Exploring the Impact of AI Anxiety on First-Year University Students' Data Science Education

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Abstract
As university students have begun to use generative AI daily, their anxiety and attitudes toward AI have changed. Anxiety and attitude toward the learning object may be factors that prevent students from being motivated to learn. This study explores the impact of AI anxiety on first-year university students' willingness to learn and satisfaction with their data science education. We developed questions on impressions of AI from a questionnaire based on the Artificial Intelligence Anxiety Scale and the General Attitudes Towards Artificial Intelligence Scale. The survey was administered to students entering Hiroshima University in 2024. We conducted a factor analysis and identified six factors measuring impressions of AI. We hypothesized two processes as the influence of impressions of AI on university students' education: 1) a three-stage influence of negative attitudes towards AI on their willingness to learn and, consequently, on their teaching on data science; 2) a direct influence of negative attitudes towards AI on their teaching on data science. We tested these assumptions through a covariance structure analysis. We found that negative attitudes towards AI affect the willingness to learn negatively, and the willingness to learn AI positively affects students' sufficiency in class. This means that the hypothesis 1) is confirmed. We also found that the negative attitude did not affect students' ability to be sufficient in class. We can show the possibility of an effective class design for students regardless of their attitude toward AI.

Keywords: AI Anxiety, Generative AI, First-Year University, Data Science Education, Scale Development

Introduction

Data science forms a crucial foundation for the modern information society, making it essential knowledge for all university students. AI literacy has become increasingly important with the growing integration of artificial intelligence (AI) technologies across various domains. However, the Ministry of Internal Affairs and Communications (2024) reports that the individual utilization rate of generative AI in Japan is only 9.1%, significantly lower than that of countries like China (56.3%) and the United States (46.3%). This stark disparity highlights the pressing need for enhanced AI education to bridge the gap and equip Japanese students with the skills to navigate an increasingly AI-driven global landscape. Addressing these challenges requires a strategic approach to AI education, particularly at the university level.

Japan Inter-University Consortium for Mathematics, Data Science, and Al Education (2024) published a model curriculum in 2018, emphasizing the promotion of AI education. In its revised 2024 edition, the curriculum incorporated generative AI content, reflecting this technology's rapid spread and transformative impact. This proliferation of generative AI has significantly influenced how students perceive AI, necessitating adjustments in educational approaches to AI instruction. Understanding these shifting perceptions is key to designing effective AI education.

Although AI education aims to enhance students' understanding and utilization of AI technologies, previous studies have highlighted that some students hold negative attitudes toward AI, characterized by concerns such as job displacement, misuse, or loss of control. These concerns are often linked to "AI anxiety," a concept encompassing apprehension about learning and using AI technologies and fears about their societal implications. The anxiety has been shown to affect students' motivation to learn and their willingness to engage with AI-related content, which are critical factors for educational success. Investigating these factors provides insights into addressing the barriers to effective AI education.

This study explores the perceptions and concerns of first-year university students at Hiroshima University regarding AI and generative AI. Specifically, it investigates how AI anxiety and attitudes influence students' learning motivation and satisfaction with data science education. By examining these relationships, the study seeks to provide insights into effective educational practices that address students' evolving needs in the era of generative AI. These findings will contribute to developing tailored strategies for overcoming AI-related barriers in higher education.

Background

The concept of AI anxiety has been extensively studied, with researchers identifying multiple dimensions, such as learning-related anxiety, fear of job displacement, concerns about sociotechnical blind spots, and discomfort with humanoid AI configurations (Wang & Wang, 2022). Among these, fears regarding AI's societal and ethical implications resonate strongly with the rapid and widespread adoption of advanced technologies. Supporting this, a recent study conducted at an international university in Japan found that 65% of students identified unemployment as the most pressing ethical issue related to AI (Ghotbi & Mantello, 2022). Additionally, 13% of students highlighted concerns about AI's impact on human emotions and behaviors. These findings underscore the significant role of societal problems, such as job displacement and emotional AI, in shaping students' attitudes toward AI. Addressing these concerns in educational contexts is critical to alleviating AI-related anxieties and fostering positive engagement with AI technology.

Japan's national education goals emphasize that all university students should have the foundational knowledge of data science and AI. However, the data science curricula in Japanese universities have space for improvement in the rapid proliferation of generative AI. Generative AI accessibility has made AI more familiar to students. Still, their perceptions of AI have been complicated, and an educational approach is required to address these nuanced and evolving attitudes.

Given these factors, it is crucial to reassess students' perceptions of AI, including their anxieties and attitudes, in light of the rapid advancements in AI technologies. Understanding these aspects can contribute to designing effective data science education programs, such as integrating AI ethics discussions and hands-on activities with generative AI tools that mitigate negative attitudes and foster a more positive and productive engagement with AI.

Method

Development of a Scale

To evaluate first-year university students' perceptions of AI, this study utilized and adapted existing scales: the Artificial Intelligence Anxiety Scale (AIAS) (Wang & Wang, 2022) and the General Attitudes towards Artificial Intelligence Scale (GAAIS) (Schepman & Rodway, 2020). These scales were used as the basis for creating a questionnaire tailored to the context of Japanese university students. Below, we review each of its features and subscales.

The AIAS (Wang & Wang, 2022) is a validated scale designed to measure individuals' anxiety about AI. This scale identifies four key dimensions of AI anxiety: learning anxiety, job replacement anxiety, sociotechnical blindness, and AI configuration anxiety**.** For this study, three items with the highest factor loadings from each subscale (12 items) were translated into Japanese and included in the questionnaire. This allowed for a comprehensive evaluation of students' anxieties regarding AI in various contexts.

The GAAIS (Schepman & Rodway, 2020) measures individuals' general attitudes toward AI, distinguishing between positive and negative perceptions. This study focused exclusively on the positive subscale, as its items differed from the AI anxiety scale. Positive items include statements reflecting curiosity and perceived benefits of AI, such as its ability to enhance societal progress and personal convenience.

All items are presented on a seven-point Likert scale, ranging from 1 ("Strongly disagree") to 7 ("Strongly agree"). They were translated into Japanese to ensure cultural and linguistic appropriateness for the target population. The items were also pilot-tested to confirm clarity and alignment with the measured constructs.

To refine the scale and determine its factor structure, an exploratory factor analysis (EFA) was conducted using the initial questionnaire responses. The number of factors was estimated using a scree plot and further evaluated based on fit indices, including Root Mean Square Error of Approximation (RMSEA) and Bayesian Information Criterion (BIC). This process guided the selection of the factor structure most appropriate for the data.

McDonald's omega coefficients were calculated to evaluate the internal consistency of the identified factors. Factors with omega values above the generally accepted threshold of 0.7 were considered reliable, while factors slightly below this threshold were retained if they demonstrated conceptual validity.

Participants and Survey Environment

The survey targeted first-year students enrolled at Hiroshima University in April and June 2024. A total of 1816 students responded from various faculties, including Medicine, Law, Dentistry, Pharmacy, Engineering, Information Sciences, Education, Letters, Science, Applied Biological Science, Economics, and the Faculty of Integrated Arts and Sciences. The participants' diverse academic backgrounds allowed for a broad assessment of perceptions toward AI across disciplines.

The questionnaire survey was conducted in a foundational data science course titled "Introduction to Information and Data Sciences." This course aims to provide students with essential knowledge and skills in information science and data science. The course included lectures, individual assignments, and group discussions. The students completed a questionnaire survey before the start of the course content to capture students' initial perceptions of AI without the influence of the course materials. During group discussions, students experienced a generative AI tool, such as HiGPT (Murakami et al., 2024). The tool facilitates communication, summarizes ideas, and provides an authentic context for interacting with AI applications.

The structure of the course was as follows:

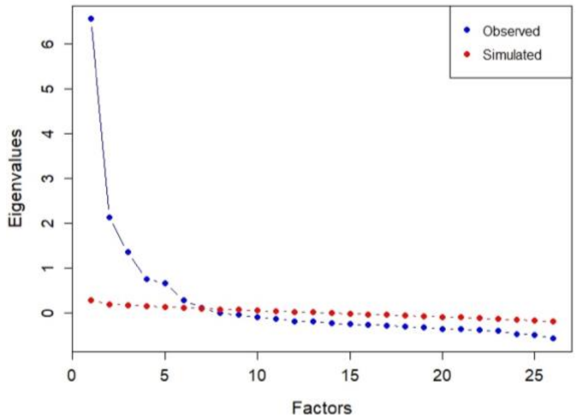
- Pre-class survey: Students completed a questionnaire measuring AI anxiety, motivation, and impressions of AI.
- Lectures and Videos: The course introduced generative AI tools such as HiGPT through instructional videos and discussions.
- Group Discussions: Students participated in group discussions facilitated by the generative AI tool HiGPT on topics like "Can humans and AI become friends?" The tool supported communication, summarized ideas, and enhanced collaborative discussions.
- Post-class survey: Students were asked to evaluate their satisfaction with course components, including the videos, discussions, and generative AI tools. The survey environment was carefully designed to align with the course's objectives while maintaining the integrity of the data collection process. This educational context provided a rich environment for exploring the relationship between students' AI anxiety and motivation and the effectiveness of generative AI tools in a collaborative learning setting.

Model Construction and Fit Evaluation

To investigate the relationship between students' AI anxiety, motivation, and satisfaction with data science education, we adopted a structural equation modeling (SEM) approach. Wang et al. (2022) investigated the impact of AI anxiety on students' AI learning behavior. They used structural equation modeling to examine how learning motivation and self-efficacy affect AI learning intentions. Based on this research, we examined the impact of each of the three elements individually:

1. Negative Attitudes Toward AI (Anxiety): Represented by five factors derived from the AI anxiety scale, including concerns such as job replacement and sociotechnical blind spots.
2. Motivation: Defined using items from the Intrinsic Motivation Inventory (IMI) and the positive factors identified from the questionnaire (Center for Self-Determination Theory (CSDT), 2024).
3. Class Satisfaction: Assessed through students' ratings of their satisfaction with course components, including videos, group discussions, and generative AI tools like HiGPT.

Figure 1: Parallel Analysis Scree Plot



Note: Eigenvalues of actual data (blue) compared with those obtained from resampled data (red).

The proposed SEM model hypothesized two pathways:

1. Negative attitudes toward AI influence motivation, affecting class satisfaction.
2. Negative attitudes toward AI directly influence class satisfaction.

The model was evaluated using fit indices such as the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and RMSEA. The pathways with statistically significant coefficients ($p<0.05$) were interpreted as evidence for hypothesized relationships.

Result

AI-Related Factors Contributing to Anxiety

An exploratory factor analysis was conducted based on the results of a questionnaire about AI and anxiety about generated AI. Figure 1 shows a scree plot of the parallel analysis. Simulated represents eigenvalues based on resampled data, and Observed represents eigenvalues based on actual data. Considering the relationship between the eigenvalues based on the observed and simulated, we determined that six factors were appropriate. The Likelihood Chi-Square value was 967.21 ($p<0.001$) with 184 degrees of freedom, indicating the model's statistical significance. The RMSEA was 0.048, with 90% confidence intervals ranging from 0.045 to 0.051, suggesting a good model fit. The TLI was 0.937, the root mean square of the residuals (RMSR) was 0.02, and the df-corrected RMSR was 0.03, indicating minimal residual error. The BIC for the model was -414.61, highlighting a favorable balance between model complexity and fit quality. The fit based on off-diagonal values was 0.99, demonstrating the model's robustness in capturing the factor structure.

Regarding the factor score adequacy, the correlation of regression scores with factors ranged from 0.81 to 0.96 across the six factors. The multiple R-squared values for scores with factors ranged from 0.66 to 0.93, indicating strong relationships between observed variables and their respective latent factors. The minimum correlation of possible factor scores ranged from 0.32 to 0.86, providing additional evidence of the factors' validity. These results confirm that the six-factor model provides a well-fitting and reliable representation of the data, enabling a nuanced understanding of the constructs under investigation.

Table 1 shows the estimated results of the factor loadings for the loading ratio of 0.45 and above. The questions in each row correspond to those in the Appendix. The internal consistency based on these factor structures was evaluated using McDonald's omega, ω.

Table 1: Estimation Results of Factor Loadings (Loadings below 0.45 are omitted)

	mr3	mr1	mr2	mr4	mr5	mr6
ω	0.93	0.90	0.77	0.86	0.77	0.67
c01	0.76					
c02	0.91					
c03	0.88					
c04						0.66
c05						0.72
c06						
c07				0.76		
c08				0.73		
c09				0.65		
c10		0.78				
c11		0.77				
c12		0.78				
d01			0.63			
d10			0.46			
d11			0.53			
d12						
d19					0.51	
e01						
e02						
e03			0.53			
e04						
e05			0.70			
e06			0.66			
e07					0.57	
e08					0.61	
e09					0.50	

Table 2 summarizes the interpretation of the factors and the questions that fall into each category. Factors mr1, mr3, mr4, and m6 correspond to the subscales of the AIAS (Wang & Wang, 2022). A question item of mr5 is about problems and trust in using AI, which was interpreted as distrust of AI. mr2 indicates a positive attitude toward AI, such as a desire to use AI for learning and work. Based on this interpretation, these factors were incorporated into the motivation construct in the structural equation model.

Table 2: Interpretation of Observed Factors

Factor	Summary	Question
mr1	Concerns about AI setup	c10, c11, c12
mr2	Expectations for AI	d01, d10, d11, e03, e05, e06
mr3	Concerns about learning about AI	c01, c02, c03
mr4	Concerns about lack of awareness of social technologies	c07, c08, c09
mr5	Distrust of AI	d19, e07, e08, e09
mr6	Anxiety about job replacement	c04, c05

Table 3: Interpretation of Observed Factors

Construct	**Factor**	**Description**
Negative Attitudes toward AI	mr1	Concerns about AI setup.
(anx)	mr3	Concerns about learning about AI.
	mr4	Concerns about lack of awareness of social technologies.
	mr5	Distrust of AI.
	mr6	Anxiety about job replacement.
Motivation toward AI	imi01	Values for learning AI.
(imi)	imi02	Interest in learning AI.
	imi03	Perceived choice of class enrolment.
	mr2	Expectations for AI
Class satisfaction (cls)	v04	Satisfaction with pre-class instructional videos.
	w04	Satisfaction with group discussions using generative AI tools.
	h04	Satisfaction with the use of generative AI tools, such as HiGPT, in class.

The Structural Equation Modeling (SEM) Analysis

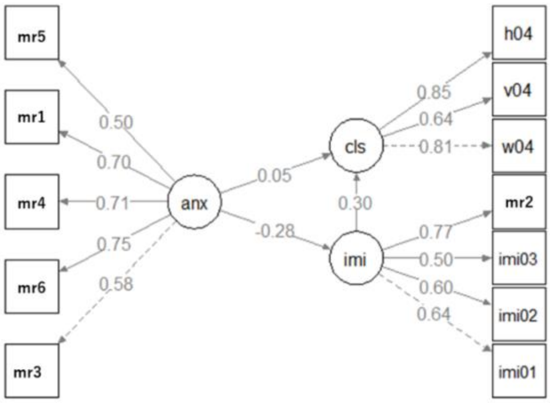
As shown in Table 3, we conducted an SEM analysis of the structural factors of negative attitudes towards AI (anx), motivation to learn AI (imi), and satisfaction with the class (cls).

The model's fit indices indicated an acceptable fit, with a CFI of 0.940, a TLI of 0.922, and a RMSEA of 0.063 (90% confidence interval: 0.056-0.071). This suggests that the fit is somewhat low, but when these fit indices are compared with the criteria recommended by Hu et al. (1999), they are within the acceptable range. The Standardized Root Mean Square Residual (SRMR) was 0.050, further supporting the model's adequacy. Although the Chi-square test was statistically significant (Chi-square=263, degrees of freedom=51, $p<0.001$), this result is typical for models with large sample sizes.

Figure 2 shows the standardized regression coefficients from the SEM. These values represent the effect size of each variable in standard deviation units. The factor loadings demonstrated that the latent variable "negative attitudes toward AI" (anx) significantly loaded on five observed variables (anx01, anx02, anx03, anx04, anx05). Similarly, "intrinsic motivation" (imi) showed significant loadings on imi01, imi02, imi03, and imi04. The latent variable "class satisfaction" (cls) significantly loaded on three observed variables (w04, v04, h04), indicating that these observed variables adequately represent their respective latent constructs.

The standardized regression coefficient for the path from intrinsic motivation (imi) to class satisfaction (cls) was $\beta=0.30$, indicating a significant positive relationship ($p<0.001$). This suggests that higher motivation levels enhance students' satisfaction with AI-related classes. Negative attitudes toward AI (anx) significantly negatively affect intrinsic motivation ($\beta=-0.28$, $p<0.001$), highlighting an indirect pathway through which negative attitudes can impact satisfaction by reducing motivation. Negative attitudes toward AI (anx) did not significantly affect class satisfaction (cls) ($\beta=0.05$, $p=0.238$), indicating that such attitudes do not directly influence students' satisfaction.

Figure 2: The Factor Loadings of SEM



These findings underscore the mediating role of intrinsic motivation in the relationship between negative attitudes toward AI and class satisfaction. While negative attitudes alone do not directly affect satisfaction, their influence on motivation highlights the importance of addressing students' perceptions of AI to foster a more positive and engaging learning environment. This suggests that educational interventions to increase motivation could mitigate the adverse effects of negative attitudes toward AI, ultimately improving students' satisfaction with AI-related education.

Discussion

This study examined the influence of AI anxiety and attitudes on first-year university students' willingness to learn and satisfaction with their data science education. The findings from the SEM analysis illuminate the challenges and opportunities in designing AI education programs catering to students' diverse perceptions and motivations.

The results indicate that negative attitudes toward AI are mediated by intrinsic motivation. Specifically, higher levels of AI anxiety correlate with reduced motivation, which, in turn, leads to decreased satisfaction with AI-related coursework. These findings underscore the complexity of students' emotional and cognitive engagement with AI education. While negative perceptions may not directly hinder their immediate classroom experiences, their indirect effects through reduced motivation highlight the need for targeted interventions.

Contrary to the detrimental effects of negative attitudes, the analysis revealed that positive impressions of AI, reflected in the motivation factor, significantly enhance class satisfaction. Students who exhibit curiosity and recognize AI's potential societal contributions are likelier to enjoy and benefit from AI-related education. This suggests that fostering positive attitudes and intrinsic interest in AI can play a pivotal role in mitigating the adverse effects of AI anxiety, thus creating a more engaging and effective learning environment.

The findings provide actionable insights for designing AI education programs:

1. Addressing negative perceptions: Educational strategies that demystify AI and highlight its ethical and societal benefits can help reduce anxiety. For example, incorporating discussions that explore AI's limitations and safeguards may alleviate concerns about job displacement and sociotechnical risks.
2. Promoting positive engagement: Integrating hands-on experiences with generative AI tools, such as HiGPT, can foster a sense of familiarity and utility, enhancing students' willingness to engage with technology. The emphasis should be placed on showing how AI can complement human skills rather than replace them.
3. Motivational support: Providing autonomy in learning, such as allowing students to explore AI applications aligned with their interests, may strengthen their intrinsic motivation. This autonomy can also help bridge the gap between students with varying prior exposure to AI.

As this study demonstrates, integrating generative AI tools into classroom activities highlights their potential to transform educational practices. These tools serve as learning aids and platforms for fostering collaboration and critical thinking. However, the rapid proliferation of such technologies necessitates continuous evaluation of their pedagogical impact, particularly concerning students' psychological and motivational responses.

Conclusion

This study focuses on first-year university students, providing a snapshot of their initial perceptions of AI. However, the evolving nature of AI technologies and their integration into various disciplines suggest the need for longitudinal studies that track changes in students' attitudes and learning outcomes over time. Additionally, exploring the interplay between cultural factors and AI anxiety could offer a more nuanced understanding of how educational strategies might be tailored to different contexts.

The results of this study show the importance of addressing the negative and positive dimensions of students' attitudes toward AI. By fostering a balanced perspective that reduces anxiety while promoting curiosity and motivation, educators can enhance the effectiveness of AI-related education. These efforts are critical for equipping students with the skills and confidence to navigate an increasingly AI-driven world.

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References

Center for Self-Determination Theory (CSDT). (2024). Intrinsic Motivation Inventory (IMI). Retrieved from https://selfdeterminationtheory.org/intrinsic-motivation-inventory/

Ghotbi, N., Ho, M. T., & Mantello, P. (2022). Attitude of college students towards ethical issues of artificial intelligence in an international university in Japan. *AI & Society, 37*, 283–290. https://doi.org/10.1007/s00146-021-01168-2

Hu, L.-T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Japan Inter-University Consortium for Mathematics, Data Science and AI Education. (2024). Model curriculum (literacy level). http://www.mi.u-tokyo.ac.jp/consortium/model_literacy.html

Ministry of Internal Affairs and Communications. (2024). White paper on information and communications in Japan: 2024 edition. https://www.soumu.go.jp/johotsusintokei/whitepaper/ja/r06/

Murakami, Y., Inagaki, T., Takahashi, T., & Tsuchimoto, Y. (2024). Classroom practice of HiGPT, a group learning support tool using generative AI. Research Report on Computers and Education (CE), 2024-CE-175(8), 1–7. (In Japanese)

Schepman, A., & Rodway, P. (2020). Initial validation of the general attitudes towards Artificial Intelligence Scale. *Computers in Human Behavior Reports, 1*, 100014. https://doi.org/10.1016/j.chbr.2020.100014

Wang, Y., & Wang, Y. S. (2022). Development and validation of an artificial intelligence anxiety scale: An initial application in predicting motivated learning behavior. *Interactive Learning Environments, 30*(4), 619–634.

Wang, Y. M., Wei, C. L., Lin, H. H., Wang, S. C., & Wang, Y. S. (2022). What drives students' AI learning behavior: A perspective of AI anxiety. *Interactive Learning Environments, 32*(6), 2584–2600.

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Appendix

Questionnaire

The items named "c" and "d" are based on the AIAS (Wang & Wang, 2022) and GAAIS (Schepman & Rodway, 2020), respectively. The items named "e" are the original ones.

c01	Learning to understand all of the specialized features related to AI technology and the products that use it makes me uneasy.
c02	Learning about AI technology and how to use products that use it makes me uneasy.
c03	Learning to use AI technology and certain features of products that use it makes me uneasy.
c04	I am concerned that we will become dependent on AI technology and products that use it.
c05	I worry that AI technology and the products that use it will make us lazier.
c06	I fear that AI technology and products using it will replace humans.
c07	I am afraid that AI technology and products using it will be misused.
c08	I am afraid of the various potential problems with AI technology and the products that use it.
c09	I am concerned that we will become dependent on AI technology and products that use it.
c10	I find humanoid AI technology and products using it (e.g., humanoid robots) scary.
c11	I find humanoid AI technology and products using it (e.g., humanoid robots) intimidating.
c12	I don't know why, but I am afraid of humanoid AI technology and products that use it (e.g. humanoid robots).
d01	I am interested in using AI technology and products that use it.
d10	AI technology and products that use it can perform better than humans.
d11	Society would benefit from the widespread use of AI technology and products that use it.
d12	I would rather interact with AI technology and products that use it than humans.
d19	I think AI technology and products using it make a lot of mistakes.
e01	Using AI technology and products that use it for learning feels like cheating.
e02	AI technology and the products that use it can properly evaluate you.
e03	I feel that AI technology and the use of products that use it can help you discover new aspects of yourself
e04	AI technology and products using it can fool humans.
e05	I want to use AI technology and products that use it for learning.
e06	I want to use AI technology and products that use it in my work.
e07	I think there is a problem with the use of AI technology and products that use it.
e08	The output content of AI technology and products that use it cannot be trusted.
e09	Input into AI technology and the products that use it could be leaked.