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Practice and Evaluation of Data Science Education for First-Year Students in Foreign Language Faculties - A Case Study of an On-Demand Course Using BI Tools -

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Abstract

This study presents the design, implementation, and evaluation of an introductory data science (hereinafter, DS) course tailored specifically for first-year non-STEM students at Kanda University of International Studies (KUIS), focusing on the 2024 academic year cohort. Recognizing common barriers faced by non-STEM students, such as limited mathematical literacy, inadequate ICT skills, and low motivation, the course employed accessible methods to foster engagement and effective DS education. Key features included an emphasis on numerical reasoning over complex mathematics, utilizing student-centered activities using authentic datasets, and extensive practical exercises utilizing Tableau, a no-code business intelligence (BI) tool. Delivered in an on-demand format to approximately 900 students, the course achieved a 90.3% pass rate and led to significant improvement in students' self-assessed DS competencies. It effectively bridged knowledge and skill gaps between students with and without prior DS experience. However, motivational gains were modest, indicating areas for pedagogical improvement. Future research should address potential biases from voluntary survey participation, deepen motivational analyses, and explore strategies that explicitly link DS education with broader career relevance.

Keywords:Data Science Education, Non-STEM Students, Tableau, BI, On-Demand Learning.

1 Introduction - Background and Issues -

In recent years, data science (hereinafter, DS) education has rapidly expanded within Japanese higher education. Data science, which extracts valuable insights from large datasets, is increasingly recognized as an essential literacy skill, often referred to as "reading, writing, and arithmetic for the digital era." In its "AI Strategy 2019," the Japanese government set a goal for all university students, regardless of major, to acquire fundamental mathematical and data analysis skills [1]. Subsequently, in 2021, the Ministry of Education, Culture, Sports, Science and Technology (MEXT) introduced the "Mathematics, Data Science, and AI Education Program Accreditation System," significantly boosting the nationwide implementation of DS education. Encouraged by this initiative, many universities began integrating DS education across disciplines, including mandatory introductory DS courses and specialized DS minors accessible to both STEM and non-STEM students [2]. According to a survey by the Nikkei newspaper, approximately 70% of major universities in Japan require basic DS courses [3]. Thus, fostering DS literacy is widely recognized as a crucial goal in Japanese higher education.

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Nevertheless, several challenges accompany the implementation of DS education at the university level, particularly for non-STEM students. Four main issues were identified in this study. First, there is a shortage of qualified instructors. The lack of specialized faculty limits educational quality, especially in humanities-centric institutions or smaller universities where securing capable DS instructors remains problematic [4]. Second, many non-STEM students enter university with insufficient mathematical and statistical literacy due to Japan's high school system, which often separates students into STEM or non-STEM tracks early. As a result, many first-year non-STEM undergraduates have not adequately studied mathematics or information technology, creating substantial barriers to learning DS. Indeed, non-STEM departments often omit mathematics from entrance examinations, leading many students to view math negatively and avoid DS courses altogether [5]. In addition, non-STEM students often lack confidence in ICT applications and feel overwhelmed by programming or complex software [6]. The third issue is motivational. many non-STEM students fail to see the personal relevance of DS education, perceiving it as disconnected from their daily lives [6]. Coupled with anxiety about mathematics and computer use, this further diminishes their motivation to engage in DS [7]. A survey examining attitudes toward DS education found that among non-STEM students, business majors showed the most interest in data science, while foreign language students were the least comfortable with it [8]. The fourth issue concerns curricular integration. Incorporating DS education into existing curricula is challenging, particularly in non-STEM faculties where connections to DS are limited. Allocating adequate instructional hours for DS education and harmonizing them with existing coursework requires thoughtful planning and curricular adjustments.

Addressing these issues requires DS courses specifically designed for non-STEM students. Effective DS education must offer accessible materials and instructional methods appropriate for students with limited numeracy and ICT skills, aiming to enhance outcomes and motivation. Recognizing these challenges, the author designed, implemented, and evaluated an on-demand DS course for first-year non-STEM students in their home institution's foreign languages faculty. This paper reports on this initiative and provides background information, implementation details, and outcomes.

2 Literature Review and Positioning of This Study

Focusing on non-STEM (particularly humanities) students, this paper surveyed existing literature on DS education tailored for this audience. Among pioneering examples, Seijo University, a non-STEM university, began offering comprehensive DS education as a general education subject across all faculties in 2015 [9]. The analysis from Seijo University emphasized the importance of designing curricula that engage non-STEM students, suggesting thematic combinations, such as practical AI and digital transformation cases, to spark student interest without overemphasizing computer science concepts [9].

Another notable case recognized by MEXT in 2023 is Hokuriku University, which adopted Tableau, a no-code business intelligence (BI) tool, enabling students without programming experience to engage effectively in data analysis and visualization [10]. Hokuriku University's courses used real-world data from campus stores and cafeterias, significantly enhancing students' motivation and data literacy.

Additionally, Tokyo Metropolitan University provided a relevant case study [11]. In research involving both STEM and non-STEM students, three essential elements were identified to support non-STEM learners: (1) directly linking course content with students' primary fields of study; (2) simplifying technical setup processes; and (3) providing swift feedback through ICT.

Aoki et al. (2024) reported on an introductory DS course at a non-STEM university and demonstrated that hands-on practice with user-friendly analytical tools significantly deepened students' conceptual understanding and stimulated their interest in DS technology [12].

From these studies, three key insights emerge. First, user-friendly tools and accessible technological environments are essential for students unfamiliar with programming or digital tools. Second, aligning DS education with students' specialized majors or social contexts can effectively boost motivation. Third, incorporating real-world datasets into hands-on activities enhances understanding and engagement. Future DS programs for non-STEM students should integrate these design elements.

Studies have also explored program design and evaluation methodologies. Matsuo and Tamada (2022) examined the challenges of DS literacy at a private, non-STEM-focused university, recommending differentiated content for freshmen-level courses that focus on statistical literacy and data application, and advanced-level courses connecting DS to specialized academic fields [7]. However, effective strategies for sustainably increasing intrinsic motivation remain unclear. Similarly, Yasuda and Usami (2023) evaluated a freshman-level DS literacy course in a non-STEM faculty, reporting significant increases in student confidence and interest in DS after a 15-session program [5]. Yet, retention of theoretical knowledge in statistics and AI remained a challenge, highlighting the need for improved instructional design. Their study also stressed the importance of evaluating confidence in information use and DS knowledge before and after course participation [5].

Building on these prior studies, this paper describes a DS education program explicitly designed with beginner-friendly tools, content relevant to students' majors, and real-world data in practical exercises. The author implemented this DS program in an on-demand format to address constraints such as staffing and limited class hours. It's effectiveness was evaluated through course grades and pre-post- surveys measuring student attitudes and experiences. This study empirically tested the effectiveness of previously suggested educational strategies and expected learning outcomes in DS education for non-STEM students.

3 Course Design and Implementation

3.1 Overview of the University and Faculty for the Practical Case

This case study was implemented in the Faculty of Foreign Languages (four departments, nine majors) at Kanda University of International Studies (KUIS), where the author is affiliated. KUIS, comprised of two faculties, the Faculty of Foreign Languages and the Faculty of Global Liberal Arts, is a private university primarily comprising of non-STEM students focusing on languages and international relations. According to the "THE Japan University Rankings 2025" by Times Higher Education (THE), KUIS ranks 35th overall (including public universities), 9th nationwide in "educational quality," and 18th in "internationalization," highlighting its strengths in education and global engagement [13].

Within the Faculty of Foreign Languages, a new foundational course titled "METHODS IN STUDIES II" was introduced in the 2023 academic year to provide first-year students with DS education. This compulsory on-demand course, conducted during the second semester, enrolls approximately 900 students annually (excluding repeaters). The 15-session course emphasizes academic literacy essential for effective university learning and comprises three main components: "Critical Reading," "Academic Writing," and "Numerical Reasoning." Of these, the "Numerical Reasoning" constitutes the mandatory DS education component and is delivered over five sessions, and is delivered primarily through hands-on exercises using the tool Tableau. The structure of these five sessions is shown in Figure 1.

Session 1: Measuring Events Numerically (Size, Proportion)	Session 2: Measuring Events Numerically (Changes)
Overview of numerical thinking (Movie)	Goals and contents of this session (Movie)
Goals and contents of this session (Movie)	Obtaining long-term/monthly visitor data by purpose (Movie, Teaching Material)
Finding reliable data (Movie)	Connecting the acquired data (Movie)
Confirming data definitions (Movie)	Learning various ways to measure proportions (Movie)
Obtaining data (Movie, Teaching Material)	Measuring various changes (1) (Movie 1, Movie 2, Movie 3)
Loading data and basic configuration in Tableau (Movie)	Measuring various changes (2) (Movie 1, Movie 2, Movie 3)
Creating a report measuring size (Movie 1, Movie 2, Movie 3)	Summarizing graphs into a story (Movie)
Creating a report measuring proportions (Movie 1, Movie 2)	Enumerating facts and opinions derived from graphs (Movie, Workshop)
Summarizing the report on a dashboard (Movie, Workshop)	Reflection and summary (Movie)
Enumerating facts and opinions derived from graphs (Movie, Workshop)	
Reflection and summary (Movie)	

Session 3: Measuring Events Numerically (Size, Proportion, Change)	Session 4: Measuring Events Numerically (Dispersion and Central Tendency)
Goals and contents of this session (Movie)	Goals and contents of this session (Movie)
Obtaining world CO_2 emission data (Movie, Teaching Material)	Measuring central tendency and dispersion (1) (Movie 1, Movie 2)
Importing and organizing CO_2 emission data (Movie)	Measuring dispersion (2) (Movie 1, Movie 2, Teaching Material)
Measuring the size of CO_2 emissions (Movie 1, Movie 2)	Viewing dispersion (1): Histograms (Movie 1, Movie 2, Movie 3)
Measuring changes in CO_2 emissions (Movie 1, Movie 2, Movie 3)	Viewing dispersion (2): Frequency distributions (Movie 1, Movie 2)
Measuring the proportion of CO_2 emissions (Movie 1, Movie 2)	Viewing dispersion (3): Boxplots (Movie 1, Movie 2)
Other expressions and dashboard summary (Teaching Material, Movie, Workshop)	Summarizing dispersion graphs into a story (Movie, Workshop)
Enumerating facts and opinions derived from graphs (1) (Workshop, Movie)	Enumerating facts and opinions derived from graphs (Movie, Workshop, Movie 2)
Obtaining and organizing Japan's greenhouse gas emission data (Movie 1, Teaching Material, Movie 2)	Reflection (Movie, Quiz)
Measuring size, proportion, and changes in greenhouse gas emissions (Movie 1, Movie 2, Workshop)	
Enumerating facts and opinions derived from graphs (2) (Workshop, Movie)	
Reflection and summary (Movie, Quiz)	

Session 5: Measuring Events Numerically (Relationships)
Goals and contents of this session (Movie)
What does it mean to measure numerical relationships? (Movie 1, Movie 2)
Relationship between qualitative variables (cross-tabulation) (Movie 1, Movie 2, Movie 3)
Relationship between quantitative variables (scatter plots and trendlines) (Movie 1, Movie 2, Movie 3)
Enumerating facts and opinions derived from graphs (1) (Movie, Workshop)
Cautions when describing relationships: Distinguishing correlation and causation (Movie 1, Movie 2)
Cross-tabulation by segments (Movie)
Drawing scatter plots and trendlines by segments (Movie 1, Movie 2, Workshop)
Enumerating facts and opinions derived from graphs (2) (Workshop, Movie)
Summary of Session 5 (Movie, Quiz)
Summary of the entire course (Movie)

* Contents
Movie = Lectures and Explanations
Teaching Material = Handout data and materials
Workshop = Submission of a Tableau workbook or description of results and discussion based on the workbook
Quiz = Correct or fill-in-the-blank questions for keywords (all questions must be answered correctly to pass)

Figure 1: Content and structure of all five classes

3.2 Distinctive Features of Course Design

The course design features three key characteristics. First, consistent with the title "Numerical Reasoning," the course focuses on interpreting events using numbers rather than mathematical formulas. It emphasizes understanding and explaining numerical facts without introducing statistical terminology upfront. Sessions are named after measurement activities, such as "Measuring Events Numerically (Size, Proportion)," "Measuring Events Numerically (Changes)," "Measuring Events Numerically (Size, Proportion, Change)," "Measuring Events Numerically (Dispersion and Central Tendency)," and "Measuring Events Numerically (Relationships)." The third session serves as a synthesis of the first two. This naming strategy helps avoid intimidating students unfamiliar with DS, potentially improving motivation. After completing the exercises, statistical concepts like histograms and boxplots (Session 4), and correlations (Session 5) were subsequently introduced, reinforcing students' statistical understanding.

Second, the course emphasizes hands-on activities using real-world data or simulated data based on real trends, reflecting inquiry-based practices common in university education. For example, in the first session, a preliminary video introduces a student interested in international migration and tourism. Students then access the Japan Tourism Agency's official website, identify relevant public statistics ("Visitor Arrivals Statistics"), verifying definitions, and download data. In the third session, students interested in environmental gather greenhouse gas emission data from sources such as Our World in Data and Japan's National Institute for Environmental Studies (actual data used in assignments is provided as teaching material). They use Tableau Desktop to visualize data trends related to size, proportion, change, dispersion, and relationships. Instructional videos provide step-by-step guidance, and students submit their Tableau workbooks in workshops. Beyond submission, students describe findings from their visualizations, draw insights from external references or web resources, and complete quizzes to consolidate understanding. This approach simulates realistic future data-driven tasks and enhances practical DS skills through active learning.

The third feature is the use of a Tableau, a BI tool, selected for four key reasons. First, this decision was informed by the successful DS education program at Hokuriku University, which was recognized by MEXT as exemplary. Notably, that program reported no motivational differences between STEM and non-STEM students' after completing the course, suggesting that Tableau may effectively support DS motivation among non-STEM learners. Second, Tableau does not requires programming knowledge, which is critical for first-year students who lack prior experience in coding or advanced ICT skills and have limited time to acquire them. Third, Tableau offers temporary free licenses for educational purposes, helping to lower cost-related barriers. Fourth, Tableau's growing adoption and its potential to serve as an alternative to traditional tools such as Excel were taken into account. A 2020 report by the Ministry of Internal Affairs and Communications on digital data utilization [14] indicated that while 86.0% of respondents used basic software like Excel or Access, 39.0% used BI tools or data analysis software, a figure that rose to 47.0% in the information and communication industry. Given ongoing industry trends, BI tools like Tableau are expected to become increasingly widespread. Furthermore, Tableau surpasses Excel in its default capability for data manipulation, connectivity, and visualization, thereby significantly enhancing the effectiveness of DS learning.

Note that DS education at KUIS is accredited at the literacy level of MEXT's Mathematics, AI, and DS accreditation system, and this course corresponds to "Reading Data," "Explaining Data," and "Handling Data" in the Foundations: Data Literacy and the optional "Data Handling" course. However, we would like to add that DS education at KUIS was never started with the aim of receiving certification, but rather in conjunction with curriculum reform based on the idea that "data science is a partner in inquiry activities and, like natural language, one of the tools for communication across borders".

With these distinctive features, a five-session on-demand course was implemented in the 2023 academic year, targeting first-year students in the Faculty of Foreign Languages at KUIS. The results and evaluation data collected from the 2024 cohort are presented in the following section.

4 Results and Evaluation

4.1 Overview of Implementation and Evaluation Methods

The Data Science (DS) on-demand course for the 2024 academic year was conducted during the fall semester, from September 17, 2024, to January 17, 2025. Excluding the students who repeated the course, 930 first-year undergraduate students participated. Questionnaire surveys were administered before (beginning in September) and after (beginning in January) the course. These surveys collected information on students' prior learning experiences with data science (pre-only), self-assessments of knowledge and skills (pre- and post-), and learning motivation (pre- and post-). Students' responses to these surveys, along with their final performance data, were used for evaluation.

4.2 Overall Results

(1) Pass Rate, Total Score, and Progress Rate: The Faculty of Foreign Languages comprises four language departments. Table 1 presents the average total score for the DS module (maximum score: 25), pass rate (pass_fail), and average progress rate of the learning materials (maximum score: 100), disaggregated by department. The total score and progress rate were strongly correlated, and a score of 80 or higher for both was set as the minimum passing threshold. These metrics accounted for students' video-viewing completion, workshop attendance, and quiz submission records.

The results showed an overall pass rate of 90.3%, with an average total score of 22.0 points and an average progress rate of 88.3%. Although the course was a required component for first-year students, it was delivered asynchronously and was not a formal requirement for academic progression. Thus, the outcomes were broadly consistent with expectations.

Table 1: Grading and pass/fail for each department (n=930)

department	total_score (max=25)	pass_fail	progress_rate (max=100)
Asian Languages (n=175)	22.5	93.7%	90.4
English (n=382)	21.5	89.3%	86.6
International Communication (n=243)	22.2	89.7%	89.3
Spanish&Portuguese (n=130)	22.1	90.0%	88.7
All	22.0	90.3%	88.3

(2) Changes in Knowledge and Skills: Based on the Japanese version of the Statistical Literacy Self-Efficacy Scale developed by Ikawa et al. (2020) [15], ten evaluation items were formulated to assess students' statistical and numerical reasoning skills in alignment with the course content. Table 2 summarizes the item labels, pre- and post-survey means and standard deviations, mean differences, and the results of the paired t-tests for each item. All items were rated using a five-point Likert scale ranging from "5. Confident" to "1. Not confident." These answers were used in the analysis on a numerical scale with 5 points for selecting "5. Confident" and 1 point for selecting "1. Not confident."

For this analysis, only students who completed both the pre- and post-course surveys and provided complete responses to all relevant items were included. The resulting sample comprised of 497 students, accounting for 53.4% of the total cohort of 930 students.

As shown in Table 2, all knowledge and skill items demonstrated statistically significant improvement from pre- to post-course assessments ($p < .001$). For example, the item "Obtain reliable data from online sources" showed a substantial mean increase of 0.96 (2.90 → 3.86), indicating improved ability to evaluate data reliability. Similarly, "Accurately represent changes over time using tables and graphs" increased by 0.86 (2.11 → 2.97), and for "Understand data distribution by observing variability" improved by 0.99 (2.46 → 3.45), reflecting greater confidence in analyzing changes and variability. Although these items did not directly assess understanding of statistical terms such as variance or standard deviation, the results suggested enhanced visual interpretation skills related to change and variability through DS learning.

Table 2: Pre-post- comparison of knowledge and skills and corresponding t-test results (n=497)

Knowledge & Skills	Pre_Mean	Pre_SD	Post_Mean	Post_SD	post-pre mean difference	P value
Obtain reliable data from online sources	2.90	1.11	3.86	0.91	0.96	***
Prepare data for aggregation and analysis	2.47	1.12	3.34	1.03	0.87	***
Accurately represent quantities and proportions using tables and graphs	2.50	1.12	3.35	1.00	0.85	***
Accurately represent changes over time using tables and graphs	2.50	1.12	3.27	1.02	0.77	***
Explain methods for calculating multiple changes to friends	2.10	1.00	2.97	1.04	0.87	***
Interpret trends using averages and medians	2.38	1.12	3.34	1.07	0.96	***
Understand data distribution by observing variability	2.46	1.12	3.44	1.03	0.98	***
Investigate the relationship between two datasets	2.61	1.17	3.53	0.99	0.92	***
Identify errors in tables and graphs created by others	2.43	1.07	3.22	1.07	0.79	***
Explain the meaning of tables and graphs found in newspapers or online	2.58	1.13	3.48	1.01	0.90	***

***:p<0.001 **:p<0.01 *:p<0.05 n.s:p>0.05

(3) Changes in Motivation: Motivation was assessed using the same filtering method as the knowledge and skills analysis, utilizing a sample of 497 students who responded to both surveys.

The motivation survey included three items evaluating different dimensions of DS motivation: ongoing interest in learning, intention to broadly apply DS knowledge in the workforce or society, and specific interest in pursuing a data-analysis-related career. Although the wording of some items varied slightly between the pre- and post-surveys, their intent remained consistent in tracking motivational changes. Table 3 summarizes these results.

The findings are as follows: For the statement, "I want to learn about data science through multiple university courses in the future," the proportion of students responding "Somewhat true" or "Very true" increased by approximately 8 percentage points (pre-: 34.2% → post-: 42.2%). For the statement, ‘I want to use data science knowledge and skills in my future job or society after graduation,’ the proportion showed a modest increase (pre-: 38.1%; post-: 41.5%). Lastly, for the statement "I want to pursue a career that involves data analysis itself," the proportion increased by over 10 percentage points (pre-: 11.4% → post-: 23.3%).

Table 3: Changes in Motivation between Pre- and Post-surveys (n=497)

		Not at all true	Not very true	Somewhat true	Very true
I want to learn about data science through multiple university courses in the future.(*)	Pre	24.1%	41.6%	28.2%	6.0%
	Post	18.1%	39.6%	35.4%	6.8%
I want to use data science knowledge and skills in my future job or in society after graduation.(**)	Pre	21.4%	40.5%	30.2%	7.9%
	Post	22.1%	36.4%	32.8%	8.7%
I want to pursue a career that involves data analysis itself.	Pre	51.1%	37.4%	8.0%	3.4%
	Post	35.4%	41.2%	19.5%	3.8%

* In the post-survey, participants were asked, "I want to learn about data analysis."

** In the post-survey, participants were asked, "I want to pursue a career that involves data analysis itself."

4.2 Comparison by Prior DS Learning Experience

Even within the same non-STEM student group from the Faculty of Foreign Languages, some students had prior DS learning experience in secondary education, while others did not. This difference arose because some students graduated from high schools with advanced educational programs, whereas others shifted from STEM to non-STEM tracks upon entering university.

In the pre-course survey, 246 out of 497 students (49.5%) reported having prior DS learning experience, while 251 students (50.5%) reported having none, an almost even split. Among those who answered "Yes" (multiple responses allowed), 213 students (86.6%) indicated that they had learned DS in high school. Regarding specific content, 210 students (85.3%) mentioned Excel practice, and 129 students (52.4%) cited statistical knowledge.

Given this study's focus on DS education for non-STEM beginners, special attention was paid to the group without prior DS learning experience. Accordingly, the evaluation metrics described earlier were compared between students with and without such experience. The analysis was conducted on the 497 students who fully completed both surveys without missing data.

(1) Pass Rate, Total Score, and Progress Rate: Table 4 presents the results. Possibly due to the self-selection of students who responded to both surveys, all three indicators were consistently high, and differences between the two groups were minimal. Independent-sample t-tests revealed revealed no statistically significant differences.

Table 4: Total Scores, Pass Rates, and Results of t-tests by Prior DS Learning Experience

DS Learning Experience before this DS Education	total_score (max=25)	p value	pass_fail	p value	progress_rate (max=100)	p value
YES(n=246)	24.0	n.s	98.8%	n.s	96.5	n.s
No(n=251)	24.1		99.6%		96.5	

***:p<0.001 **:p<0.01 *:p<0.05 n.s:p>0.05

(2) Changes in Knowledge and Skills: Similar to earlier analyses, paired-sample t-tests were conducted separately for students with and without prior DS learning experience, examining the mean differences in the ten evaluation items measuring statistical and numerical reasoning skills. The results are summarized in Tables 5 and 6.

Two main findings emerged. First, students without prior DS learning experience demonstrated larger mean gains (post-pre) for all items compared to those with previous experience. Second, although students with prior exposure initially rated their confidence higher, the post-course scores between the two groups converged closely, indicating that the course effectively narrowed the knowledge and skill gaps. This convergence is further illustrated in Figure 2, which presents Kernel Density Estimation (KDE) plots of total scores across the ten items (maximum of five points per item, total score of 50). Before the course, the score distribution for inexperienced students (blue curve) was skewed toward lower values with multiple peaks. After the course, both distributions aligned more closely, with one or two peaks, clearly suggesting the course substantially reduced disparities in DS competencies between groups.

Table 5: [The above YES group] (n=246)

Pre-post- comparison of skills and corresponding t-test results

Knowledge & Skills	Pre_Mean	Pre_SD	Post_Mean	Post_SD	post-pre mean difference	P value
Obtain reliable data from online sources	3.04	1.10	3.91	0.86	0.87	***
Prepare data for aggregation and analysis	2.63	1.15	3.47	1.03	0.83	***
Accurately represent quantities and proportions using tables and graphs	2.67	1.11	3.44	0.98	0.77	***
Accurately represent changes over time using tables and graphs	2.67	1.10	3.39	1.01	0.72	***
Explain methods for calculating multiple changes to friends	2.24	1.03	3.05	1.01	0.81	***
Interpret trends using averages and medians	2.59	1.12	3.48	1.05	0.89	***
Understand data distribution by observing variability	2.65	1.10	3.54	1.00	0.89	***
Investigate the relationship between two datasets	2.81	1.16	3.61	0.97	0.79	***
Identify errors in tables and graphs created by others	2.55	1.04	3.28	1.06	0.73	***
Explain the meaning of tables and graphs found in newspapers or online	2.76	1.11	3.57	1.01	0.80	***

***:p<0.001 **:p<0.01 *:p<0.05 n.s:p>0.05

Table 6: [The above NO group] (n=251)

Pre-post- comparison of skills and corresponding t-test results

Knowledge & Skills	Pre_Mean	Pre_SD	Post_Mean	Post_SD	post-pre mean difference	P value
Obtain reliable data from online sources	2.76	1.11	3.81	0.96	1.05	***
Prepare data for aggregation and analysis	2.31	1.08	3.22	1.02	0.91	***
Accurately represent quantities and proportions using tables and graphs	2.33	1.10	3.26	1.00	0.93	***
Accurately represent changes over time using tables and graphs	2.33	1.10	3.16	1.03	0.83	***
Explain methods for calculating multiple changes to friends	1.97	0.95	2.89	1.06	0.92	***
Interpret trends using averages and medians	2.17	1.08	3.20	1.07	1.03	***
Understand data distribution by observing variability	2.27	1.12	3.34	1.04	1.07	***
Investigate the relationship between two datasets	2.41	1.15	3.45	1.00	1.04	***
Identify errors in tables and graphs created by others	2.32	1.09	3.16	1.07	0.84	***
Explain the meaning of tables and graphs found in newspapers or online	2.40	1.12	3.40	1.01	1.00	***

***:p<0.001 **:p<0.01 *:p<0.05 n.s:p>0.05

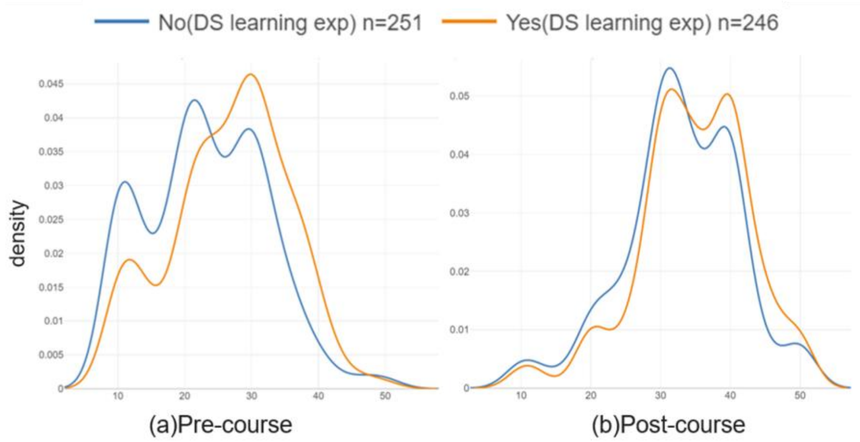

Figure 2: Comparison of (a) Pre-course and (b) Post-course
Total Knowledge and Skill Score Distributions (Kernel Density Estimation)

(3) Changes in Motivation: Table 7 summarizes the changes in motivation, similar to earlier analyses. Two key findings emerged. For the statement "I want to learn about data science through multiple university courses in the future," there was an 8-point increase (pre-: 34.2% → post-: 42.2%). Next, for the statement "I want to pursue a career that involves data analysis itself," the proportion answering "Somewhat true" or "Very true" increased by over 10 points for both groups: DS-experienced students (15.1% → 26.0%) and DS-inexperienced students (8.0% → 20.7%). Additionally, for the statement "I want to learn about data science through multiple university courses in the future," the proportion increased notably (by over 10 points) among DS-inexperienced students (28.7% → 39.5%).

Table 7: Changes in Motivation between Pre-and Post-surveys (By DS Learning Experience)

Motivation	DS Learning Experience		Not at all true	Not very true	Somewhat true	Very true
I want to learn about data science through multiple university courses in the future.(*)	YES(n=246)	Pre	18.7%	41.5%	33.3%	6.5%
		Post	13.0%	41.9%	36.2%	8.9%
	No(n=251)	Pre	29.5%	41.8%	23.1%	5.6%
		Post	23.1%	37.5%	34.7%	4.8%
I want to use data science knowledge and skills in my future job or in society after graduation.(**)	YES(n=246)	Pre	19.5%	41.1%	28.9%	10.6%
		Post	18.7%	37.0%	33.7%	10.6%
	No(n=251)	Pre	29.5%	40.6%	22.3%	7.6%
		Post	25.5%	35.9%	31.9%	6.8%
I want to pursue a career that involves data analysis itself.	YES(n=246)	Pre	48.8%	36.2%	11.0%	4.1%
		Post	32.9%	41.1%	21.1%	4.9%
	No(n=251)	Pre	53.4%	38.6%	5.2%	2.8%
		Post	37.8%	41.4%	17.9%	2.8%

* In the post-survey, participants were asked, "I want to learn about data analysis."

** In the post-survey, participants were asked, "I want to pursue a career that involves data analysis itself."

5 Discussion

This study demonstrated the effective implementation of an introductory DS course tailored specifically for first-year non-STEM students at KUIS. The course's effectiveness was evidenced by its high pass rate (90.3%) and statistically significant improvements in students' self-assessed knowledge and skills.

Moreover, analyses comparing students with and without prior DS learning experience revealed valuable insights. Students lacking prior experience showed greater gains in all knowledge and skill areas, effectively closing the gaps with their peers. This finding underscores the course's effectiveness in supporting students without prior DS exposure and validates the suitability of the instructional design for DS beginners.

In terms of motivation, there was a meaningful increase in students' interest in pursuing careers involving data analysis, highlighting the course's positive impact on career aspirations. However, other aspects of motivation showed only modest improvement, suggesting pedagogical refinement. Future iterations of the course might strengthen motivational outcomes by incorporating more real-world applications, such as case studies from diverse industries or guest speakers representing various professional backgrounds, and by drawing clearer connections between DS and students' future careers.

6 Summary and Issues

This study successfully addressed common challenges in non-STEM DS education—limited numeracy, ICT skills, and low motivation—through the careful course design of a course that utilized accessible tools and practical, real-world data analysis exercises using Tableau. The positive outcomes highlight the course's ability to significantly improve student competency, particularly among DS beginners.

However, several critical issues remain. First, the reliance on voluntary pre- and post-survey responses (covering approximately half the enrolled students) may introduce sampling bias, limiting generalizability. Future evaluations should consider strategies such as mandatory participation, alternative data collection methods, or statistical adjustments to address non-response bias. Second, students' knowledge and skills improved markedly, motivational gains, especially those not directly tied to career aspirations, were less substantial. To address this, future instructional strategies should make explicit connections between DS education and various professional fields, such as international relations, tourism, and media analysis, using testimonials from industry professionals.

While this course provided a strong foundation in DS for non-STEM students at KUIS, further research should address limitations. Ongoing refinement of instructional models, including hybrid delivery formats and targeted strategies to enhance motivation will be essential to sustain and expand the impact of DS education for non-STEM students.

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