (Basturk, 2005). Relatedly, *use of applications* is firmly established in the calls made by introduction to statistics course materials (e.g., GAISE; Carver et al., 2016). Finally, Nolan and Temple Lang (2010) made theoretical claims about the use of computation for analyzing real/complex data and the importance of preparing students for the evolving landscape of tools used by statisticians. This supports our students' perceptions of *career readiness*.

This study is suggestive of several avenues of future work. Foremost, while it was beyond the scope of this research report, the data collected from our survey offers the opportunity to compare, quantitatively, how students' perceptions differed based on the tool used in their course, their background experiences, and their professor. For example, Minitab users simultaneously perceived *ease of use* and *conceptual understanding* most frequently, but R users' perceptions more frequently aligned with *use for applications*. This emergent result warrants further inquiry. Additionally, several studies have identified a difference between professors' intentions and students' perceptions (e.g., Lew et al., 2016). As such, our identified themes offer a framework to compare professors' motivations behind their use of computation, generally, and a given tool, specifically, to how their students responded to our survey. While many of the perceptions we identified are grounded in the literature, it remains an open question whether they align with the professor's goals or are a product of a broader narrative.

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