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Students' perspective on mastering software skills through a lab-based, hands-on assignment approach

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ABSTRACT

This study examines students' perspectives on developing software skills through "lab-based, hands-on assignments" in higher education. The study employed a survey design to examine the perceived effectiveness of structured preparation, guided laboratory practice, and supervised assessment in enhancing software proficiency, practical problem-solving skills, and student engagement. Data were collected from 222 students enrolled in statistics and numerical methods courses at a Canadian university using convenience sampling and a structured questionnaire comprising Likert-scale and open-ended questions. Quantitative data were analyzed using R, while qualitative responses underwent thematic analysis. Findings indicate that 84.3% of students considered "pre-lab materials" helpful, while 76.3% agreed that supervised laboratory assessments reduced opportunities for academic misconduct. These findings suggest that structured, hands-on learning may support authentic software skill development and create conditions that discourage unauthorized use of generative artificial intelligence. However, these findings reflect students' perceptions and should not be interpreted as direct evidence of reduced artificial intelligence use or academic misconduct.

Keywords: artificial intelligence, software proficiency, student engagement, academic integrity

INTRODUCTION

In recent years, the demand for software proficiency has become increasingly important in higher education, particularly in disciplines that rely on data analysis, computational methods, and digital tools (OECD, 2023; World Economic Forum, 2023). As industries continue to evolve with rapid technological advancement, graduates are expected to not only understand theoretical concepts, but also to demonstrate practical competence in using software for real-world problem-solving. This shift has increased the importance of pedagogical approaches that emphasize active learning and experiential skill development, which are consistently shown to be more effective than passive, lecture-based instruction for promoting deep understanding and practical skills in higher education (Bond et al., 2020). Recent research continues to support active learning as an effective approach to improving student learning outcomes in STEM education (Stains et al., 2018; Theobald et al., 2020).

To address the limitations of lecture-centered instruction, experiential and lab-based learning approaches have gained increasing attention. According to Kolb's (1984) experiential learning theory, learning is most effective when students actively engage in concrete experiences, reflect on their actions, and apply knowledge in practical contexts. More recent research on active and experiential learning similarly emphasizes the importance of engaging students in meaningful, application-oriented learning activities that connect theoretical knowledge with practice (Mohammad et al., 2023b; Stains et al., 2018; Theobald et al., 2020). In software-related education, "lab-based, hands-on assignments" allow students to interact directly with software tools, experiment with functions, and develop problem-solving skills through practice. Such approaches provide students with opportunities to apply theoretical knowledge in authentic tasks while developing confidence and practical software skills.

However, with the increasing use of take-home assignments and remote coursework, concerns have emerged regarding academic integrity and the authenticity of student work, particularly due to the rapid rise of artificial intelligence (AI)-based tools (Cotton et al., 2024; Kasneci et al., 2023; Perkins, 2023). While AI systems can support learning by providing feedback and assistance, the emergence of generative artificial intelligence (GenAI) has also created new challenges for assessment validity, authorship, and academic integrity in higher education (Lodge et al., 2023a; Sullivan et

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al., 2023). Recent literature suggests that the use of GenAI requires educators to reconsider how learning and student performance are assessed, particularly when assignments can be completed with substantial assistance from AI systems (Cotton et al., 2024; Lodge et al., 2023a). This growing challenge highlights the need for assessment designs that balance flexibility in learning with mechanisms that promote genuine engagement and reduce opportunities for academic misconduct (Cotton et al., 2024).

This issue is particularly relevant to software-focused courses because software proficiency involves not only knowing concepts but also demonstrating the ability to apply those concepts independently through practical tasks. Thus, the development of software skills and the assessment of those skills are closely connected to concerns about AI-assisted academic misconduct. Supervised, hands-on assessment provides students with opportunities to practice software skills while allowing instructors to observe students' application of those skills directly. In this way, supervised laboratory assessment may help create a learning environment that supports both authentic skill development and academic integrity.

Despite these advantages and challenges, there remains a need to better understand how students perceive the effectiveness of lab-based learning environments in mastering software skills, particularly in applied courses such as statistics and mathematics. Student perceptions are widely used in higher education research as indicators of instructional effectiveness, as they reflect engagement, motivation, and perceived learning outcomes (Bond et al., 2020). Recent research also emphasizes the importance of student motivation and related learning behaviors in the tertiary education context (Riego de Dios & Asio, 2026). Understanding these perceptions is particularly relevant when hands-on learning is combined with structured preparation, instructional support, and supervised assessment.

Although active learning and experiential instruction are well supported in higher education, less is known about students' experiences of supervised, lab-based assignments specifically designed to develop software skills while also addressing concerns about AI-assisted academic misconduct (Kasneci et al., 2023). Recent research on GenAI in education further highlights the need to consider how instructional and assessment practices can support meaningful student engagement and authentic demonstrations of learning when students have access to AI tools (Cotton et al., 2024; Lodge et al., 2023b). At the same time, student motivation and learning behaviors are important considerations in understanding students' engagement with academic tasks and learning environments (Riego de Dios & Asio, 2026). However, there remains limited research examining how students perceive the combined role of hands-on software learning, structured instructional support, supervised assessment, and academic integrity in courses where practical software skills are a central learning outcome. However, further research is needed to understand how students experience these elements within supervised, hands-on software learning environments and how they perceive their relationship to software confidence, engagement, task challenges, and academic integrity.

Therefore, this study examines students' perspectives on a supervised, lab-based, hands-on assignment approach implemented in two software-focused courses: *biostatistics for integrative biology* (*STAT*2230*) and *numerical methods* (*MATH*2130*). Specifically, the study investigates students' perceptions of supervised assignment completion, including lab duration, graduate teaching assistant (GTA) support, peer collaboration, and in-lab challenges; their confidence in software skills and problem-solving and the course components they found most helpful; their engagement with software tools and the overall effectiveness of the lab-based format compared with traditional assignments; and the role of supervised assessment in supporting academic integrity and reducing reliance on external AI tools, including ChatGPT.

Accordingly, the study addresses the following research questions:

1. How do students perceive supervised, lab-based assignment completion in terms of lab duration, GTA support, peer collaboration, and in-lab challenges?
2. How do students perceive the lab-based format in relation to their confidence in software skills and problem-solving, and which course components do they find most helpful?
3. How do students perceive their engagement with software tools and the overall effectiveness of the lab-based format compared with traditional assignments?
4. How do students perceive the supervised lab format in relation to academic integrity and reliance on external AI tools, including ChatGPT?

LITERATURE REVIEW

Student Attitudes and Emotions Toward Software Learning

Students' emotional responses to quantitative and software-based coursework are consistently linked to their academic performance. Grounded in Pekrun's (2006) control-value theory, achievement emotions such as enjoyment, boredom, anxiety, and frustration arise from students' perceived control over a task and the value they assign to it. A meta-analysis of 68 studies found that enjoyment positively predicts academic performance, whereas boredom and anger predict lower academic outcomes, with the emotional climate of hands-on activities playing a significant role (Camacho-Morles et al., 2021). These patterns are particularly evident in statistics and mathematics courses, where students often enter with negative pre-existing associations (Hernández de la Hera et al., 2023).

Anxiety related to statistical software appears to be shaped by familiarity with the tool rather than general math anxiety. When R programming was introduced into a first-year statistics curriculum, both mathematics and biomedical sciences students reported significant anxiety, with biomedical sciences students reporting higher levels, likely due to less prior computing experience (Miller & Pyper, 2024). In an undergraduate ecology course using R, overall anxiety decreased and self-concept improved across the semester, although women reported consistently higher anxiety than

men (Forrester et al., 2022). Attitudes toward statistics are often measured using the SATS instrument which captures affect, cognitive competence, value, and difficulty and is widely used to quantify attitudinal change (Schau et al., 1995). Software selection also influences students' affective experiences. A review of free statistical programs found that ease of use and accessibility directly affected student confidence and willingness to engage, with Jamovi and JASP rated most accessible and R offering greater depth at a higher learning cost (Shepherd & Richardson, 2024). Technology-enhanced collaborative learning and supportive instruction have been shown to improve attitudes toward statistics (Al-Haddad et al., 2024; Espinosa-Garza et al., 2024). Together, this literature highlights the importance of familiarity, instructional support, accessibility, and task design in shaping students' emotional and attitudinal responses to software-based learning, providing a relevant foundation for examining these experiences in the supervised lab settings of *STAT*2230* and *MATH*2130*.

Hands-On and Lab-Based Assignment Learning

Active learning is strongly supported across undergraduate STEM education. A meta-analysis of 225 studies found that active learning increased exam scores and reduced failure rates compared to traditional lecturing (Freeman et al., 2014). Lab-based assignments, where students work collaboratively during class time, have also been associated with positive experiences and improved resource-use skills (Mohammad et al., 2023b).

Authentic, software-based assignments have been associated with increased engagement and confidence. Learner-generated video assignments improved perceived learning and performance (Wut & Wong, 2025). Data science courses using real-world datasets reported increased engagement and transferable skill development (Donoghue et al., 2021). Task authenticity and iterative assignment structures have also been linked to higher engagement in data analytics courses (Alenezi & Alenezi, 2025). These findings highlight the instructional value of structured, hands-on tasks in supporting software skill development (Alenezi & Alenezi, 2025; Wut & Wong, 2025).

Taken together, these findings provide a basis for examining how supervised, hands-on software assignments support engagement, confidence, and practical skill development in the *STAT*2230* and *MATH**2130 lab settings examined in the present study.

Technological Infrastructure and Assignment Management

Digital infrastructure plays a role in supporting lab-based learning. A web-based tool used across six class groups improved progress monitoring, paperless submission, and knowledge sharing, receiving positive evaluations from over 90% of students and instructors (Kautsar & Sarno, 2019). Technology use more broadly predicts self-directed engagement and academic performance (Rashid & Asghar, 2016).

System-quality research shows that functionality, information quality, and service support predict student satisfaction and continued use of digital learning systems (Al-Fraihat et al., 2020). Interaction-based models further demonstrate that learner-content interaction, learner-instructor interaction, and internet self-efficacy predict satisfaction in technology supported environments (Kuo et al., 2014). These findings indicate that well-designed infrastructure and support structures can facilitate student participation and task completion in lab-based courses (Al-Fraihat et al., 2020; Kuo et al., 2014).

Together, this literature provides a foundation for examining how the technological infrastructure, submission processes, and instructional support used in the supervised lab settings of *STAT*2230* and *MATH*2130* may shape students' experiences with software-based assignments.

Feedback, Assessment, and Self-Regulation

Formative assessment practices such as descriptive feedback and low-stakes testing improve learning outcomes (Morris et al., 2021). Feedback that targets process and self-regulation levels produces more durable gains than grade-focused responses (Hattie & Timperley, 2007). Making quality criteria explicit through rubrics or worked examples supports students' ability to evaluate their own work (Sadler, 1989).

These practices align with Zimmerman's (2002) model of self-regulated learning, which emphasizes forethought, performance monitoring, and reflection. Iterative lab assignments naturally support these cycles. Students valued feedback and discussion-based elements in digital tools, though engagement decreased when features felt disconnected from learning needs (Aderibigbe et al., 2022; Alenezi & Alenezi, 2025). Students' perceptions of their learning often diverge from actual learning outcomes. In a calculus course comparison, students in traditional lectures reported higher satisfaction and belonging than those in flipped formats, despite the latter offering more collaborative engagement (Mohammad et al., 2023a). Students in active learning environments also tend to underestimate their learning relative to their performance (Deslauriers et al., 2019).

Research on metacognitive judgments shows that students often equate cognitive fluency with learning, leading to inaccurate self-assessments (Carpenter et al., 2020). An integrative review similarly found that students frequently confused performance ease with long-term learning (Soderstrom & Bjork, 2015).

This body of research is particularly relevant to the present study because the supervised lab assignments in *STAT*2230* and *MATH*2130* incorporate opportunities for feedback, guided practice, and reflection, allowing students to apply and monitor their learning during software-based tasks.

Student Motivation and Self-Efficacy in Technology Courses

Self-determination theory (SDT) proposes that motivation depends on autonomy, competence, and relatedness (Ryan & Deci, 2000). Lab-based software assignments that provide scaffolded challenge, collaboration, and feedback align with these needs. In STEM classrooms, SDT-aligned practices such as small-group discussions and in-class worksheets have been associated with higher motivation, though effects vary by implementation (Stieha et al., 2024).

Self-efficacy supports persistence and deeper engagement (Ryan & Deci, 2000). Mastery experiences, such as iterative software assignments, contribute to self-efficacy development. In data analytics courses, cognitive interest and self-efficacy predicted students' intention to continue learning, with software quality and instructor interactivity strengthening these effects (Liu et al., 2023). Riego de Dios and Asio (2026) found that college students had high levels of motivation and good study habits, with a moderate positive relationship between motivation and study habits. The findings suggest that higher motivation is associated with more effective study behaviors. Technology use also predicts self-directed learning and engagement (Rashid & Asghar, 2016). Students' perceptions of support, challenge, and connection shape their engagement in mathematics and statistics courses (Mohammad et al., 2024, 2025).

This literature is directly relevant to the present study, as the supervised software assignments in *STAT*2230* and *MATH*2130* provide opportunities for guided practice, feedback, and successful task completion that may shape students' motivation, self-efficacy, and engagement with software-based learning.

Statistical Software in Undergraduate Education

Software selection influences both skill development and affective responses. Students' first encounters with R, SPSS, or Python shape their confidence and anxiety (Miller & Pyper, 2024). Accessibility varies across platforms: Jamovi and JASP are rated most accessible, SPSS is familiar, and R offers the greatest depth at the highest learning cost (Shepherd & Richardson, 2024).

Students' perceived competence is shaped by how software is introduced and scaffolded. Anxiety around R varies by discipline and prior computing experience (Miller & Pyper, 2024). In data analytics courses, software quality, content quality, and instructor interactivity predict self-efficacy, which in turn predicts intention to continue learning (Liu et al., 2023). Active engagement with software tasks has been associated with skill gains and confidence (Medina & Dogucu, 2026; Wut & Wong, 2025).

These findings provide a relevant context for examining students' experiences with the software used in *STAT*2230* and *MATH*2130*, particularly how software familiarity, accessibility, instructional scaffolding, and hands-on practice relate to confidence and engagement.

METHODOLOGY

Research Design

This study investigated two second-year undergraduate courses at the University of Guelph: *STAT*2230* and *MATH*2130*, representing the statistics and mathematics disciplines, respectively. Both courses were delivered in an in-person format.

Course context and instructional structure

*STAT*2230* introduced students to the design, completion, and interpretation of research projects, including identifying categories of research questions, types of data, data collection methods, efficient graphical and numerical methods for summarizing data, standard statistical analyses involving parameter estimation and hypothesis testing, and interpretation of results in the context of research goals. Statistical concepts underlying practical aspects of biological research were emphasized. Computer-intensive laboratory sessions focused on practical data organization, visualization, statistical analysis using software, and interpretation and communication of statistical results.

The course included three hours of weekly lectures, and a two-hour laboratory component delivered across eight lab sections, each supported by two GTAs. Over the term, students completed four graded "lab-based, hands-on assignments," with the lowest grade dropped. Each assignment was worth 8% of the final course grade. In addition, students were provided with detailed "pre-lab materials" at the beginning of each week to support adequate preparation prior to attending the laboratory sessions.

*MATH*2130* provided a theoretical and practical introduction to numerical methods for approximating the solution(s) of linear and nonlinear problems in the applied sciences. The topics covered include solution of a single nonlinear equation; polynomial interpolation; numerical differentiation and integration; solution of initial value and boundary value problems; and the solution of systems of linear and nonlinear algebraic equations.

The course included three hours of weekly lectures, and a one-hour laboratory component delivered across thirteen lab sections, each supported by two GTAs. Over the term, students completed four graded "lab-based, hands-on assignments," with the lowest grade dropped. Each assignment was worth 8% of the final course grade. In addition, students were provided with detailed "pre-lab materials" at the beginning of each week to support adequate preparation prior to attending the laboratory sessions.

Substantial instructional support was available throughout both courses. During non-graded lab sessions, GTAs focused on helping students develop both conceptual understanding and coding skills. Students could also access additional support at the University of Guelph through the Mathematics & Statistics Learning Centre, the instructors' office hours, and discipline-specific resources: the R drop-in for *STAT*2230*, and drop-in access to the MATLAB teaching laboratory for *MATH*2130*.

The graded lab assignments were designed to reflect the material covered in lectures and laboratory sessions, with questions closely aligned to the examples and concepts provided throughout the course. This alignment ensured that students who engaged with course resources and participated in available support activities had opportunities to develop the knowledge and skills required to successfully complete the assignments.

Pre-laboratory materials

In *STAT*2230,* the "pre-lab materials" consisted of instructor-prepared PowerPoint lecture notes that explained how R functions were used to implement and analyze the concepts introduced in the course. The slides included

explanatory content, example R code, the corresponding outputs, and application examples that integrated the lecture concepts with the appropriate R functions to demonstrate their use in practice, *MATH*2130* followed the same approach using MATLAB. Instructor-prepared "pre-lab materials" explained how MATLAB was used to implement the numerical methods introduced in lectures and included worked examples together with the corresponding code and output.

In both courses, laboratory sessions alternated between non-graded preparation weeks and graded assignment weeks. During preparation weeks, the pre-laboratory materials were released to students at the beginning of each week, allowing sufficient time for students to review and engage with the materials before attending the lab. Students were expected to complete this preparation to support their participation in laboratory activities. During laboratory sessions, GTAs reinforced the pre-laboratory content by reviewing key concepts, demonstrating example analyses, responding to students' questions, and providing opportunities for guided hands-on practice using software. These structured preparation and practice activities supported students' development of software proficiency and prepared them for the subsequent graded "lab-based, hands-on assignments."

Lab-based, hands-on assignment procedures

During graded laboratory sessions, students completed assignments in a supervised, open-book environment. Students were permitted to use all course materials, including lecture notes, laboratory notes, and examples, and were encouraged to collaborate and support one another in small teams. They were also allowed to ask questions when clarification was required. Multiple GTAs were present to invigilate the sessions and to provide limited clarification when appropriate. Unauthorized use of GenAI tools was flagged as potential academic misconduct, and this was communicated to students in advance. Assessment design was also intended to reduce the perceived benefit of using AI tools: graded questions were closely modelled on examples from the pre-laboratory materials for which full solutions had already been provided, and collaboration was permitted, so that students who had engaged with the preparatory material could complete the assignment without external assistance.

Students were required to complete and submit their solutions through Gradescope within the designated laboratory period. The submission window closed at the end of the session, and late submissions were not accepted. Students were therefore expected to complete their work during their scheduled laboratory time and submit it within the allotted time period to maintain academic integrity.

Marked assignments were returned to students via email approximately one week after the due date. Students were responsible for answering all assignment questions to support preparation for course examinations. Students could submit regrade requests through Gradescope and communicate with the teaching assistants assigned to their lab sections for clarification and feedback.

To further support fairness, the assignments were designed such that, with appropriate preparation, they could typically be completed within approximately half of the allocated laboratory period. Students were provided with the full scheduled laboratory time to complete the assignments, allowing additional time for reviewing instructions, applying concepts, troubleshooting software issues, and seeking clarification when needed.

Participants

Recruitment and sampling

During the Winter 2026 semester, when the survey was administered, 300 students were enrolled in *STAT*2230* and 653 students were enrolled in *MATH*2130* at the University of Guelph. Of these students, 233 participated in the survey (25% response rate). Prior to analysis, the dataset was cleaned to remove incomplete and ineligible records. One response was excluded because the participant did not provide electronic consent for their data to be used. An additional 10 responses were removed because the participants did not answer any survey questions, leaving all survey items blank. Following these systematic exclusions, the final analytic sample consisted of 222 participants. Because participants could skip individual items without withdrawing from the survey entirely, item-level response rates varied; analyses are based on non-missing responses for each item with valid n ranging from 207 to 222 across measures. Announcements describing the study, inviting participation, and providing a link to the survey were posted on the course websites and made available to all students enrolled in the two courses. In addition, students were given time during class to complete the survey if they chose to participate. Participation was voluntary, with no compensation or incentives offered, and participants incurred no costs by taking part in the study. The voluntary nature of participation and the 25% response rate may have introduced potential volunteer and nonresponse bias, as students who chose to participate may have differed from those who did not. All information was kept confidential, and the investigators had access to the information only after all final grades were submitted to the registrar's office.

Ethical considerations

This study was conducted in the researchers' own classroom and received approval from the Research Ethics Board prior to survey distribution (#2055, August 25, 2025). The survey was anonymous, with no names or identification used. All information was kept confidential, and the investigator had access to the information only after all final grades were submitted to the registrar's office. There were no known risks to the students.

Demographics

Table 1 presents the demographic characteristics of the final analytical sample (n = 222). The sample consisted predominantly of second-year students, who accounted for 188 respondents (84.7%). Most participants were enrolled in the college of biological science (152 respondents, 68.5%). In addition, most participants identified as female (136 respondents, 61.3%), were between 18 and 21 years of age (200 respondents, 90.1%), and reported domestic student status (211 respondents, 95.0%).

Table 1. Demographic characteristics of participants: frequency counts and percentage

Category		Frequency (n)	Percentage (%)
College	Biological science	152	68.4
	Computational, mathematical, and physical sciences	17	7.7
	Engineering	43	19.4
	Ontario agricultural college	10	4.5
Year of study	1st year	2	0.9
	2nd year	188	84.7
	3rd year	24	10.8
	4th year	5	2.3
	5th year	2	0.9
	Non-degree	1	0.4
Gender identity	Female	136	61.3
	Male	68	30.6
	Non-binary	3	1.4
	Gender queer	3	1.4
	Agender	2	0.9
	Prefer not to answer	10	4.5
Age	18-19	112	50.5
	20-21	88	39.6
	22-23	15	6.8
	24+	7	3.1

Research Instrument

Survey structure and components

Data were collected using a structured survey questionnaire designed to capture students' perceptions and experiences of the supervised, lab-based, hands-on assignment approach. The questionnaire included multiple-choice, multiple-select, Likert-scale, and open-ended questions. The survey items addressed areas such as pre-laboratory preparation, lab duration, GTA support, peer collaboration, software confidence, engagement, task challenges, overall effectiveness, and academic integrity. The open-ended questions provided students with opportunities to elaborate on their experiences, identify helpful aspects of the lab-based approach, and describe challenges or suggestions for improvement.

Measures

The survey instrument consisted of 18 items organized into three sections. The first section collected five demographic variables: college of enrollment, year of study, gender identity, age group, and student status (domestic or international). The second section contained one item addressing students' perceptions of the helpfulness of pre-laboratory instructional materials. The third section comprised 12 items addressing students' perceptions and experiences related to the lab-based approach. Item types included multiple-choice, multiple-select, and Likert-scale questions. Three of these items also included open-ended response options, inviting students to elaborate on lab challenges, reasons for preferring traditional assignments, and suggestions for improvement. These items assessed students' perceptions of laboratory duration, GTA support, peer collaboration, software confidence, engagement, task challenges, overall effectiveness, and academic integrity. Because the questionnaire comprised individual items assessing distinct constructs rather than multi-item scales, internal-consistency reliability was not applicable.

Accordingly, Cronbach's alpha was not calculated. The survey was brief and required approximately 10 minutes or less to complete.

Statistical Analysis

Data analysis was conducted in R (version 4.6.1) using R Markdown to integrate code, output, and narrative reporting (Xie et al., 2018). Data cleaning and preparation were performed using the tidyverse (Wickham et al., 2019) and janitor (Firke, 2024) packages. Statistical significance was set at $p < 0.05$ for all inferential tests. Spearman's (1904) rank-order correlation was used to assess monotonic associations among ordinal variables, with positive coefficients indicating that higher values on one variable tended to be associated with higher values on another and negative coefficients indicating inverse relationships. Chi-square tests of independence were used to examine associations between categorical demographic variables and ordinal outcome measures, and Cramér's (1946) V was reported to indicate the strength of association. Kruskal-Wallis tests were used to compare ordinal outcomes across three or more independent groups (Kruskal & Wallis, 1952); when significant omnibus effects were observed, Dunn's (1964) post hoc pairwise comparisons were conducted with Holm (1979) adjustment to control the familywise error rate. For open-ended responses, two coders independently conducted thematic analysis, and inter-rater reliability was evaluated using Cohen's (1960) kappa (κ). Agreement was substantial for the item on challenges experienced during the lab session ($\kappa = 0.87$), substantial for the item comparing the lab-based approach with traditional homework ($\kappa = 0.73$), and substantial for the item on desired methodological changes to improve learning ($\kappa = 0.76$); the pooled κ across items was ($\kappa = 0.79$), indicating substantial overall coding agreement.

Table 2. Perceived helpfulness of pre-laboratory instructional slides in preparing students for the assignments

Response	Frequency (n)	Percentage (%)
Very helpful	118	53.2
Somewhat helpful	69	31.1
Neutral	19	8.6
Slightly helpful	13	5.9
Not helpful at all	3	1.2

RESULTS

Pre-Lab Preparation and Lab Session Experience

This section presents student responses to survey items related to pre-lab preparation and the in-lab experience, including session organization, timing, GTA support, peer collaboration, and reported challenges.

Perceived helpfulness of pre-lab instructional materials

As shown in **Table 2**, most respondents perceived the pre-lab instructional materials as helpful, with 84.3% rating them as either *very helpful* or *somewhat helpful*. Only a very small proportion of students rated the materials as not helpful at all (1.2%).

As shown in **Figure 1**, Spearman's (1904) rank-order correlation was used to assess the associations and strength of relationships between variables. The helpfulness of the "pre-lab materials" demonstrated *moderate positive associations* with the perceived helpfulness of GTA support ($\rho = 0.33$, $p < 0.001$), engagement ($\rho = 0.31$, $p < 0.001$), software confidence ($\rho = 0.34$, $p < 0.001$), and overall effectiveness ($\rho = 0.37$, $p < 0.001$). In contrast, *no significant associations* were found between the helpfulness of the pre-laboratory materials and demographic characteristics, including college, year of study, gender, and age group.

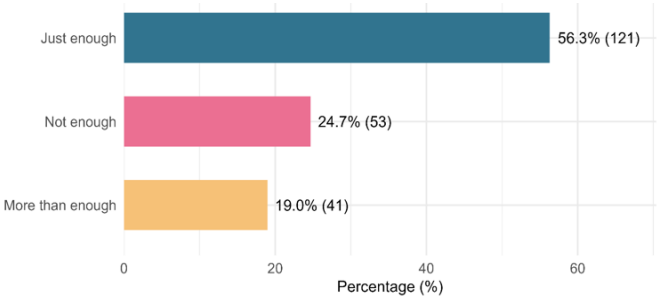


Figure 2. Perceived sufficiency of lab session duration (Bars represent the percentage of total responses within each category; Values in parentheses represent frequency counts) (the authors' own elaboration)

Lab session duration

Figure 2 shows that most students considered the scheduled lab duration sufficient to complete the assignment. Overall, 162 respondents (75.4%) reported that the allotted time was either just enough or more than enough, whereas 53 (24.7%) indicated that the allotted time was not enough.

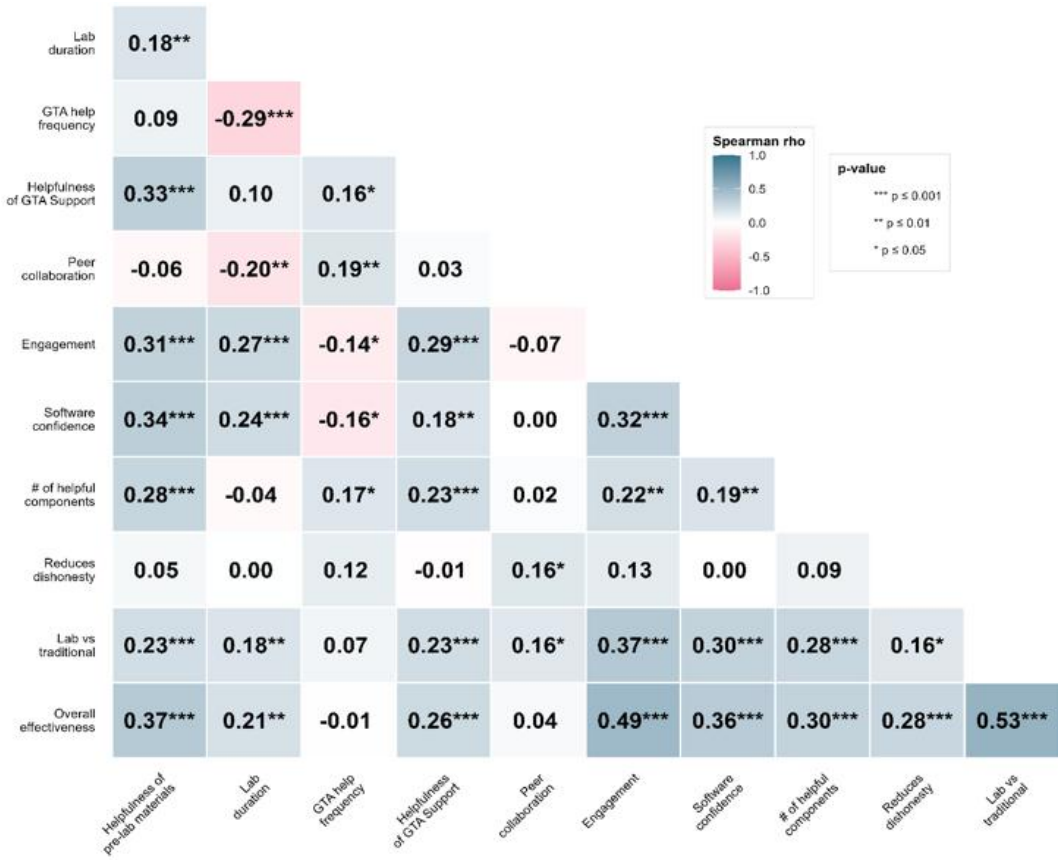


Figure 1. Spearman's ρ correlations (Spearman's rho correlations among ordinal survey items; pre-lab preparation, lab experience, confidence, collaboration, engagement, perceived helpfulness, and overall effectiveness) (the authors' own elaboration)

Table 3. Frequency of GTA support requests during lab sessions

Response	Frequency (n)	Percentage (%)
Frequently	43	20.0
Occasionally	116	54.0
Rarely	48	22.3
Not at all	8	3.7

Table 4. Perceived helpfulness of GTA support during lab session

Response	Frequency (n)	Percentage (%)
Very helpful	107	49.8
Somewhat helpful	100	46.5
Not helpful	8	3.7

Student requests for GTA support

As shown in **Table 3**, most students sought GTA support during laboratory sessions, with 74.0% reporting that they sought assistance at least occasionally. Furthermore, the frequency of GTA support requests was weakly and negatively associated with the perceived adequacy of laboratory session duration ($\rho = -0.29$, $p < 0.001$) (see **Figure 1**).

Perceived helpfulness of GTA support

As shown in **Table 4**, students generally perceived GTA support during laboratory sessions as helpful, with 96.3% rating the support as either very helpful or somewhat helpful. Furthermore, perceived helpfulness of GTA support was *weakly and positively associated* with engagement ($\rho = 0.29$, $p < 0.001$) and *very weakly and positively associated* with software confidence ($\rho = 0.18$, $p = 0.009$) (see **Figure 1**).

Peer discussion in labs

Figure 3 shows that peer discussion was common during laboratory sessions. Overall, 83.3% of respondents reported participating in peer discussion, while 16.7% completed the work independently.

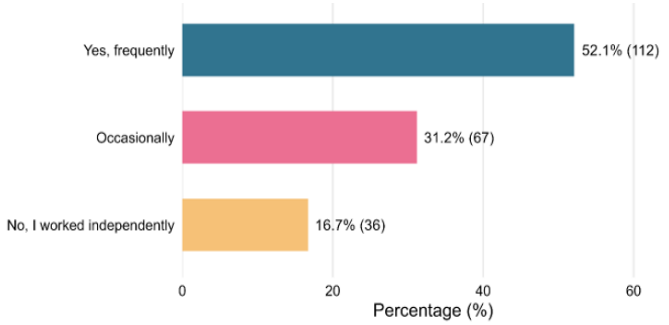


Figure 3. Peer discussion during lab sessions (Bars represent the percentage of total responses within each category; Values in parentheses represent frequency counts) (the authors' own elaboration)

Challenges in lab sessions

This analysis was based on responses to the open-ended survey question, *"What challenges did you face during the lab session?"* A total of 189 unique respondents provided qualitative comments. Because participants could identify multiple challenges in a single response, more than one subtheme could be assigned to each response; therefore, frequencies do not sum to the total 189 individual responses.

Figure 4 presents the distribution of coded challenge themes and subthemes. Overall, time constraints were the most frequently reported challenge (84 respondents), followed by programming and syntax difficulties (30 respondents) and unclear assessment prompts (24 respondents). Fewer students reported difficulties with conceptual understanding of statistical content, with 10 respondents identifying this challenge.

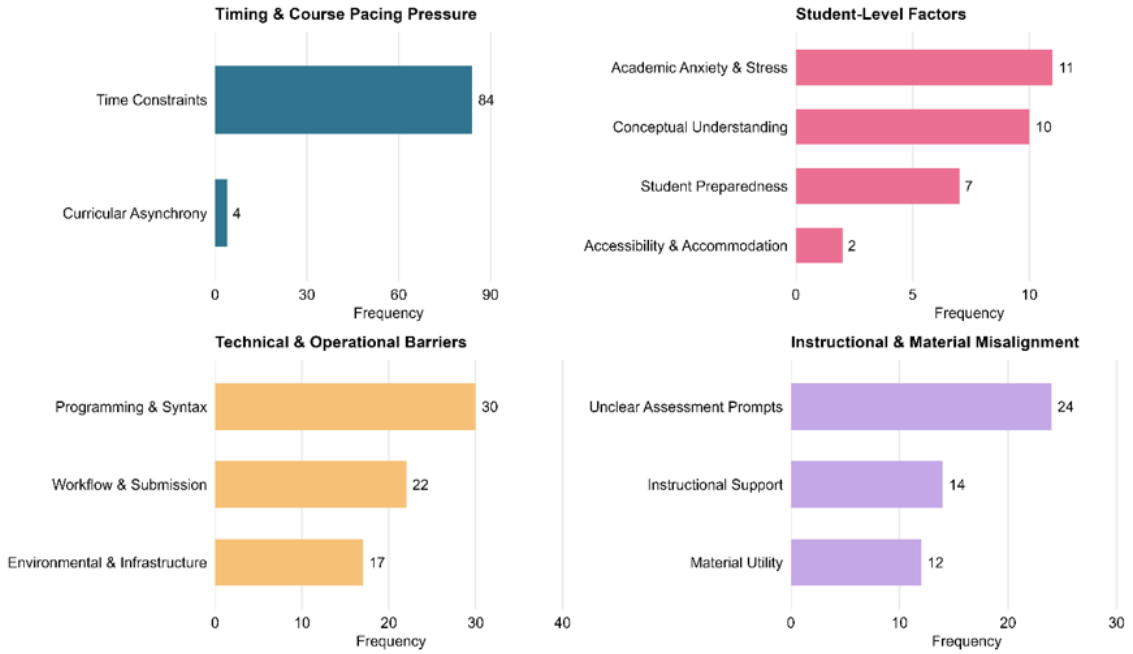


Figure 4. Student-reported lab challenges (Relative frequency and proportional density of qualitative themes and subthemes derived from student-reported lab challenges) (the authors' own elaboration)

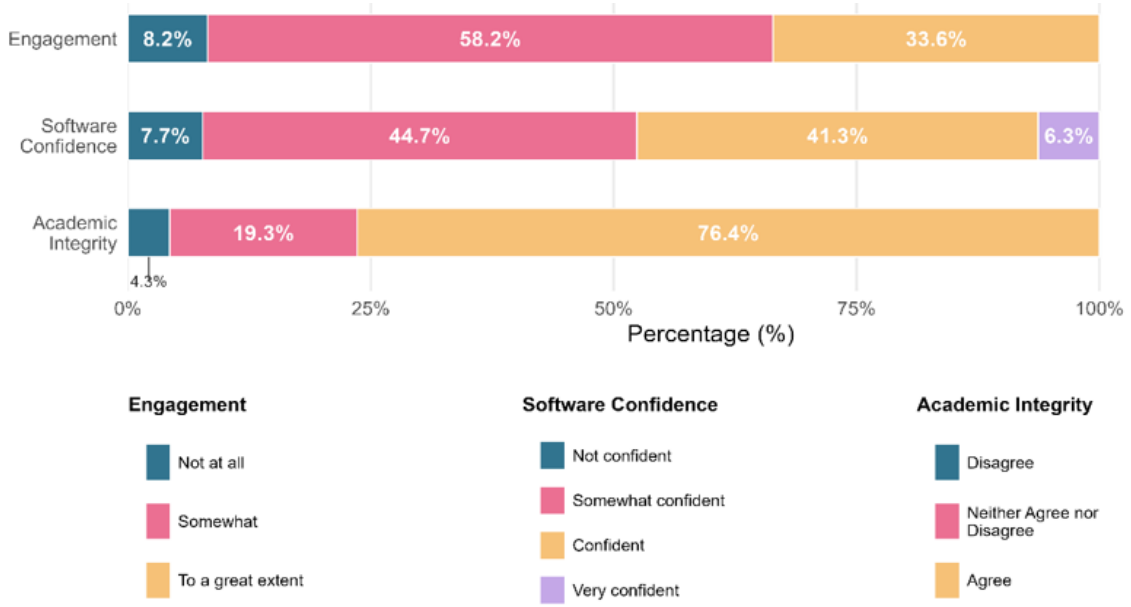


Figure 5. Student learning outcomes: Engagement, confidence, and integrity (Student-reported engagement, software confidence, and perceived academic integrity following the lab-based, hands-on assignments) (the authors' own elaboration)

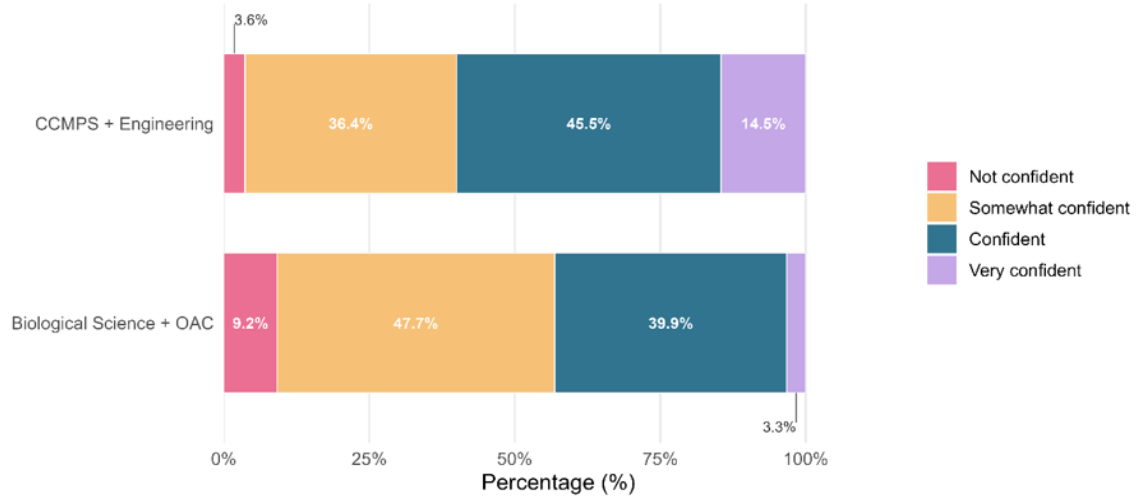


Figure 6. Software confidence by college (Bars represent student college groupings; Colored blocks represent students' self-reported software confidence) (the authors' own elaboration)

Software Confidence and Skill Mastery

This section examines students' self-reported software confidence following the lab-based assignment. It also explores the course components students identified as most helpful in developing software skills, as well as differences in confidence outcomes across student groups.

Software confidence

Figure 5 presents student-reported outcomes following the lab-based assignment across engagement, software confidence, and academic integrity. Overall, responses were predominantly positive across all three areas. Engagement was generally high, with 91.9% of students reporting engagement to at least some extent. Software confidence also showed a positive pattern, with 92.3% of students reporting being at least somewhat confident after completing the assignment. Similarly, perceptions of academic integrity were favorable, with a large majority (76.3%) of students indicating agreement with the integrity expectations.

To examine whether software confidence differed according to prior software exposure, colleges were grouped into two categories: CCMPS and engineering, and biological science and OAC, motivated by the disciplinary comparison reported by Miller and Pyper (2024). As shown in **Figure 6**, students in the CCMPS and engineering group reported higher levels of software confidence than those in the biological science and OAC group. This difference was statistically significant, $\chi^2(df = 3, n = 208) = 11.30$, $p = 0.010$, with a weak association (Cramér's $V = 0.23$).

Software confidence was moderately positively associated with the helpfulness of the pre-laboratory materials ($\rho = 0.34$, $p < 0.001$), engagement ($\rho = 0.32$, $p < 0.001$), and overall effectiveness ($\rho = 0.36$, $p < 0.001$), and weakly positively associated with the perceived adequacy of laboratory session duration ($\rho = 0.24$, $p = 0.005$) (see **Figure 1**).

Table 5. Student responses about which course components were most helpful for mastering the software

Response	Frequency (n)	Percentage (%)
Pre-lab materials	143	69.8
Hands-on lab session	138	67.3
GTA support during lab	86	42.0
GTA introductory session	64	31.2
Feedback on assignments	48	23.4

Although the Kruskal-Wallis test comparing software confidence across lab challenge groups did not reach the conventional threshold for statistical significance, $H(2) = 5.95$, $p = 0.051$, the result was close to the significance level; therefore, Dunn's (1964) post-hoc comparisons were conducted. These indicated that students reporting no challenges had significantly higher software confidence than those reporting time constraints alone (adjusted $p = 0.041$) or both time and other constraints (adjusted $p = 0.028$).

Components most helpful in mastering the software

Table 5 presents the course components students identified as most helpful in mastering the software. The most frequently selected supports were "pre-lab materials" (69.8%) and hands-on lab sessions (67.3%). As multiple responses were allowed, percentages exceed 100%.

Additionally, the number of helpful components selected was weakly positively associated with software confidence ($\rho = 0.19$, $p = 0.006$) and moderately positively associated with overall effectiveness ($\rho = 0.30$, $p < 0.001$) (see **Figure 1**).

Engagement and Perceptions of the Lab-Based Approach

This section examines student engagement during laboratory sessions and explores broader perceptions of the lab-based approach. It also considers student comparisons between lab-based and traditional assignment formats, as well as suggested improvements for enhancing the lab experience.

Perceived effectiveness of the lab-based approach

Figure 7 shows that students generally evaluated the lab-based approach positively compared to the traditional approach. A total of 151 respondents (72.6%) rated the approach as effective in enhancing learning and performance, and 97 (46.6%) indicated that the lab-based approach was more engaging and effective for learning software skills than traditional homework assignments.

Students' perceived engagement was moderately and positively associated with the helpfulness of "pre-lab materials" ($\rho = 0.31$, $p < 0.001$), software confidence ($\rho = 0.32$, $p < 0.001$), and overall effectiveness ($\rho = 0.49$, $p < 0.001$), and weakly positively associated with lab duration sufficiency ($\rho = 0.27$, $p < 0.001$) and perceived helpfulness of GTA support ($\rho = 0.29$, $p < 0.001$) (see **Figure 1**).

Year of study was significantly associated with students' comparison of the lab-based approach with traditional assignments, $\chi^2(df = 6, n = 208) = 17.212$, $p = 0.009$, Cramér's $V = 0.20$, indicating a small-to-moderate association. Second-year students were more likely to rate the lab-based approach positively, whereas third year and other-year students were more likely to prefer traditional assignments. Chi-square analyses indicated no significant associations between perceptions of comparison with traditional assignments and demographic characteristics, including college, $\chi^2(6, n = 208) = 5.02$, $p = 0.541$, Cramér's $V = 0.11$; gender, $\chi^2(6, n = 208) = 3.19$, $p = 0.785$, Cramér's $V = 0.09$; and age group, $\chi^2(6, n = 208) = 10.83$, $p = 0.094$, Cramér's $V = 0.16$. The corresponding Cramér's V values indicate small effect sizes. Overall effectiveness showed the strongest correlations in the matrix (**Figure 1**), particularly with comparison to traditional assignments ($\rho = 0.53$, $p < 0.001$) and engagement ($\rho = 0.49$, $p < 0.001$).

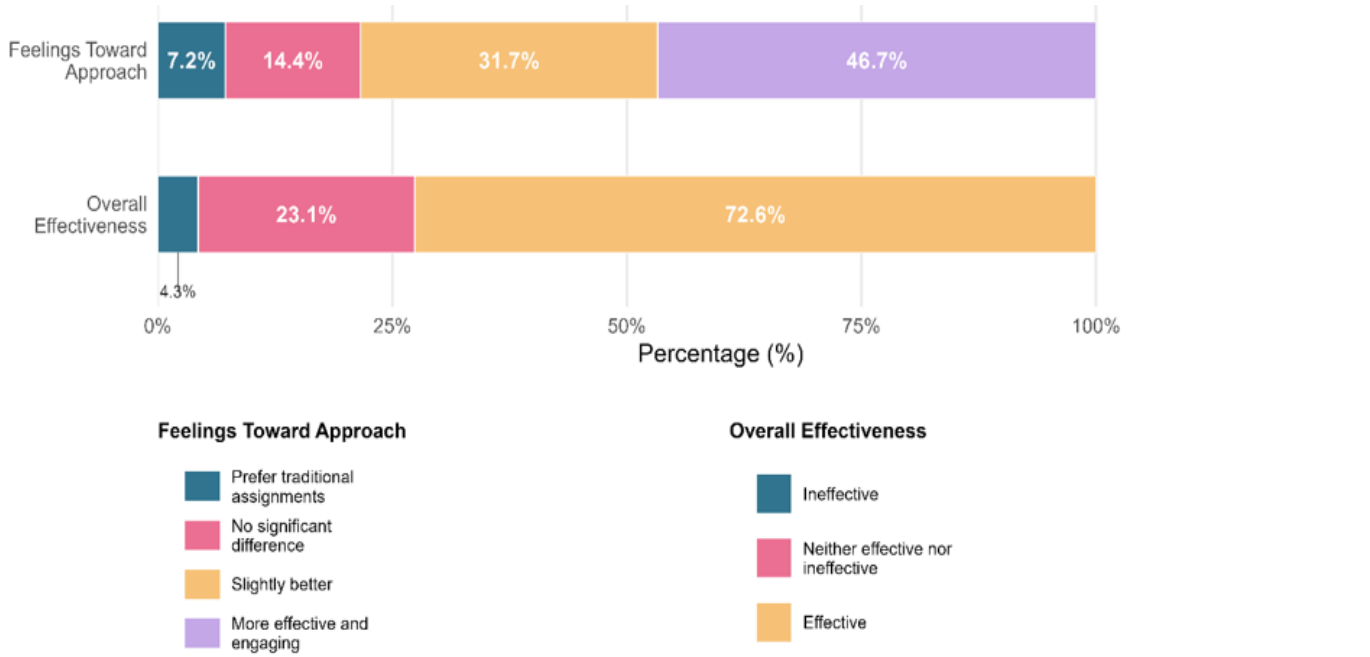


Figure 7. Student perceptions of the lab-based approach: Feelings and effectiveness (Student perceptions of the lab-based, hands-on assignments: overall effectiveness and comparison with traditional assignments) (the authors' own elaboration)

Lab-based, hands-on assignment experience

Among students who preferred traditional take-home assignments, 14 open-ended responses were thematically coded with respect to the lab-based, hands-on assignment experience. The most frequently reported theme was *conceptual depth*, cited by 5 respondents, followed by *time pressure*, reported by 5 respondents. Other salient themes included *evaluation-induced stress* and the *software learning curve*, each reported by 3 respondents. Less frequently reported considerations were grouped under *individualized factors*, which collectively accounted for 6 responses. These included preferences for *quiet, distraction-free work environments, accessibility-related concerns, commuting constraints, and perceived future relevance of project-based work*. A single additional coded response noted a positive reflection on the lab format's ability to encourage proactive study habits and reduce procrastination. Because individual responses could be coded into more than one theme, frequencies are reported at the code level and do not sum to the 14 unique responses.

Student suggestions for improving "lab-based, hands-on assignments"

A total of 101 unique students provided suggestions for improving the lab-based, hands-on assignment experience. These suggestions were organized into three overarching categories: pacing and logistical modifications, pedagogical and instructional enhancements, and individualized or counter-narrative perspectives.

Within pacing and logistical modifications, deadline extension was the most frequently suggested change, reported by 32 students, and included buffered submission windows or the option to complete work at home to reduce stress. Task structural changes were also common, reported by 17 students, and emphasized smaller, more frequent, lower-stakes, or individual tasks.

Pedagogical and instructional enhancements included interactive skill replication and scaffolded practice with examples, each reported by 17 students, both of which called for more active, structured learning during labs. GTA instructional training was also identified by 16 students and focused on improving TA engagement, communication, and software troubleshooting support.

Individualized and counter-narrative perspectives were less commonly reported, including concerns related to student accessibility services accommodation, reported by 2 students, curricular synchronization issues, reported by 5 students, and rigor adjustments, also reported by 5 students, such as requests for strictly solo assignments or attendance verification. In addition, 7 students expressed positive views of the current structure, describing it as fair and effective or as a useful grade boost.

Academic Integrity and GenAI Use

Students' perceptions of whether supervised lab sessions reduced reliance on AI tools and external resources were examined using the academic integrity item. As shown in the academic integrity panel of **Figure 5**, 158 respondents (76.3%) agreed that the supervised lab environment reduced the likelihood of academic dishonesty.

Students' agreement that the lab-based approach reduced academic dishonesty showed very weak positive associations with peer collaboration frequency ($\rho = 0.16$, $p = 0.021$) and preference for the lab-based approach over traditional assignments ($\rho = 0.16$, $p = 0.021$), and a weak positive association with perceived overall effectiveness ($\rho = 0.28$, $p < 0.001$).

Open-ended responses from 14 students who preferred traditional assignments were analyzed to provide qualitative context regarding AI reliance and academic integrity. These responses are reported in the student perceptions section of the laboratory-based approach. Given the small subsample size ($n = 14$), no quantitative analysis was undertaken.

DISCUSSION

Pre-Lab Preparation

Students' ratings of the "pre-lab materials" suggest that advance preparation supported greater perceived readiness and confidence before entering the laboratory. The positive associations between perceived helpfulness, engagement, and software confidence further support this relationship. This is consistent with feedback and self-regulation research showing that explicit criteria, worked examples, and descriptive guidance help students monitor their progress and improve performance (Hattie & Timperley, 2007; Morris et al., 2021; Sadler, 1989; Zimmerman, 2002). It also aligns with previous work showing that structured preparation improves participation and skill development in software-focused learning environments (Kautsar & Sarno, 2019; Wut & Wong, 2025).

GTA Support and Collaboration

Students viewed GTA support as highly helpful, and those who perceived stronger GTA support were also more engaged and slightly more confident, suggesting that instructor presence helped students persist through technical difficulty. This finding is consistent with SDT and self-efficacy research showing that relatedness, competence support, and mastery experiences strengthen motivation and continued learning (Liu et al., 2023; Ryan & Deci, 2000). Peer discussion was also common, which suggests that collaborative problem solving may have helped students work through software tasks and normalize uncertainty during the lab session. Similar collaborative benefits have been reported in active learning and lab-based instructional studies where structured peer interaction supported engagement and skill development (Freeman et al., 2014; Mohammad et al., 2023b; Stieha et al., 2024).

Time Pressure and Prompts

Time constraints were the most reported challenge, followed by programming or syntax difficulties and unclear prompts. This pattern suggests that the primary barriers were practical and procedural rather than conceptual. Students may therefore have required either more time or more explicit task framing to translate their preparation into successful

performance, particularly when applying programming skills under supervised, time-limited conditions. This interpretation is consistent with previous research showing that active learning activities can feel effortful and cognitively demanding, even when they improve learning outcomes (Deslauriers et al., 2019; Freeman et al., 2014), and with work indicating that real-world tasks benefit from multiple scaffolds to reduce cognitive load and support problem solving (Doering & Veletsianos, 2007). It also aligns with critiques of authentic assessment that emphasize the need for thoughtful, contextualized design rather than assuming authenticity alone will solve learning or inclusion problems (Fawns et al., 2025), as well as evidence that clear quality criteria and explicit expectations support formative assessment and student self-regulation (Sadler, 1989). These findings may help explain why some students perceived the assessment format as stressful despite its educational benefits. They also align with research suggesting that authentic, iterative assignments can enhance engagement but still require appropriate pacing and instructional scaffolding to minimize cognitive overload (Alenezi & Alenezi, 2025).

An important nuance emerges when the quantitative and qualitative findings are considered together. Although 75.4% of students reported that the assessment duration was "just enough" or "more than enough" in the closed-ended items (**Figure 2**), "time constraints" was the most frequently reported qualitative challenge, with 84 students identifying time pressure as a concern (**Figure 4**). These findings are not necessarily contradictory, as students may have considered the overall assessment duration reasonable while still experiencing periods of substantial time pressure during the coding process. Timed software tasks require students to interpret prompts, recall syntax, apply previously learned concepts, troubleshoot errors, and manage the remaining assessment time simultaneously. The qualitative responses may therefore capture the cognitive demands experienced during particular stages of the assessment that are not fully reflected in students' overall judgments of whether the total duration was sufficient.

Importantly, students in these courses were provided with preparatory materials and guided practice activities before the assessments, and the assignments were designed to evaluate skills that had already been introduced, practiced, and reinforced through the instructional activities. Thus, the reported time pressure appears to reflect the cognitive load of applying and integrating previously learned skills under timed and supervised conditions, rather than a lack of conceptual understanding or exposure to new material. These findings suggest that future improvements should focus primarily on assessment design, such as refining time allocation, rather than making substantial changes to the instructional content. This approach is particularly relevant as higher education continues to adapt its assessment practices in response to the challenges and opportunities presented by GenAI (Xia et al., 2024).

Software Confidence

Most students reported feeling confident after the "lab-based, hands-on assignments," and confidence was positively associated with pre-lab helpfulness, engagement, and overall effectiveness. This supports the interpretation that repeated, guided practice can build mastery experiences, which are central to self-efficacy development (Ryan & Deci, 2000; Zimmerman, 2002). The college difference, with higher confidence among students in computational and engineering programs, is also consistent with prior work showing that familiarity and prior exposure shape software anxiety and confidence (Miller & Pyper, 2024). At the same time, the weak effect size suggests that instructional design mattered, but prior background still influenced how students experienced the courses.

Overall Effectiveness

Students generally judged the lab-based approach as more effective and more engaging than traditional homework, which supports the value of active, authentic, in-class assignment formats. This is in line with evidence that active learning improves outcomes in STEM and that authentic tasks can strengthen engagement and skill confidence (Alenezi & Alenezi, 2025; Donoghue et al., 2021; Freeman et al., 2014; Wut & Wong, 2025). However, comments from students who preferred traditional assignments remind us that perceived effectiveness is also subjective and may be shaped by workload, preferred work style, and tolerance for in-lab pressure. This contrast matters because prior studies also show that students do not always evaluate active learning more favorably, even when it improves performance (Deslauriers et al., 2019; Mohammad et al., 2023a).

Academic Integrity

Students' agreement that supervised lab sessions reduced academic dishonesty suggests that the assessment design was perceived as effective for limiting external assistance, including AI use. This aligns with broader concerns that unsupervised take-home work creates more opportunity for inappropriate AI reliance and makes authenticity harder to verify (Cotton et al., 2024; Kasneci et al., 2023; Lancaster & Cotarlan, 2021; Perkins, 2023). At the same time, the 76.3% agreement reflects students' perceptions of the assessment's ability to limit academic dishonesty rather than direct behavioral evidence of reduced misconduct; the study did not collect audit logs or other objective measures of AI use**.** These perceptions may also be subject to social desirability bias, whereby students may have been inclined to provide responses they viewed as more acceptable or consistent with academic integrity expectations. Future research should test whether supervised lab formats reduce AI-assisted completion using behavioral or audit-based measures rather than relying on self-reported data.

CONCLUSION

Survey respondents from *STAT*2230* and *MATH*2130* at the University of Guelph during the Winter 2026 semester generally viewed the supervised, lab-based, hands-on assignment model positively. They reported that the "pre-lab materials" and GTA support were helpful, that the format increased engagement and software confidence, and that the supervised setting supported academic integrity in the context of increasing AI use. These findings suggest that carefully

structured, in-class software assignments can help students build practical skills while maintaining accountability. At the same time, the results indicate that implementation details are critical. Time pressure and programming or syntax difficulties were the most frequently reported challenges, suggesting that pacing, clarity of instructions, and appropriate levels of scaffolding remain important determinants of student success. Overall, the findings support the use of supervised, "lab-based, hands-on assignments" as an effective approach to software learning, provided that instructors integrate structured preparation, guided practice, and sufficient time for task completion.

For university educators designing lab-based software assessments, three actionable considerations emerge from these findings. First, instructors should provide clear "pre-lab materials" and opportunities for guided practice so that students enter the lab prepared for the assigned tasks. Second, lab activities should include accessible instructional support, such as GTA assistance and appropriate scaffolding, particularly for students experiencing programming or syntax difficulties. Third, instructors should allocate sufficient time and design tasks with realistic workloads to reduce unnecessary time pressure while preserving the supervised nature of the assessment.

Limitations

The study had a response rate of 25% across *STAT*2230* and *MATH*2130*. This relatively low response rate raises the possibility of volunteer and nonresponse bias, as students who chose to participate may have differed from those who did not. Consequently, the findings may not fully represent the perspectives of all students enrolled in the two courses and should be interpreted with this limitation in mind. Several additional limitations should also be considered. The research was conducted within a single statistics software course and a single mathematics software course at one Canadian university, which may limit the generalizability of the findings to other educational contexts. In addition, the study relied partly on self-reported survey data and did not directly assess long-term retention of software skills or broader academic outcomes. Future empirical research could address these limitations by using quasi-experimental designs or audit-based approaches that incorporate objective measures of student engagement, software use, skill development, and learning outcomes rather than relying solely on students' self-reported perceptions.

Recommendations and Future Directions

The findings of this study support the continued use of lab-based, hands-on learning approaches in software-related courses to enhance student engagement, practical problem-solving abilities, and technical skill development. Educators should consider incorporating supervised, application-focused assignments that encourage active participation while maintaining academic integrity in increasingly AI-enabled learning environments. Providing structured preparatory materials, collaborative learning opportunities, and timely feedback may further strengthen student learning outcomes.

Future research could expand this work by examining similar instructional approaches across multiple institutions, disciplines, and course levels to improve the generalizability of the findings. Additional studies may also investigate the long-term retention of software competencies, the relationship between hands-on learning and academic performance, and the evolving role of AI tools in higher education. Comparing different assessment designs and levels of instructional support may also provide further insight into effective strategies for promoting authentic learning and skill development. In particular, future empirical studies could directly compare supervised, in-lab coding assessments with unproctored take-home assignments in which students have access to AI tools. Such comparative studies could examine differences in student performance, software skill development, engagement, perceived confidence, and the nature and extent of AI use across assessment conditions.

Future research should also examine how supervised AI use can be incorporated into lab-based environments in pedagogically responsible ways. Rather than framing AI solely as a threat to academic integrity, studies could explore how structured models in which students are permitted to use approved AI tools under clearly defined conditions, such as for debugging, feedback, or code explanation, while still being required to demonstrate independent reasoning and procedural understanding. Comparing fully restricted, partially supervised, and explicitly integrated AI conditions may provide valuable insight into how lab-based assessment can balance authentic skill development, transparency, and integrity in increasingly AI-enabled learning environments.

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AI statement: The authors stated that generative AI tools (ChatGPT) were used only for language editing of the manuscript. All interpretations, analyses, and final decisions regarding the content belong to the authors.

Declaration of interest: No conflict of interest is declared by the authors.

Data sharing statement: Data supporting the findings and conclusions are available upon request from the corresponding author. Fulfillment of these requests will be subject to the permission of the Research Ethics Board at University of Guelph.

REFERENCES

Aderibigbe, S. A., Hamdi, W. B., Alzouebi, K., Frick, W., & Companioni, A. A. (2022). Understanding student perceptions of social computing and online tools to enhance learning. *PLoS ONE, 17*(10), Article e0276490. https://doi.org/10.1371/journal.pone.0276490

Alenezi, A., & Alenezi, A. (2025). Data analytics in online course design and student engagement. *Revista Eduweb, 19*(3), 139-152. https://doi.org/10.46502/issn.1856-7576/2025.19.03.9

Al-Fraihat, D., Joy, M., Masa'deh, R., & Sinclair, J. (2020). Evaluating e-learning systems success: An empirical study. *Computers in Human Behavior, 102*, 67-86. https://doi.org/10.1016/j.chb.2019.08.004

Al-Haddad, S., Chick, N., & Safi, F. (2024). Teaching statistics: A technology-enhanced supportive instruction (TSI) model during the COVID-19 pandemic and beyond. *Journal of Statistics and Data Science Education, 32*(2), 129-142. https://doi.org/10.1080/26939169.2024.2315939

Bond, M., Buntins, K., Bedenlier, S., Zawacki-Richter, O., & Kerres, M. (2020). Mapping research in student engagement and educational technology in higher education: A systematic evidence map. *International Journal of Educational Technology in Higher Education, 17*(1), Article 2. https://doi.org/10.1186/s41239-019-0176-8

Camacho-Morles, J., Slemp, G. R., Pekrun, R., Loderer, K., Hou, H., & Oades, L. G. (2021). Activity achievement emotions and academic performance: A meta-analysis. *Educational Psychology Review, 33*(3), 1051-1095. https://doi.org/10.1007/s10648-020-09585-3

Carpenter, S. K., Witherby, A. E., & Tauber, S. K. (2020). On students' (mis)judgments of learning and the role of effortful processing. *Journal of Applied Research in Memory and Cognition, 9*(2), 137-151. https://doi.org/10.1016/j.jarmac.2019.12.009

Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement, 20*(1), 37-46. https://doi.org/10.1177/001316446002000104

Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International, 61*(2), 228-239. https://doi.org/10.1080/14703297.2023.2190148

Cramér, H. (1946). *Mathematical methods of statistics*. Princeton University Press. https://doi.org/10.1515/9781400883868

Deslauriers, L., McCarty, L. S., Miller, K., Callaghan, K., & Kestin, G. (2019). Measuring actual learning versus feeling of learning in response to being actively engaged in the classroom. *Proceedings of the National Academy of Sciences, 116*(39), 19251-19257. https://doi.org/10.1073/pnas.1821936116

Doering, A., & Veletsianos, G. (2007). Multi-scaffolding environment: An analysis of scaffolding and its impact on cognitive load and problem-solving ability. *Journal of Educational Computing Research, 37*(2), 107-129. https://doi.org/10.2190/Q58T-4388-8015-8141

Donoghue, T., Voytek, B., & Ellis, S. E. (2021). Teaching creative and practical data science at scale. *Journal of Statistics and Data Science Education, 29*(sup1), S27-S39. https://doi.org/10.1080/10691898.2020.1860725

Dunn, O. J. (1964). Multiple comparisons using rank sums. *Technometrics, 6*(3), 241-252. https://doi.org/10.1080/00401706.1964.10490181

Espinosa-Garza, G., Romero-Jiménez, M., & Núñez-Velázquez, I. (2024). Enhancing students' attitudes towards statistics through innovative technology-enhanced, collaborative, and data-driven project-based learning. *Humanities and Social Sciences Communications, 11*, Article 1158. https://doi.org/10.1057/s41599-024-03469-5

Fawns, T., Bearman, M., Dawson, P., Nieminen, J. H., Ashford-Rowe, K., Willey, K., Jensen, L. X., Damşa, C., & Press, N. (2025). Authentic assessment: From panacea to criticality. *Assessment & Evaluation in Higher Education, 50*(3), 396-408. https://doi.org/10.1080/02602938.2024.2404634

Firke, S. (2024). janitor: Simple tools for examining and cleaning dirty data [R package]. *CRAN*. https://CRAN.R-project.org/package=janitor

Forrester, C., Schwikert, S., Foster, J., & Corwin, L. (2022). Undergraduate R programming anxiety in ecology: Persistent gender gaps and coping strategies. *CBE—Life Sciences Education, 21*(2), Article ar29. https://doi.org/10.1187/cbe.21-05-0133

Freeman, S., Eddy, S. L., McDonough, M., Smith, M. K., Okoroafor, N., Jordt, H., & Wenderoth, M. P. (2014). Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences, 111*(23), 8410-8415. https://doi.org/10.1073/pnas.1319030111

Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research, 77*(1), 81-112. https://doi.org/10.3102/003465430298487

Hernández de la Hera, J. M., Morales-Rodríguez, F. M., Rodríguez-Gobiet, J. P., & Martínez-Ramón, J. P. (2023). Attitudes toward mathematics/statistics, anxiety, self-efficacy and academic performance: An artificial neural network. *Frontiers in Psychology, 14*. https://doi.org/10.3389/fpsyg.2023.1214892

Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics, 6*(2), 65-70.

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., … Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, Article 102274. https://doi.org/10.1016/j.lindif.2023.102274

Kautsar, I. A., & Sarno, R. (2019). A supportive tool for project-based learning and laboratory-based education. *International Journal on Advanced Science, Engineering and Information Technology, 9*(2), 630-639. https://doi.org/10.18517/ijaseit.9.2.7067

Kolb, D. A. (1984). *Experiential learning: Experience as the source of learning and development*. Prentice-Hall.

Kruskal, W. H., & Wallis, W. A. (1952). Use of ranks in one-criterion variance analysis. *Journal of the American Statistical Association, 47*, 583-621. https://doi.org/10.1080/01621459.1952.10483441

Kuo, Y.-C., Walker, A. E., Schroder, K. E. E., & Belland, B. R. (2014). Interaction, Internet self-efficacy, and self-regulated learning as predictors of student satisfaction in online education courses. *The Internet and Higher Education, 20*, 35-50. https://doi.org/10.1016/j.iheduc.2013.10.001

Lancaster, T., & Cotarlan, C. (2021). Contract cheating by STEM students through a file sharing website: A COVID-19 pandemic perspective. *International Journal for Educational Integrity, 17*, Article 3. https://doi.org/10.1007/s40979-021-00070-0

Liu, L., Ye, P., & Tan, J. (2023). Exploring college students' continuance learning intention in data analysis technology courses: The moderating role of self-efficacy. *Frontiers in Psychology, 14*. https://doi.org/10.3389/fpsyg.2023.1241693

Lodge, J. M., Thompson, K., & Corrin, L. (2023b). Mapping out a research agenda for generative artificial intelligence in tertiary education. *Australasian Journal of Educational Technology, 39*(1), 1-8. https://doi.org/10.14742/ajet.8695

Lodge, J., Henderson, M., Slade, C., & Deneen, C. (2023a). Adapting assessment for/despite generative artificial intelligence: A national guidance framework. In *Proceedings of the ASCILITE 2023 Conference*. https://doi.org/10.14742/apubs.2023.554

Medina, C. M., & Dogucu, M. (2026). *Engaging students with statistics through choice of real data context on homework*. arXiv. https://doi.org/10.48550/arXiv.2603.04541

Miller, A., & Pyper, K. (2024). Anxiety around learning R in first year undergraduate students: Mathematics versus biomedical sciences students. *Journal of Statistics and Data Science Education, 32*(1), 47-53. https://doi.org/10.1080/26939169.2023.2190010

Mohammad, N. M., Demers, M., & Kopel, K. (2023a). A comparison of flipped learning with traditional (face-to-face) learning: The effects on students' mathematics achievement and cognitive engagement. *Journal of Mathematics and Science Teacher, 3*(2), Article em051. https://doi.org/10.29333/mathsciteacher/13720

Mohammad, N. M., Kraus, D., Richards, G., & McCubbin, E. (2025). Students' perception on blending mathematics teaching with kindness. *Journal of Mathematics and Science Teacher, 5*(2), Article em077. https://doi.org/10.29333/mathsciteacher/16057

Mohammad, N. M., Nica, M., Kraus, D., Levere, K. M., & Okner, R. (2024). Student experience using synchronous and asynchronous learning in mathematics classes. *Pedagogical Research, 9*(2), Article em0194. https://doi.org/10.29333/pr/14244

Mohammad, N. M., Nica, M., Levere, K. M., & Okner, R. (2023b). Promoting engagement via engaged mathematics labs and supportive learning. *International Electronic Journal of Mathematics Education, 18*(2), Article em0732. https://doi.org/10.29333/iejme/12960

Morris, R., Perry, T., & Wardle, L. (2021). Formative assessment and feedback for learning in higher education: A systematic review. *Review of Education, 9*(3), Article e3292. https://doi.org/10.1002/rev3.3292

OECD. (2023). *OECD skills outlook 2023: Skills for a resilient green and digital transition*. OECD Publishing. https://doi.org/10.1787/27452f29-en

Pekrun, R. (2006). The control-value theory of achievement emotions: Assumptions, corollaries, and implications for educational research and practice. *Educational Psychology Review, 18*(4), 315-341. https://doi.org/10.1007/s10648-006-9029-9

Perkins, M. (2023). Academic integrity considerations of AI large language models in the post-pandemic era: ChatGPT and beyond. *Journal of University Teaching & Learning Practice, 20*(2), Article 7. https://doi.org/10.53761/1.20.02.07

Rashid, T., & Asghar, H. M. (2016). Technology use, self-directed learning, student engagement and academic performance: Examining the interrelations. *Computers in Human Behavior, 63*, 604-612. https://doi.org/10.1016/j.chb.2016.05.084

Riego de Dios, E. E., & Asio, J. M. R. (2026). Students' motivation, self-esteem, and study habits: Interrelationships, variances, and implications. *Indonesian Journal of Education and Social Science, 5*(1), 32-45.

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist, 55*(1), 68-78. https://doi.org/10.1037/0003-066X.55.1.68

Sadler, D. R. (1989). Formative assessment and the design of instructional systems. *Instructional Science, 18*(2), 119-144. https://doi.org/10.1007/BF00117714

Schau, C., Stevens, J., Dauphinee, T. L., & Del Vecchio, A. (1995). The development and validation of the survey of attitudes toward statistics. *Educational and Psychological Measurement, 55*(5), 868-875. https://doi.org/10.1177/0013164495055005022

Shepherd, M. A., & Richardson, E. J. (2024). Opting for open-source? A review of free statistical software programs. *Teaching Statistics, 46*(2), 53-63. https://doi.org/10.1111/test.12360

Soderstrom, N. C., & Bjork, R. A. (2015). Learning versus performance: An integrative review. *Perspectives on Psychological Science, 10*(2), 176-199. https://doi.org/10.1177/1745691615569000

Spearman, C. (1904). The proof and measurement of association between two things. *The American Journal of Psychology, 15*(1), 72-101. https://doi.org/10.2307/1412159

Stains, M., Harshman, J., Barker, M. K., Chasteen, S. V., Cole, R., DeChenne-Peters, S. E., Eagan, M. K., Esson, J. M., Knight, J. K., Laski, F. A., Levis-Fitzgerald, M., Lee, C. J., Lo, S. M., McDonnell, L. M., McKay, T. A., Michelotti, N., Musgrove, A., Palmer, M. S., Plank, K. M., ... Young, A. M. (2018). Anatomy of STEM teaching in North American universities. *Science, 359*(6383), 1468-1470. https://doi.org/10.1126/science.aap8892

Stieha, V., Earl, B., Hagens, H., Haynes, M., Ulappa, A., Bond, L., & Oxford, J. T. (2024). An exploration of the relationship between active learning and student motivation in STEM: A mixed methods study. *Advances in Physiology Education, 48*(3), 621-638. https://doi.org/10.1152/advan.00247.2022

Sullivan, M., Kelly, A., & McLaughlan, P. (2023). ChatGPT in higher education: Considerations for academic integrity and student learning. *Journal of Applied Learning and Teaching, 6*, 31-40. https://doi.org/10.37074/jalt.2023.6.1.17

Theobald, E. J., Hill, M. J., Tran, E., Agrawal, S., Arroyo, E. N., Behling, S., Chambwe, N., Cintrón, D. L., Cooper, J. D., Dunster, G., Grummer, J. A., Hennessey, K., Hsiao, J., Iranon, N., Jones, L., Jordt, H., Keller, M., Lacey, M. E., Littlefield, C. E., … Freeman, S. (2020). Active learning narrows achievement gaps for underrepresented students in undergraduate science, technology, engineering, and math. *Proceedings of the National Academy of Sciences, 117*(12), 6476-6483. https://doi.org/10.1073/pnas.1916903117

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M., Müller, K., Ooms, J., Robinson, D., Seidel, D., Spinu, V., … Yutani, H. (2019). Welcome to the tidyverse. *Journal of Open Source Software, 4*(43), Article 1686. https://doi.org/10.21105/joss.01686

World Economic Forum. (2023). The future of jobs report 2023. *World Economic Forum*. https://www.weforum.org/publications/the-future-of-jobs-report-2023/

Wut, T. M., & Wong, H. S. M. (2025). Students' perceived learning and satisfaction in using a statistical software by learner-generated video. *Technology, Knowledge and Learning, 31*, 1481-1493. https://doi.org/10.1007/s10758-025-09838-6

Xia, Q., Weng, X., Ouyang, F., Lin, T. J., & Chiu, T. K. F. (2024). A scoping review on how generative artificial intelligence transforms assessment in higher education. *International Journal of Educational Technology in Higher Education, 21*, Article 40. https://doi.org/10.1186/s41239-024-00468-z

Xie, Y., Allaire, J. J., & Grolemund, G. (2018). *R markdown: The definitive guide*. Chapman & Hall/CRC. https://doi.org/10.1201/9781138359444

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory Into Practice, 41*(2), 64-70. https://doi.org/10.1207/s15430421tip4102_2