Designing Inclusive Data Science Literacy for Non-STEM Majors: A 2023 Baseline and Design-Based Extensions Through 2025

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Abstract

Japan's government has strongly promoted mathematics, data science, and AI literacy across higher education. However, universities respond differently depending on student demographics and institutional philosophy, leading to unique designs for data science education. Against this backdrop, we asked a common question: Does such education raise students' motivation to engage with data science? In 2023, we delivered a university-wide, on-demand literacy course to students from seven faculties ($N \approx 2{,}000$). Pre/post surveys with eight Likert items (mapped to Self-Determination Theory: autonomy, competence, relatedness) were analyzed using two-way repeated-measures ANOVA (time × faculty). Open-ended comments and learning-management logs were used to enrich interpretation. Results showed significant pre–post change on most items, but with notable faculty-level interactions. Gains in perceived fairness of AI and enthusiasm were clear in some groups. In contrast, competence-related confidence declined among others, suggesting that a scalable, on-demand format does not support all learners equally. Guided by these findings and informed by national initiatives at comparable universities, we designed a 2024–2025 expansion plan. This includes exploring the introduction of collaborative learning supported by generative AI, aligning tasks with SDT to strengthen autonomy and competence, and refining documentation of course architecture and engagement metrics. We present the 2023 baseline, explain how it influenced subsequent redesigns, and outline a 2026 evaluation plan that links attitudinal change with behavioral indicators. This work highlights how national policy meets local educational diversity, and how design-based improvement can advance scalable yet inclusive data science literacy.

Keywords: AI literacy, generative AI, first-year university students, data science education, self-determination theory, design-based research

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Introduction

Data science and AI literacy have become foundational competencies for all university students, not only those in STEM disciplines (OECD, 2019). In Japan, national initiatives such as Society 5.0 and the AI Strategy 2019 have heightened expectations that higher education will provide scalable, institution-wide training in data science and AI (Cabinet Office, n.d.; Integrated Innovation Strategy Promotion Council, 2019). However, “one-size-fits-all” course designs can unintentionally amplify disparities: students’ prior experience, academic identity, and learning environment shape whether large-scale education improves motivation and confidence.

This study reports on the 2023 baseline implementation of an on-demand AI/data science literacy course at a private university and connects the baseline findings to a design-based extension through 2025, in a new reality: generative AI has become embedded in everyday academic life (OpenAI, 2023; UNESCO, 2023). Rather than treating 2023 and 2025 as directly comparable datasets, we emphasize the reinterpretation of how the meanings of students’ motivation and competence shift in a post–generative AI context.

Policy Background and Problem Shift (2023 to 2025)

Japan’s policy vision for a “super-smart society” positions data science and AI literacy as key drivers of innovation across sectors (Cabinet Office, n.d.; MEXT, 2022). Universities are therefore expected to provide basic literacy to all students. Previous studies have examined how existing computer literacy courses can be adapted to data science education in Japanese universities, highlighting both opportunities and limitations in curriculum reuse (Arahira & Hashizume, 2022). However, institutional responses vary substantially depending on mission, curriculum structures, and student populations. For example, national universities such as Shiga University have developed institution-wide frameworks to foster data science human resources, illustrating how institutional mission shapes educational design (Tanaka et al., 2022). These differences are especially salient for non-STEM majors, who may have limited prior exposure to technical content and may not see immediate relevance to their academic goals.

The educational landscape changed dramatically between 2023 and 2025. In 2023, many students had little hands-on experience with generative AI. By 2025, generative AI tools will be widely accessible and routinely used for learning and productivity (OpenAI, 2023; UNESCO, 2023). This diffusion creates a methodological and interpretive challenge: the same survey item (e.g., perceived competence) can reflect different underlying concerns before and after generative AI becomes ubiquitous.

Research Questions

This study aims to examine first-year university students’ impressions of AI, with particular attention to how these impressions should be interpreted in the current era of generative AI. It focuses on both students’ initial impressions and the changes observed during course participation. The following questions guide the research:

- RQ1. What impressions of AI (including generative AI) do first-year university students hold at the beginning of an introductory data science course?
- RQ2. How do these impressions change before and after participation in the course?

By addressing these questions, this study seeks to clarify how early-stage university interventions may influence students' perceptions of generative AI and to provide insights into the design of AI literacy education.

Methods

Course Context (2023 Baseline)

We implemented a university-wide, on-demand literacy course intended for broad participation across seven faculties. At Kokushikan University, this literacy course is positioned within the university's AI and Data Science minor program, and the core subject "AI and Science" has been implemented as a university-wide, on-demand requirement since 2023 (Itoh et al., 2024). The course aimed to raise awareness of AI and data science in daily life, while introducing basic concepts and applications. Because the 2023 baseline survey was administered before generative AI became widely adopted in the classroom, the items were originally framed in terms of "AI" in general; in this paper, we interpret these responses as a baseline for students' emerging perceptions of generative AI in later course contexts (Murakami et al., 2018).

Participants and Data

In 2023, pre- and post-course questionnaires were administered to over 2,000 enrolled students, yielding approximately 1,600 valid responses per survey wave across seven faculties. Items were rated on a 7-point Likert scale. In addition, learning management system (LMS) quiz submission records were used descriptively to examine engagement patterns across units. Open-ended comments were collected to enrich interpretation. Survey's target faculties were: Political Science and Economics (F1), Physical Education (F2), Science and Engineering (F3), Law (F4), Literature (F5), Twenty-First Asia (F6), and Business Administration (F7).

Measures and Theoretical Framing

To interpret student motivation, we adopted Self-Determination Theory (SDT), which emphasizes three basic psychological needs—autonomy, competence, and relatedness—as conditions for sustained engagement. Survey items were mapped to SDT-inspired categories and analyzed at both the item and category levels (Deci & Ryan, 1985, 2000; Ryan & Deci, 2017).

In this study, SDT-inspired categories were operationalized as follows. Autonomy was assessed using items Q1 and Q6. Relatedness was assessed using items Q2 and Q3, which reflect students' perceptions of social connection and relevance in learning about AI (including generative AI in later course contexts). Competence was assessed using items Q4, Q5, Q7, and Q8, which captured students' perceived ability, confidence, and understanding of AI (including generative AI in later course contexts). These categorizations were used consistently across descriptive and pre–post analyses. All responses were coded so that higher scores indicate stronger agreement (1 = strongly disagree, 7 = strongly agree).

Analytical Approach

Baseline Analysis (2023)

We conducted a two-way repeated-measures ANOVA with Time (pre/post) as the within-subjects factor and Faculty as the between-subjects factor, using paired responses from students who completed both surveys. Qualitative comments and LMS logs were referenced to contextualize patterns and to suggest plausible mechanisms behind the changes.

Interpretive Extension (2025)

To discuss changes under a post–generative AI environment, we reorganized questionnaire items into three SDT-inspired categories and compared category means descriptively across datasets. Importantly, our goal is not a strict statistical comparison across years, but rather to clarify how the meanings of “motivation” and “competence” evolve as generative AI becomes embedded in academic life (OpenAI, 2023; UNESCO, 2023).

Results

2023 Baseline Study (Before Generative AI Became Ubiquitous)

The on-demand course increased students’ interest in AI and their perception of its relevance to their lives. Across multiple items, significant pre–post changes were observed, and faculty-level interactions indicated that some student groups benefited more than others. Table 1 summarizes the results of the two-way repeated-measures ANOVA examining pre–post changes and faculty differences.

Table 1
Results of a Two-Way Analysis of Variance (ANOVA) for Each Survey Item

SDT Category	Item	Source	F-value	p-value	Partial η^2
Autonomy	Q1	Faculty	5.2859	< .0001	.0112
		Pre/Post Class	5.0906	.0242	.0014
	Q6	Faculty	5.0107	< .0001	.0133
		Pre/Post Class	5.2658	.0219	.0009
Relatedness	Q2	Faculty	1.8956	.0782	.0041
		Pre/Post Class	927.69	< .0001	.1586
	Q3	Faculty	4.8931	.0001	.0123
		Pre/Post Class	2.6005	.1070	.0005
Competence	Q4	Faculty	6.4226	< .0001	.0164
		Pre/Post Class	6.3177	.0121	.0012
	Q5	Faculty	2.6851	.0135	.0066
		Pre/Post Class	39.4221	< .0001	.0083
	Q7	Faculty	2.1221	.0481	.0055
		Pre/Post Class	4.1911	.0408	.0008
	Q8	Faculty	3.4573	.0021	.0091
		Pre/Post Class	58.6774	< .0001	.0107

Note. Partial η^2 indicates effect size.

To facilitate interpretation of these results, Table 2 presents faculty-level mean scores for each item at the pre- and post-survey timings. A key pattern was an “interest–competence gap.” While autonomy- and relatedness-related indicators improved (e.g., greater interest and perceived societal relevance), competence-related confidence did not improve commensurately and in some groups even declined. This suggests that scalable online instruction may raise awareness and curiosity without consistently developing technical self-efficacy.

Table 2
Faculty-Level Mean Scores for Each Survey Item

SDT Category	Item	Period	F1	F2	F3	F4	F5	F6	F7
Autonomy	**Q1**	Pre	5.19	5.09	5.37	5.07	5.35	5.04	5.39
		Post	5.31	5.07	5.54	5.36	5.27	5.09	5.55
	Q6	Pre	5.37	5.45	5.72	5.62	5.37	5.18	5.70
		Post	5.40	5.23	5.61	5.50	5.27	5.61	5.70
Relatedness	**Q2**	Pre	3.04	2.82	3.05	3.17	2.92	2.85	2.91
		Post	4.25	4.15	4.35	4.32	4.04	4.22	4.35
	Q3	Pre	5.48	5.55	5.83	5.88	5.65	5.60	5.66
		Post	5.48	5.38	5.73	5.74	5.63	5.51	5.80
Competence	**Q4**	Pre	4.52	4.69	4.50	4.80	4.22	4.57	4.70
		Post	4.61	4.69	4.79	4.57	4.22	4.92	4.92
	Q5	Pre	5.26	5.24	5.31	5.41	4.97	5.27	5.59
		Post	5.40	5.45	5.57	5.50	5.35	5.32	5.34
	Q7	Pre	4.44	4.68	4.46	4.17	4.32	4.80	4.39
		Post	4.40	4.49	4.36	4.39	4.56	4.42	4.39
	Q8	Pre	4.68	4.59	4.85	4.81	4.66	4.73	4.91
		Post	4.97	4.92	5.22	5.06	4.88	4.79	5.33

Note. Analyses are based on students who responded at each survey timing within each faculty. Due to late attendance and additional responses collected during class, sample sizes differ between pre- and post-surveys across faculties. (e.g., F1: Pre N = 443, Post N = 379; F2: Pre N = 341, Post N = 376; F3: Pre N = 274, Post N = 237; F4: Pre N = 351, Post N = 281; F5: Pre N = 327, Post N = 296; F6: Pre N = 260, Post N = 243; F7: Pre N = 224, Post N = 188). The ANOVA was conducted using available paired responses within faculties.

Interpretive Extension (2025) results are summarized separately to avoid conflating datasets. Table 3 reports unpaired descriptive statistics for the SDT-based category aggregates in 2025 across two survey waves. Because the 2025 results are presented for interpretive purposes rather than for direct pre–post testing, they should not be statistically compared with the 2023 baseline results.

However, the interpretation of “low competence” changes. In 2023, lower competence primarily reflected limited prior exposure and fewer opportunities for hands-on learning. In 2025, similar responses may capture qualitatively different concerns, such as (a) reliance on AI as a cognitive shortcut, (b) anxiety about excessive or inappropriate use, and (c) blurred boundaries between “knowing” and “using AI.” Therefore, time-aware interpretation is essential when using stable survey items across rapidly changing technology contexts.

Table 3
Category Means From Two Survey Waves (Unpaired)

SDT Category	Mean (Pre wave) N = 1764	Mean (Post wave) N = 2053	Δ (Post–Pre)
Autonomy	5.25	5.51	+0.26
Relatedness	4.53	4.72	+0.19
Competence	2.93	3.44	+0.51

Note. Table 3 summarizes 2025 descriptive results at the category level across two survey waves labeled "Pre" and "Post." These waves are not based on matched individual pairs; therefore, the Ns may differ (e.g., due to late participation or additional respondents), and the values should be interpreted as unpaired descriptive summaries rather than as within-student pre–post changes.

Design-Based Extensions (2024–2025) and 2026 Evaluation Plan

Guided by the 2023 baseline, we designed a 2024–2025 expansion plan to improve inclusiveness and support competence development. Related case studies have shown that carefully designed instructional interventions can enhance undergraduate students' motivation to engage with AI-related topics (Murakami et al., 2024). Key directions include introducing collaborative learning opportunities, aligning tasks with SDT (Deci & Ryan, 2000; Ryan & Deci, 2017) to strengthen autonomy and competence, and leveraging generative AI to reduce language and communication barriers in group activities.

For 2026, we outline an evaluation plan that connects attitudinal change with behavioral indicators. In addition to pre- and post-surveys, we plan to incorporate engagement traces (e.g., LMS activity, assignment/quiz submissions) and to document course architecture and learning support structures to enable transparent replication and cross-institutional comparison (UNESCO, 2023).

Discussion

This study illustrates how shared policy-level goals for AI literacy may play out differently in local course settings. Even when learning objectives are aligned, students' responses and perceived learning outcomes can vary depending on faculty characteristics and the learning environment. The observed interest-competence gap suggests that raising interest is necessary but insufficient for inclusive AI literacy; learners also need structured opportunities to build competence and confidence through guided practice, timely feedback, and social support (Ryan & Deci, 2017).

While this study does not provide a direct institutional comparison, the results indicate that differences in course design and educational context can meaningfully shape how first-year students interpret and respond to generative AI. Therefore, the design of introductory courses should prioritize not only motivating content but also scaffolding that reduces anxiety and supports early success experiences (UNESCO, 2023).

The post–generative AI environment complicates the interpretation of "AI readiness." As generative AI becomes a routine tool, educational research should distinguish between confidence in tool use and conceptual understanding, and address emerging ethical and epistemic concerns, including overreliance and the appropriateness of its use in academic work.

Conclusion

In the pre–generative AI baseline (RQ1), the 2023 baseline revealed a clear interest–competence gap in students' perceptions. In the post–generative AI context (RQ2), the same pattern persists, but the meaning of competence-related responses must be reinterpreted under new learning conditions. Overall, time-aware, design-based perspectives are essential for advancing scalable yet inclusive AI and data science literacy.

The revised 2025 survey instrument is publicly available to promote transparency and facilitate future collaboration.[1]

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Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

The author declares that Grammarly, an AI-assisted writing tool, was used to proofread and refine the manuscript's language. The use was limited to correcting grammatical and spelling errors and to rephrasing statements to improve accuracy and clarity. The author further declares that, apart from Grammarly, no other AI or AI-assisted technologies have been used to generate content in writing the manuscript. The ideas, design, procedures, findings, analyses, and discussion are original and derived from the appropriate and systematic conduct of the research.

[1] The survey instrument is available via Microsoft Forms at: https://forms.office.com/Pages/ShareFormPage.aspx?id=3VQExGOyJkmGjY4SZA03UFixcM1E-VdBqU845cOTGLRUNTY4WDhQMFA2VlRLUlYwRldBQzE2Q1dTOS4u&sharetoken=wQTyHjDtHMAse4lbTd85

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