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ANALYSIS OF IMPACT OF DATA SCIENCE AND ARTIFICIAL INTELLIGENCE EDUCATION ON MOTIVATION AND CAREER DEVELOPMENT

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Abstract. *As social expectations of data science and Artificial Intelligence (AI) increase and their application to various industrial fields advances, greater emphasis is being placed on data science and AI related education. In this study, we ascertained the impact of data science and AI education on learners' motivation and career development by analyzing a lecture-style course offered as part of mathematical and data science education at Tokyo City University, Japan. The course analyzed was Data Science Literacy 1 (DS1). The analysis period spanned three academic years, from 2020 to 2022. The analyzed items were three motivational factors derived from expectancy-value theory, namely intrinsic value, attainment utility value, and expectations for success. A fourth factor, career development, was also analyzed. We collected data pertaining to the four factors, that is, the three above mentioned motivational factors and career development, through questionnaires administered to DS1 learners. Regarding data analysis, learners were classified according to the values (high vs. low) they reported for each of the four factors of interest at the beginning of the course. These were compared to the values reported at the end of the course. Results showed increases in all the motivation factors. The increasing trend was particularly pronounced among learners who initially reported low values. Although trends differed from year to year, the results suggest that data science and AI education can positively impact motivational factors and related career development.*
Keywords: Data science and AI education, Motivation, Career development, Expectancy-value theory, Questionnaire survey

1. **Introduction.** In recent years, the amount of data that can be obtained through the Internet of Things (IoT) devices and Social Networking Services (SNSs) circulating in society has become enormous, and the way in which data are utilized has become increasingly important. To realize Society 5.0 [1], the government of Japan adopted the Artificial Intelligence (AI) Strategy [2] in 2019 and set a goal that all university and technical college students should acquire basic knowledge of data science and AI by 2025, with about half gaining proficiency at the applied level. Data science and AI related

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education is currently attracting attention and being recognized as important across the sciences as well as the humanities.

The expectancy-value theory [3] is widely used to explain and predict learners' learning performance, persistence and aspirations, e.g., in the STEM (Science, Technology, Engineering, and Mathematics) education [4] and in the language learning [5]. The definitions of crucial constructs in the model, including ability beliefs, expectancies for success, and the components of subjective task values, are discussed in [6, 7].

Omae et al. [8] investigated the impact of AI educational practices on motivation and career development among elementary school students. The educational practices of interest were conducted from December 2019 to the end of January 2020 among fifth graders in Yamanashi Prefecture, Japan. Specifically, Educational Practice A focuses on providing knowledge about AI, and Educational Practice B has learners propose AI. The evaluation criteria for these practices are as follows. AI career development is defined as "acquiring a desire to contribute to society using AI". Motivational factors are defined by referencing American educational psychologist Eccles' expectancy-value theory [3], where intrinsic value is intrinsic learning motivation, attainment utility value is the subjective importance of success in learning and comprises attainment value and perceived utility of the learning content, and expectations for success refer to the learner's confidence in the learning content. These evaluation criteria are described in detail in Section 3, as they are closely related to this study. Omae et al. analyzed the impacts of AI educational practices on motivation and career development by administering questionnaires on intrinsic value, attainment utility value, expectations for success, and career development immediately before and after implementation of Educational Practices A and B. The results showed increases in all factors, suggesting that the educational practices had a positive impact on motivation and career development. Additionally, the results of detailed path analysis suggest that these educational practices increased AI motivational factors and that the investigated factors had an indirect impact on career development.

Lin et al. [9] discussed to model the structural relationship among primary school students' motivation to learn artificial intelligence by using Attention-Relevance-Confidence-Satisfaction model (ARCS model) [10]. Note that ARCS model is one of effective methods of understanding the influences on the motivation to learn [10]. Chen et al. [11] pointed out that there is a lack of studies adopting educational framework to investigate the learning motivation among AI learners.

In this study, we analyzed how data science and AI related education for university learners/students (hereafter, we use learners) affected their motivation and career development. Specifically, we focused on the Data Science Literacy 1 (DS1) course offered at Tokyo City University, Japan. DS1 is a part of the Basic Education Program in Mathematical and Data Science, a minor program in mathematical and data science education [12] that is offered to all departments, especially targeting those directly unrelated to information science and technology. The aim of mathematical and data science education is to cultivate data science literacy and mathematical education in all learners and enable them to play an active role in various fields, considering the current background of increasing social expectations of data science education and its application to various industrial fields. The analysis method this study adopted is based on Omae et al. [8], but this study's methodology differed in that the analysis subjects were university learners, as this study sought to investigate the impacts of the abovementioned education practices on future motivation and career development among university learners on the verge of entering the work world.

The paper is organized as follows. In Section 2, we briefly explain the outline of the lectures (DS1) on data science and AI at Tokyo City University, Japan. In Section 3, we provide an overview of the questionnaire and analysis methods, which we use in this study. In Section 4, we present the analysis results of the impacts of DS1 on motivation and career development. We also discuss the comparison of the analysis results and the content of the lecturer interviews. And Section 5 is devoted to a summary.

2. **Lectures on Data Science and AI at Tokyo City University.** The educational practice addressed in this study's data analysis was DS1 at Tokyo City University (TCU), Japan, in the academic years spanning 2020 to 2022. The course is delivered in the form of "classroom lectures" with the objective of having learners understand familiar data science applications and data visualization methods; learners engage in "group work" to confirm their understanding. The course allows learners to experience data analysis using deep learning tools, thus providing an opportunity for independent data analysis. After the lectures, learners are given quizzes to assess their level of understanding. In an interview setting, the faculty in charge of the lecture series [13] stated that DS1 is designed to have everyone understand the lecture content and enable even learner previously uninterested in data science and AI to study the topic with interest after attending the lectures. Therefore, DS1 is offered in all departments of TCU.

The lecture topics, syllabus [14], and lecture materials [15] are briefly shown in the upper half of Figure 1. Generally, the first lecture is an introduction that provides an overview of the course and explains the significance of acquiring data science literacy and learning the content to be studied. The second lecture is a group discussion on topics of interest in data science, AI, and data analysis, highlighting their advantages and disadvantages; the aim is to prompt learners to rethink what interests them about data science. The third lecture provides examples of everyday data science applications as well as applications in social and public systems. In the fourth lecture, learners form groups to discuss issues they want to resolve using data science and give related presentations detailing problem-solving strategies, the beneficiaries of the proposed solution, and the input/output information necessary to solve the problem. Lectures 5-7 are on data collection and visualization. These lectures explain the types of data, data collection methods, and open data flow and incorporate analysis exercises using open data, as well as explanations of situations requiring visualization and typical methods. Learners select text data

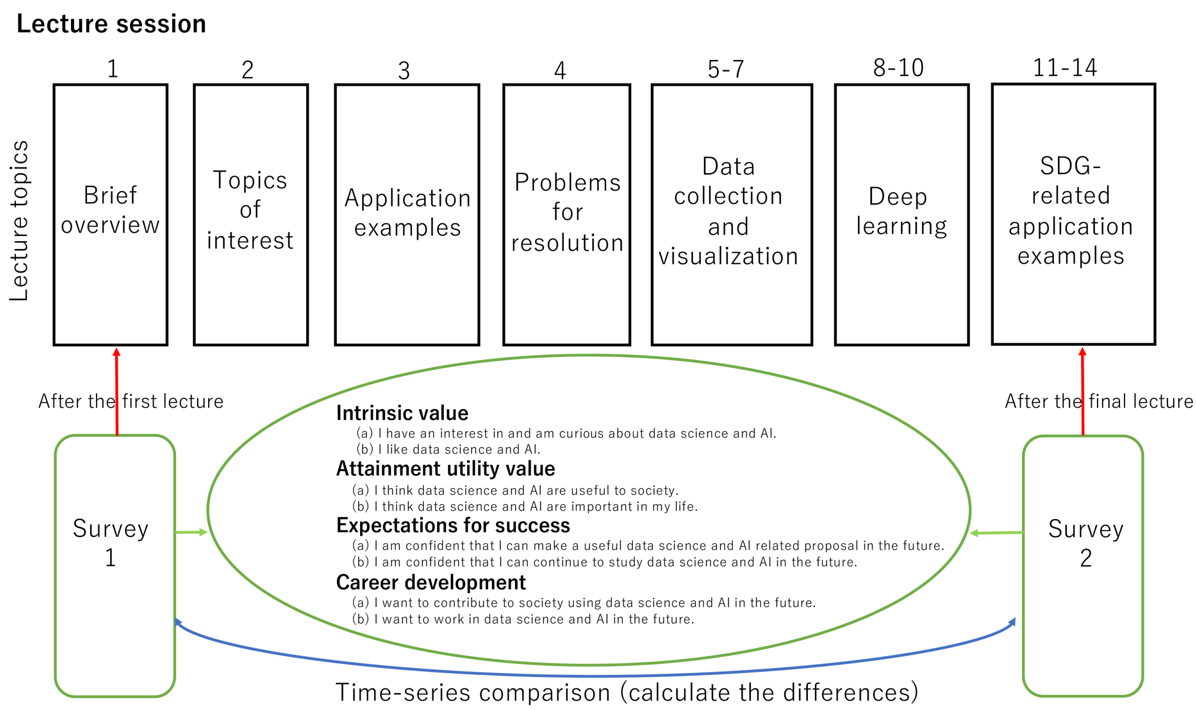

Figure 1. Overview of the DS1 lecture series and the questionnaire developed in this study

they want to analyze, examine the content using analysis techniques such as Word Cloud, and have an opportunity to participate in a group presentation and practice visualizing data using spreadsheet software. Lectures 8-10 focus on deep learning; learners are given an overview and then progress to learning about the overall structure and model-based learning methods. An example is a project that uses deep learning to identify the numbers 4 and 9 in handwriting. Specifically, to practically experience deep learning, learners build a program to discriminate numerals ranging from 0 to 9 in handwriting using Sony's Neural Network Console [16] and try to improve the discrimination accuracy. After completing the exercise, learners form groups and discuss improving the model's accuracy. The theme of the Lectures 11-14 is "Exploring the Application of Data Science to Sustainable Development Goals (SDGs)". Groups of learners select one of the SDG goals, discuss how data science can be applied to achieving it, and give a related presentation. This exercise prompts learners to summarize the course content, with the aim of helping learners realize that data science can be useful in solving social issues. (Note that due to the effects of the novel coronavirus (COVID-19) pandemic and the departmental course schedule, some iterations of DS1 in 2020 only ran for 12 lectures.)

3. Questionnaire and Analysis Methods.

3.1. Overview of the questionnaire survey. A questionnaire was administered in DS1 to investigate its impact on motivation and career development. As shown in Figure 1, the questionnaire was administered twice: once after the first lecture and again after the last lecture. The questionnaire comprises items related to three motivational factors, namely intrinsic value, attainment utility value, and expectations for success, and career development, with reference to Omae et al. [8].

Eccle's expectancy-value theory [3], which is one among the motivational theories, asserts that intrinsic value (intrinsic motivation to learn), attainment value (the subjective importance of success in learning), utility value (the perceived validity of learning items), expectations for success (the learner's confidence in the learning content), and cost (the psychological burden of learning) with respect to a particular field influence the strength of a learner's motivation to achieve. Omae et al. [17] showed that the factors comprising Eccles' expectancy-value theory can explain future career choices and noted that improvement across the five factors is desirable to promote career development. Additionally, Omae et al. [17] explained that it is not necessarily appropriate to promote career development by decreasing cost. Ichihara and Arai [18] also pointed out that there is no clear distinction between attainment value and utility value; hence, those scholars integrated them as a single concept called attainment utility value. Further, Omae et al. [8] integrated attainment value and utility value into attainment utility value and excluded cost, a precedence that the present study followed.

In this study, career development is defined as "acquiring the desire to contribute to society using data science and AI".

The following are the questionnaire items used to measure each of the four factors of interest in this study.

Intrinsic value:
- (a) I have an interest in and am curious about data science and AI.
- (b) I like data science and AI.

Attainment utility value:
- (a) I think that data science and AI are useful to society.
- (b) I think that data science and AI are important in my life.

Expectations for success:
- (a) I am confident that I can make a useful data science and AI related proposal in the future.

(b) I am confident that I can continue to study data science and AI in the future.

Career development:

(a) I want to contribute to society using data science and AI in the future.

(b) I want to work in data science and AI in the future.

The questionnaire was designed such that two items correspond to each investigated factor. During analysis of the questionnaire responses, the difference (after the first vs. last lecture) between respondents' answers to these questions was calculated, and learners whose answers to items under the same factor showed a significant difference were excluded (for a detailed description of the exclusion criteria, see Section 3.2).

The 8-item questionnaire reproduced above was administered in 2021 and 2011. In 2020, 7-item questionnaire with only one item (a) on career development was used. The question order was randomized, and responses were on a 10-point scale (ranging from 1: *strongly disagree* to 10: *strongly agree*). Participating DS1 learners were assured that completing the questionnaire would not impact their course grade. Respondents were instructed to answer each question intuitively, that is, without thinking and in approximately 5 second.

3.2. **Analysis method.** Time-series comparative analysis was performed with reference to Omae et al. [8]. As described in Section 3.1, we conducted time-series comparative analysis of an 8-item questionnaire on intrinsic value, attainment utility value, expectations for success, and career development after the first and final DS1 lectures. The exclusion criteria were as follows: Learners who attended only one of the first and last lectures were excluded from the analysis in order to facilitate time-series comparison; learners who completed the questionnaire multiple times, those who completed the questionnaire 72 hours after the end of the lecture, and those whose responses to all eight questions were identical were also excluded.

The mean of individual learners' responses was obtained for the two items measuring each of the four factors and converted to a value in the range 0-1. Means and standard deviations for all learners were then calculated. Differences were calculated to determine whether the measured factors increased significantly between the first and last lecture, and a one-tailed paired comparison t-test was conducted.

Results showed that there were some learners who reported the highest possible scores for intrinsic value, attainment utility value, expectations for success, and career development at the end of the first lecture. Since it was impossible to measure increases for these learners using the method adopted in this study, we excluded learners who reported the maximum scores at the end of the first lecture from the analysis. Considering that the mean of each factorial question pair was taken, we excluded from the analysis cases in which the difference between the two items measuring each of the four factors was clearly different from that of the other learners. Specifically, we calculated the mean and standard deviation of the differences in the responses to the two questions measuring the four factors after the first and last lectures, respectively, and excluded learners whose responses were more than $\pm 3\sigma$ (σ means standard deviation) away from the mean of the differences. The final analysis only included learners who completed the questionnaire after the first lecture and after the last lecture.

We further analyzed the results by classifying learners with high and low initial scores for the four factors. We calculated the median of the means of the four factors after the first lecture, classified the learners who scored below the median into the low initial value group and those who scored above the median into the high initial value group, and analyzed the resultant data.

4. **Analysis of the Impacts of the Educational Practice on Motivation and Career Development.** Table 1 shows the number of survey responses collected and the proportion to which Conditions 1 and 2 applied.

Condition 1: Number of learners remaining after excluding learners who responded multiple times, learners who responded 72 hours after the end of the lecture, and learners who provided identical responses to all questions.

Condition 2: Number of learners who met Condition 1 and attended both the first and the last lecture.

The number of analysis subjects was 613 in 2020, 1,031 in 2021, and 983 in 2022. The year 2020 was the first in which DS1 was offered, and thus, enrollment was low, resulting in a smaller number of respondents/analysis subjects compared to 2021 and 2022.

TABLE 1. Number of questionnaires collected

Year	First class	Final class	First class (Condition 1)	Final class (Condition 1)	Condition 2
2020	797	748	758	702	613
2021	1,385	1,199	1,324	1,108	1,031
2022	1,569	1,195	1,450	1,064	983

4.1. **Comparison of the three academic years.** To see the overall trends, we analyzed combined data. The exclusion criteria described in Section 3.2 were applied as follows:

Exclusion 1: Learners who reported maximum values as of the end of the first lecture.

Exclusion 2: Learners whose scores were more than $\pm 3\sigma$ away from the mean of the difference between the scores for the question pairs.

Table 2 shows the results of the analysis described in Section 3.2 for the period 2020-2022.

In the academic year 2020, from the upper panel of Table 2, we find that intrinsic value, attainment utility value, expectations for success, and career development increased between the first and last lectures. A paired one-tailed t-test confirmed that the increases were significant ($p < 0.01$) for all four factors. This suggests that DS1 had a positive impact on intrinsic value, attainment utility value, expectations for success, and career development.

From the middle panel of Table 2, we find that intrinsic value, attainment utility value, expectations for success, and career development increased in the academic year 2021. The t-test results confirmed that the increases were significant ($p < 0.01$) for intrinsic value, attainment utility value, and expectations for success, as well as for career development ($p < 0.10$). This suggests that the DS1 lecture series had a positive impact on intrinsic value, attainment utility value, expectations for success, and career development.

From the lower panel of Table 2, we find that intrinsic value, attainment utility value, and expectations for success increased, whereas career development decreased in academic year 2022. The t-test results showed that the increases in intrinsic value and attainment utility value were significant ($p < 0.01$), as was that for expectations for success ($p < 0.05$), and the decrease in career development was also significant ($p < 0.05$). Although the results for expectations for success were only significant at $p < 0.05$, it is suggested that the first lecture had a positive impact on the learners' intrinsic value, attainment utility value, and expectations for success. On the other hand, it cannot be said that the lecture had a positive impact on career development.

In each year of interest, the mean of attainment utility value was high, whereas that of expectations for success was low. We can also confirm that the mean of expectations for success was lower than those for the other factors, and the mean of attainment utility value was higher. Regarding attainment utility value, over 10% of the learners reported the maximum score after the first lecture. Considering the course content, we believe that attainment utility value was based on the perception that data science is useful for

Table 2. Means (standard deviations) and differences for measured factors (2020-2022). Means and standard deviations are rounded to two decimal places.

2020 Factor	Number of analysis subjects (persons)	Exclusion 1 (persons)	Exclusion 2 (persons)	First	Final	Comparison (Final − First)
Intrinsic value	561	29	23	0.60 (0.20)	0.63 (0.21)	+0.033 ***
Attainment utility value	530	71	12	0.75 (0.13)	0.79 (0.15)	+0.039 ***
Expectations for success	602	0	11	0.48 (0.19)	0.49 (0.19)	+0.016 ***
Career development	566	47	*N/A	0.59 (0.20)	0.62 (0.23)	+0.025 ***
2021 Factor	Number of analysis subjects (persons)	Exclusion 1 (persons)	Exclusion 2 (persons)	First	Final	Comparison (Final − First)
Intrinsic value	936	64	31	0.62 (0.20)	0.65 (0.22)	+0.029 ***
Attainment utility value	846	164	21	0.77 (0.14)	0.81 (0.15)	+0.037 ***
Expectations for success	1,010	4	17	0.50 (0.20)	0.52 (0.21)	+0.021 ***
Career development	975	31	25	0.56 (0.22)	0.57 (0.23)	+0.0096 *
2022 Factor	Number of analysis subjects (persons)	Exclusion 1 (persons)	Exclusion 2 (persons)	First	Final	Comparison (Final − First)
Intrinsic value	880	68	35	0.62 (0.19)	0.63 (0.21)	+0.015 ***
Attainment utility value	775	193	15	0.77 (0.13)	0.79 (0.16)	+0.020 ***
Expectations for success	957	10	16	0.49 (0.19)	0.50 (0.22)	+0.012 **
Career development	915	45	23	0.58 (0.20)	0.57 (0.22)	−0.011 **

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$
*N/A due to there being only one question on career development

solving current social issues and that lecture attendance strengthened this perception. The increase in the difference for attainment utility value was also larger than that for any other factor. Intrinsic value and attainment utility value showed significant ($p < 0.01$) increases in all three years, whereas expectations for success showed a significant ($p < 0.01$) increase in the academic years 2020 and 2021 and in academic year 2022 ($p < 0.05$). Therefore, although expectations for success significantly ($p < 0.05$) increased in 2022, the results suggest that DS1 had a positive impact on the motivational factors as the course was able to improve learners' intrinsic value, attainment utility value, and expectations for success. In particular, the lectures may have had a positive impact on attainment utility value. On the other hand, for career development, a significant ($p < 0.05$) decrease was observed in 2022, as well as a slight significant ($p < 0.10$) increase in 2021 and a significant ($p < 0.01$) increase in 2020. Although there was a significant ($p < 0.01$) increase in 2020, it should be noted that the 2020 questionnaire only included one item (a) on career development. It is possible that the lectures failed to positively impact career development among those learners not specialized in information science and technology because they could not visualize the connection with their future career.

TABLE 3. Analysis results for the high and low initial value groups showing means (standard deviation) and differences for the measured factors (2020-2022)

2020 Factor (median value)	Group (number of subjects)	Initial	Final	Comparison (Final − First)
Intrinsic value (0.61)	High value group (264)	0.77 (0.079)	0.74 (0.15)	−0.027 ***
	Low value group (297)	0.45 (0.15)	0.53 (0.20)	+0.086 ***
Attainment utility value (0.78)	High value group (200)	0.88 (0.038)	0.85 (0.12)	−0.031 ***
	Low value group (330)	0.67 (0.11)	0.75 (0.16)	+0.081 ***
Expectations for success (0.50)	High value group (241)	0.66 (0.10)	0.62 (0.16)	−0.038 ***
	Low value group (361)	0.36 (0.12)	0.41 (0.17)	+0.052 ***
Career development (0.67)	High value group (166)	0.82 (0.055)	0.77 (0.17)	−0.056 ***
	Low value group (400)	0.50 (0.16)	0.56 (0.22)	+0.058 ***
2021 **Factor (median value)**	**Group (number of subjects)**	**Initial**	**Final**	**Comparison** **(Final − First)**
Intrinsic value (0.67)	High value group (382)	0.80 (0.068)	0.77 (0.16)	−0.025 ***
	Low value group (554)	0.49 (0.16)	0.56 (0.21)	+0.065 ***
Attainment utility value (0.78)	High value group (377)	0.88 (0.040)	0.87 (0.12)	−0.0094 *
	Low value group (469)	0.68 (0.12)	0.75 (0.15)	+0.074 ***
Expectations for success (0.50)	High value group (470)	0.67 (0.10)	0.63 (0.18)	−0.041 ***
	Low value group (540)	0.35 (0.13)	0.42 (0.19)	+0.074 ***
Career development (0.56)	High value group (478)	0.74 (0.10)	0.70 (0.17)	−0.039 ***
	Low value group (497)	0.39 (0.15)	0.44 (0.21)	+0.056 ***
2022 **Factor (median value)**	**Group (number of subjects)**	**Initial**	**Final**	**Comparison** **(Final − First)**
Intrinsic value (0.67)	High value group (331)	0.81 (0.068)	0.77 (0.16)	−0.035 ***
	Low value group (549)	0.51 (0.14)	0.55 (0.20)	+0.045 ***
Attainment utility value (0.78)	High value group (336)	0.88 (0.041)	0.85 (0.14)	−0.033 ***
	Low value group (439)	0.68 (0.11)	0.74 (0.16)	+0.061 ***
Expectations for success (0.50)	High value group (416)	0.67 (0.10)	0.62 (0.18)	−0.045 ***
	Low value group (541)	0.36 (0.12)	0.41 (0.20)	+0.055 ***
Career development (0.61)	High value group (378)	0.77 (0.083)	0.71 (0.18)	−0.068 ***
	Low value group (537)	0.44 (0.14)	0.47 (0.20)	+0.030 ***

***: $p < 0.01$, *: $p < 0.10$

4.2. **High and low initial value groups.** Table 3 shows the analysis results for two groups of learners classified as of the end of the first lecture: the high initial value group, in which the mean of four factors was higher than the median, and the low initial value group, in which the mean of four factors was equal to or lower than the median.

Examining the results for the three academic years altogether, it can be confirmed that, for the high initial value group, only attainment utility value in the academic year 2021 decreased significantly ($p < 0.10$), whereas intrinsic value, attainment utility value, expectations for success, and career development decreased significantly ($p < 0.01$) for all the other years of interest.

In the low initial value group, intrinsic value, attainment utility value, expectations for success, and career development increased significantly ($p < 0.01$) across the entire period of interest. The results suggest that for learners who reported low scores for the four factors after the first lecture, the course had a positive impact on their three motivational factors and career development.

Evidently, it is difficult to affect the improvement among learners who reported high scores across the four factors after the first lecture given their already high expectations. However, for the low initial value group, intrinsic value, attainment utility value, expectations for success, and career development all increased significantly ($p < 0.01$), suggesting that lecture attendance led to enhancement in these areas. These results support the course aim of affecting improvements in learners who report low scores on motivational factors and career development at the outset.

4.3. **Comparison of analysis results and the content of the lecturer interviews.** We presented the analysis results to the DS1 lecturers and interviewed those faculty members [13].

First, we solicited their opinions on and impressions of the analysis results from the standpoint of those who designed and delivered the lectures. The interviewees indicated that the increases in intrinsic value, attainment utility value, expectations for success, and career development were in line with the lecture design and content. Although they could not give a clear reason for the lack of increase in career development in some years, it was pointed out that there may have been poor correspondence between the course content and the questionnaire content in this regard. DS1 is intended for first-year learners, and one of the main objectives is to pique the interest of learners who were not previously interested in data science and AI and help learners recognize the importance of data science generally as well as to their specialized academic pursuits. Hence, the course emphasizes the basics. Therefore, the interviewed lecturers perceived a discrepancy between the course content and the representation of career development in the questionnaire developed in this study, especially with regard to Item (b). Unlike senior learners who are hyper-focused on the job search, first-year learners may not be able to grasp a direct link between the course content and their career development. Therefore, the interviewees mentioned the necessity of changing the questionnaire items on career development to achieve better alignment with the educational content.

The interviewees also reconfirmed that the analysis results supported the aim of the course given the strong inference that "the lectures resonated well" with learners in the low initial value group. On the other hand, the interviewees interpreted the fact that "the lectures did not resonate" with the learners in the high initial value group to mean that the course may not sufficiently stimulate learners who enter with strong motivation and career development intentions, a gap that could be remedied through the addition of appropriate assignments.

The fact that attainment utility value showed high scores in all years indicated the possibility that the group work on the SDGs conducted at the end of the course had a significant impact on the questionnaire results.

The results of this analysis showed that there were some areas where the observed increase was not as expected, especially in the academic year 2022. It was deemed necessary to rethink the reason(s) for the lack of increase in 2022, including whether this was due to the characteristics of the learners in 2022. In the year 2022, the number of questions from learners increased with the post-COVID-19 resumption of face-to-face lectures, but the number of learners per classroom also increased, and lecturers felt that class management was challenging. Although it is very difficult to design a universally effective course that resonates with learners with both low and high initial motivation and career development intention, we concluded the interviews after the lecturers indicated the need for provisions to ensure that learners with high initial motivation and career development are sufficiently stimulated during the course.

5. **Summary.** In this study, we analyzed the effect of data science and AI related education on university learners' motivation and career development. Specifically, we conducted time-series analysis to investigate the impact of the DS1 course offered in the academic years 2020 to 2022 on learners' motivation and career development. Analysis results confirmed that lecture attendance contributed to increases in intrinsic value, attainment utility value, and expectations for success. Thus, although the results trends differed from year to year, the overall results suggest that the course had a positive impact on motivational factors and career development related to data science and AI.

The more detailed analysis should be performed, e.g., the detailed path analysis. We will report the results elsewhere.

Since DS1 will continue to be offered in the future, it is important to accumulate and continue to utilize course-related data and continuously sharpen the analysis methods used to approach it. Moreover, as Omae et al. [8] pointed out, because the second questionnaire is collected after the final lecture, there is no guarantee that any enhanced motivation and career development observed will be maintained in the long term. Therefore, it is necessary to continue to contemplate ways to analyze increases and decreases in factors of interest, as well as strategies for maintaining improvements in relevant areas. For instance, it is important to design educational content that maintains and further enhances improved learner motivation and career development, as well as educational material that strengthens the relationship of data science and AI to learners' diverse specialties.

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