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RESEARCH ARTICLE

Exploring the Lived Experience of Graduate Students in an Introductory AI Course

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ABSTRACT

This qualitative research examines the experiences of graduate students participating in an introductory AI course at a College of Education to enhance AI curriculum design and pedagogy. In-depth interviews with six students revealed four principal themes: various motivations, collaborative learning in diverse groups, closer to machine learning, and learning from experience. Analysis indicated the need for successful integration of AI, emphasizing the necessity of a customized curriculum that caters to diverse student backgrounds and motivations, the effective execution of collaborative projects, and the importance of connecting AI principles to real-world problems. This research enhances understanding of the qualitative aspects of AI education and supports the development of an effective AI curriculum.

Key words: Teaching-learning AI, introductory AI course, big data, higher education, phenomenological study

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Introduction

With the daily emergence of new AI technologies, AI is rapidly permeating various aspects of our lives. This swift integration has highlighted a shortage of individuals capable of critically analyzing big data challenges and possessing the necessary skills to address problems using AI technologies. Knowing how to collect, retrieve, analyze, and communicate data is becoming increasingly important in society (D'Ignazio, 2017).

AI readiness is about helping people understand enough about AI to make good decisions about procuring and using AI to meet their needs (Luckin et al., 2022). AI has been utilized in education through intelligent tutoring systems, evaluation and feedback, counselling and mentoring, administrative systems for decision-making, planning and execution, and forecasting learning outcomes (Gillani et al., 2023). Additionally, the researchers state that learners should not use AI only as end-users; they emphasized the importance of teaching learners how to apply AI concepts in different contexts and applications in everyday life. This would help learners use AI technologies in different scenarios or create possible AI-based hardware and software solutions (Ng et al., 2021).

Education should play a role in equipping people with the appropriate knowledge and technologies (Erduran & Levrini, 2024; Song & Zhu, 2017). With the advancement of AI technology, the role of AI in education is also expected to vary, penetrating the education field in various ways and resulting teachers and students inadequately prepared. Unfortunately, most students cannot access AI education due to a lack of preparedness among their teachers to deliver it (Crawford et al., 2023; Lee & Perret, 2022; Perkins, 2023). The rapid evolution of AI presents both opportunities and challenges for educators, necessitating a comprehensive understanding of its principles and applications. In this context, the role of higher education institutions, particularly colleges of education, is pivotal in preparing future educators to effectively incorporate AI into teaching and learning processes.

Teacher training programs and educator preparation must be enhanced to provide instructors with the competencies to employ AI in education properly. This includes training on AI-driven pedagogical techniques, education on AI ethics, and assistance in integrating AI into the curriculum (Erduran & Levrini, 2024). The Ministry of Education in South Korea recently implemented a policy to establish graduate schools focused on AI convergence education nationwide to train 5,000 experts within five years. This initiative aims to equip teachers with the essential knowledge and abilities to proficiently incorporate AI into their teaching practices and to develop diverse curricula that integrate multiple disciplines (MOE, 2020).

Due to the strong demand for AI specialists, many nations have established government-led AI education programs (Kong & Lai, 2022; Government of the Republic of Korea, 2019). Consequently, universities have also developed new curricula for big data analysis (Cho & Yu, 2018), and have offered AI courses to students of non-AI majors to meet the increasing demand for AI specialists in the labor market (Lin et al., 2021). The associated curriculum questions that arise such as when to educate the young, how to design the curricula, what to include for different levels of students, and the effects of such decisions warrant further research (Lin et al., 2021). When teaching AI as the course content itself, consideration should be given to learners' learning needs, previous learning experiences, and their "nearest development zone" (Yang et al., 2023). Learning AI can be challenging as many students may not have had the opportunity to learn about AI-related topics in middle or high school prior to entering university. It is also reported that programming languages and mathematics might be barriers to learn AI (Sulmont et al., 2019).

Despite the emphasis on AI education, educators currently express varying views on its content and scope, indicating a need to redefine and actively discuss the concept. There are relatively few research papers focusing on AI technology as educational content itself and how to deeply integrate AI with curriculum content (Yang et al., 2023). In particular, the published literature on AI in education discusses the use of AI to develop new educational tools, delivery methods, and impact on student learning, there is a significant lack of guidance on actual AI education, especially for AI curriculum design for students with less technical backgrounds and skills (Xu & Babaian, 2021). Recent few studies related to AI education focused on AI content knowledge and skills (Touretzky, 2019), effective AI tools (Williams et al., 2019) and instructors' perceptions on AI teaching (Chiu & Chai., 2020; Yau et al., 2023). Therefore, it is required to undertake research that presents the know-how for constructing and operating an appropriate introductory AI curriculum.

This qualitative research aims to explore the "lived experiences" of students taking an introductory AI course in higher education. The question that this study is based on fits with the way you normally look into something that is mostly vague and hard to see. It is stated as follows: “What does it mean to take an introductory AI course in higher education?” The following two sub-questions were looked at because this inquiry covers a lot of different matters that cross and are woven together, which required additional investigation:

RQ1. What are the lived experiences of taking an introductory AI course?

RQ2. What are the learner's characteristics and AI teaching-learning strategies?

Materials and Methods

Context of Study

Curriculum

This is a 14-week course titled “Big Data Analytics and Education” that was offered at a graduate school in Seoul in the second semester of 2020. It was a course given by the College of Education; any student, whether graduate or undergraduate at this university, is eligible to enroll. Classes were held every Wednesday from 6-9 p.m. Due to the COVID-19 pandemic and quarantine regulations, face-to-face sessions were restricted, necessitating Zoom-based education. Face-to-face Arduino practical sessions were held in the 10th week of the program. Group discussions and collaborative learning for team tasks took place both online and offline.

Traditional statistical learning was taught for the first four weeks, and then the classification models and generation models of machine learning were introduced for weeks five to twelve. In the second week, the Python programming language was introduced. The instructor quantified learners' math, coding, writing, and research skills through self-reported assessments. The instructor then used this data to organize teams of people with different abilities to demonstrate algorithms. These exercises provided students with a simple approach to practice Python programming while also arousing their interest in the collection and use of data. In the third week, students learned how to gather publicly available data by using a web crawling technique, allowing them to get the skills needed for data collection, preprocessing, and storage for statistical analysis and machine learning.

Furthermore, during the 10th week, participants utilized Arduino to directly acquire data. While plans initially included integrating Arduino sessions throughout the course, the requirement for face-to-face instruction led to the decision to conduct these classes during the 10th week when the COVID-19 situation had improved. Table 1 summarizes the 14-week curriculum.

Table 1. The course summary of ‘Big Data Analytics and Education.'

Weeks	Topic	Weeks	Topic
W1	Bayesian Statistics	W8	Recurrent Neural Networks
W2	Introduction to Python programming	W9	Autoencoders and principal component analysis
W3	Web Crawling	W10	Collecting data using physical computing - Arduino
W4	Linear regression and time series data	W11	Boltzmann Machine
W5	Machine Learning and back-propagation	W12	Adversarial Generative Neural Network, Variational Autoencoder
W6	Convolutional Neural Networks	W13	[Discussion] AI and Future Society
W7	[Team Project] Various Classification Models	W14	[Team Project] Presentation of a problem-solving project

Task

Individual assignments, team projects, and discussions were given throughout the semester. Students were given individual projects to build code that used each week's lecture topics. Students might annotate the instructor's model code or explore advanced applications like high-dimensional data collecting and analysis using these assignments. These activities aimed to explore various classification models, organize their findings and present them in the form of digital documents. The instructor emphasized the importance of proficiency in writing and sharing documents (in Python Jupyter Notebook format). This emphasis stemmed from the recognition that a culture of knowledge sharing has significantly contributed to the remarkable advancements witnessed in the field of computer science in recent years.

Team projects allowed students to demonstrate their AI knowledge and skills. Given the challenging goal of comprehending and implementing AI concepts in a single course, assignments were focused on practical application.

The class discussion explored diverse topics, such as (i) Is AI/big data education being over-emphasized?, (ii) Which is more important for the implementation of AI, the model (algorithm) vs. the data?, (iii) Would sharing sources and data be more beneficial to mankind?, (iv) Can AI make our lives better?, and (v) Will AI replace humans? (The emergence of strong AI). Students wrote articles about "AI and the future of society" after talking about the topic in class.

Instructor

The instructor is a theoretical physicist who has conducted data science and AI studies. The course itself has been meticulously designed by the instructor, with the primary objectives being: (1) fostering a theoretical comprehension of the fundamental principles underlying AI, (2) enabling practical application of AI across diverse domains of expertise, and (3) providing a thoughtful examination of the humanistic implications of AI, encompassing both AI literacy and digital literacy.

The instructor firmly believes that an accurate understanding of AI principles is essential, whether from the perspective of implementing AI or as a consumer utilizing its capabilities. This understanding empowers individuals to evaluate the capabilities and limitations of AI systems critically. To ensure a solid comprehension of the core principles, the instructor delivers lectures (W1, W4, W5, W6, W8, W9, W11, W12) covering foundational topics such as probability and statistics, statistical learning, machine learning algorithms for both discriminative models and generative models and the concept of dimensionality reduction in data representation.

Furthermore, by establishing a strong foundation in core principles, the curriculum aims to provide practical experiences, allowing participants to employ AI techniques within their respective specialized fields effectively. To support this, the lectures (W2, W3, W10) introduce basic Python programming and data acquisition through web crawling or physical computing and emphasize using Python notebooks for summarizing research results and combining code and text. Additionally, two team projects (W7, W14) are included, allowing students to apply their knowledge and work towards realizing their "dream" projects.

Finally, the curriculum reflects the instructor's intention to get learners to think about the profound impact of AI on human life and recognize it as one of the most important considerations. This encompasses understanding the basic principles and employing them within specialized contexts while engaging in thoughtful reflection on the broader implications for society. To accomplish this objective, an online forum is provided where participants can share noteworthy news, films, books, and discussions on topics such as ethics, law, philosophy, education, art, science, employment, and daily life as they relate to AI. These materials are shared throughout the semester, and one lecture (W13) is dedicated to a group discussion on these issues.

Students

The course enrolled 40 students (17 undergraduate students/23 graduate students, 28 male/12 female). The students represented diverse academic backgrounds, with the following majors: science education (13), physics education (10), business administration (3), physics astronomy (2), global education cooperation (2), earth science education (2), chemistry education (2), education (2), cognitive science (1), biology education (1), and ethics education (1). This range of majors shows the demand for AI education across various disciplinary domains.

Participants

Sampling adequacy in qualitative research refers to selecting participants who will offer the most significant study information according to theoretical imperatives. This study employed purposive sampling, where the researcher chose experiences of interest (Denzin & Lincoln, 2000; Morse & Field, 1995). The sample size of the qualitative research relies on saturation. Guest, Bunce, and Johnson (2006) investigated the saturation using sixty in-depth interviews and found. They looked at the data set and found that saturation happened in the first twelve interviews. However, basic elements for meta themes were present as early as the sixth interview. They explain saturation and suggest purposive sample sizes for interviews based on evidence. Our data was saturated to offer a thorough and rich account of the topic under inquiry. The research participants selected for this study were six students who took the introductory AI course. The participants were informed about the study's purpose and the study subjects' recruitment at the course orientation. Six of the students voluntarily agreed to participate in the interviews. Information about the participants is summarized in Table 2.

Table 2. Profile of the participants

Participants	Major	Gender	Grade	Note
A	Physics Education	Male	Undergraduate student Fourth-year	He plans to enter graduate school with another major, experience in coding. He is interested in combining knowledge from education and other fields and creating new convergent knowledge.
B	Global Education Cooperation (GEC)	Female	Doctoral student	She major in economics, master of policy, experience in coding. She is deeply interested in learning how to utilize AI and hopes to continue to build a solid foundation of AI knowledge in the future.
C	Physics education	Male	Graduate student	He is a Physics teacher with six years of experience, experience in coding. He is facing the challenge of implementing AI lessons in schools and wants to gain practical knowledge and skills that he can utilize in the field.
D	Physics Education	Male	Undergraduate student Fourth-year	He plans to enter machine learning-related graduate school with excellent programming skills. He has previous experience with problem-solving projects using AI, and has served as a teaching assistant in the class, helping other students with their programming.
E	Biology Education	Male	Doctoral student	He has no coding-related experience at all. He was intimidated about learning programming but thought of the importance of gaining knowledge about AI. Through this course, he realized that there are other roles that AI can play in solving problems beyond coding.
G	Physics Education	Male	Doctoral student	He is interested in informal education and experience in coding. He believes it is important to gain knowledge and skills in AI technology, as he is planning a new endeavor for informal education. After completing this course, he is taking on a new challenge: organizing a science-play.

Researcher

The study featured four researchers, one of whom was an instructor. One researcher watched the entire course, while two others attended the same course during the first semester of 2022. As a result, all researchers thoroughly understand the setting and the students' learning experiences in the course. Additionally, two of the researchers specialize in science education, while another is a science teacher.

Phenomenology Study

A phenomenology study refers to a qualitative research approach that seeks to investigate the subjective experiences of individuals associated with a certain event. The primary emphasis of this method lies in comprehending how humans interpret and derive meaning from their experiences, as opposed to relying on objective facts or measures (Giorgi, 2008). In this study, a series of comprehensive interviews were carried out with a total of six individuals. The researchers employed a bracketed approach to examine the participants' perceptions, emotions, and interpretations, purposefully suspending their own biases and assumptions to gain a comprehensive understanding of the essence of the individuals' experiences.

Interview Data and Analysis

Because human consciousness is revealed through the narrative of experience (Van Manen, 1990), the first task in phenomenological research is to describe the situation accurately. Van Manen (2016) emphasizes that phenomenology is beneficial when exploring how participants make sense of their experiences in a specific context. Six participants participated in individual interviews at the end of the semester-long course and after it ended. A preliminary survey and interview guide were created to ensure accurate descriptions and rich interviews, and detailed questions were added to the basic questions. Researchers and participants met face-to-face 1 to 3 times, lasting between 60 and 90 minutes. In the first interview, the questions were the same for everyone, but in the second and third interviews, new questions were added that were linked to what was said in the previous interview. The semi-structured interview protocol was conducted. As shown in the Table 3, the questions were categorized into two purposes.

Table 3. Interview Protocol

Category	Interview Question.
Context and Background	-Why did you become interested in big data analytics? -What did you expect to learn from this course? -What was the most fun part of the class?
Reflect on Experience	-What changes do you think big data will bring to future education? -What does taking a course mean to you? -What are the disappointing points and supplements about the subject?

Giorgi's (2004) four-step data analysis process for the phenomenological study is as follows: first, recognize the whole; second, distinguish meaning units; third, express them in academic terms; and fourth, synthesize them into general statements. Following this process, each of the four researchers read the entire transcript of the in-depth interviews several times to capture the holistic meaning of the participants' experiences. Second, the transcripts were transferred to an Excel file and the four researchers extracted meaning units from the transcribed sentences or paragraphs. Through inter-researcher consensus, overlapping meaning units were combined into a single meaning unit and only the meaning that best represented the context of the research participant was extracted. We then compared the semantic units to categorize similar content. Third, we contextualized the semantic units into academic terms to ensure that they represented the participants' actual experiences as much as possible. For instance, the terms 'good at coding' and 'good at Python' were transformed into "coding skill". Consequently, only the academic expressions described by each researcher that aligned were collected and identified as topics by identifying the central meaning from the essential elements of the meaning units. For instance, the terms 'challenging lesson', 'unfamiliar symbol', and 'lack of mathematics knowledge' were combined into a single topic because they pertain to learning difficulties in context. Semantic units were excluded if there was no consensus on the researcher's interpretation after sufficient discussion. Fourth, the themes were integrated into a general structural description from the perspective of all participants and identified as overarching themes. In the process of integrating the subtopics into the overarching themes, we repeatedly examined the overall context of the transcripts and discussed among the researchers to avoid biased interpretation.

During the data collection and analysis, we tried to ensure the validity of this study according to Lincoln, Guba, and Pilotta's (1985) criteria for qualitative research, i.e., we tried to draw out the participants' lived experiences as much as possible during the interview process, organized and analyzed the data using the feelings of these experiences, and checked the results of the analysis with the participants again to ensure the credibility of the data. In addition, to ensure consistency, we found meaningful themes through continuous comparison and discussion among the researchers and integrated the themes. Finally, to ensure neutrality, the researchers' previous biases and stereotypes were bracketed to ensure that their subjectivity did not influence the interview process or results. Van Manen (1990) highlights the need for researchers to reflect and examine to identify and set aside their assumptions. After each class observation, researchers discussed and reflectively sorted outliers. We also open-coded, shared, and discussed our data to uncover and resolve inter-researcher bias. We also conducted member checking.

The IRB of the Seoul National University Research Ethics Center approved this study.

Findings

In this study, as shown in Table 4, 103 units of meaning were derived. Each unit was classified into 16 sub-topics and 4 themes which were 'Various motivations to take the AI course', 'Collaborative learning in a diverse group', 'Closer to machine learning', and 'Learn from experience'. These topics responded to the research question presented in this study.

Table 4. Themes, topics and units of meaning

Theme	Topic	Unit of meaning
Various motivations for taking the AI course	Exploring a new career path	My major is not a good fit for me, Trying different experience
	Keeping up with the times	AI as a literacy, Desperation not to be obsolete, Policies that emphasize AI
	Interest in data utilization	Applying to the school field, One needs to use big data, Education meets data, Bridging AI to one's research interest, Support one’s research
Collaborative learning in a diverse group	Various backgrounds	Various needs and attitudes, Various domain knowledge and skills, Learning from diverse perspectives, Beyond the studying group, Expanding the network
	Coding barrier	Differences in coding skills, Beginner, Coding challenges are overwhelming, Passive participation, High coding skill have the right to make decisions, Not all need to be skilled coders, Python prerequisites, What I can’t do
	Performance vs. mastery	High evaluation standards, Despite our best efforts, Frustration, Just do it
Closer to machine learning	Understanding basic concepts	The way to understand machine learning, Explain what is big data, Dispel the myths of machine learning, Knowing how it is actually used
	Statistics and mathematics	Machine learning is statistics, The meeting of mathematics, The relationship between Bayesian statistics and big data, Mathematics is required in programming, The importance of Learning mathematics and statistics
	Course showing a forest rather than trees	Intensive teaching, Systematic curriculum, Dealing with almost every model, Schema-developed, Overall understanding
	Difficult but necessary	Challenging lessons, Unfamiliar symbols, Lack of mathematics knowledge, Prerequisite courses recommended, Reference materials needed, I am not good enough
	Outside of the classroom	Internet surfing, Supplements from books, Watching video lectures, Study-group planning, Keep going, Study while on vacation, Found directions, Enroll other classes, Making it mine, Annotating
Learn from experience	The fastest way to learn is by getting immediately involved in projects	Lions push their cubs over a cliff, Turning point, Learning new skills, Valuable experience, Coding skill improved, The developer experience, Did it at the level I could
	Communication and collaboration	Learning from team members, Communication practice, Sharing ideas and creative, Feeling satisfaction from supporting
	Weight of being together	Different topics of interest, Not sure about the project topic, Disappointment, Stress from relationships
	An opportunity for a novel perspective	Accessible learning, Machine learning is not all-mighty, Challenging to Bayesian statistics, Bias in data itself, Bayesian and literacy, Overestimation of big data, Skepticism about technological advancement, It's not that hard, I could try

Various Motivations to Take the AI Course

When asked why they envisioned an AI course, students mentioned that the times have changed, that is, the AI era has arrived and they had various motivations for taking the course. Despite the majority of participants having a major in science education, they expressed a desire to explore a new field outside of their current academic discipline. The three semantic units associated with the motivations that emerged from the interviews were grouped into three categories: ‘Exploring a new career path’, ‘Keeping up with the times’, and ‘Interest in data utilization’. The social phenomenon and public interest in AI and big data may be a factor that arouses interest and concern in individuals or acts as pressure, stimulating the motivation of the participants to take the course.

Exploring a New Career Path

Participant A is a student majoring in physics education. However, he is skeptical of National Science Curriculum studies and does not intend to pursue a teaching career after graduation. Instead, he plans to continue his studies in a new field that he finds interesting. B studied three different majors such as economics, policy studies, and education. She took the AI course as part of the "try a variety of experiences" that she has always sought because she recognized that coding is an essential career skill.

I think it's a little bit boring, it is just curriculum studies (which is what I'm majoring in), such as developing teaching materials. I'm sick and tired of thinking about whether or not I'm teaching concepts correctly (A, male, undergraduate).

Keeping up with the Times

Some students enrolled in this AI course because they felt overwhelmed by external issues such as the evaluation of other people and official policies. G felt the need to learn AI as a basic skill due to the emphasis on big data-related competencies in his lab seminar. B was also motivated to learn AI by his advisor's advice and the realization that AI is a trend. C was influenced by the Ministry of Education's emphasis on AI and big data. A expressed a heightened sense of urgency in acquiring and maintaining proficiency in AI and big data-related skills, recognizing their increasing significance.

I think I'm doing this(learning AI) to survive because I can see myself falling behind if I don't do it now (interruption omitted) It's really the age of machine learning. (B, female, doctoral)

Interest in Data Utilization

Some students who enrolled in the course decided to take it because they wanted to apply the AI and big data analytics they had learned in the course to their own research. Participant A learned how to analyze big data in the course and wants to use it in his physics education research paper. Both C, a teacher, and E, a graduate student at a teacher's college, stated that they enrolled in the course in order to conduct research using education-related data.

I'm thinking about doing some research on how to apply big data or statistical physics to the school setting. (C, male, graduate)

D, on the other hand, stated that he had enrolled in the course because he was intrigued by the nature of big data and wished to utilize it more effectively. He was majoring in physics education, but planning to enter machine learning-related graduate school.

Because big data can cover a wider range of things. That's why I got into it. Because it's fun. (D, male, undergraduate)

Collaborative Learning in a Diverse Group

The introductory AI course has diverse students from various degree programs and majors. We distinguished these characteristics under the theme 'collaborative learning in a diverse group' and classified the semantic units as 'Various backgrounds', 'Coding barrier', and 'Performance vs. mastery' topics. The diverse membership is due to 1) the fact that it is an introductory course that anyone can take, 2) the fact that it is taught by an education major rather than a computer science major, and 3) the growing interest in big data in society. The majority of participants acknowledged that belonging to such a diverse group was advantageous. If there are no prerequisites, however, the learner's prior knowledge and experience will vary considerably (Ahn & Kang, 2021). Particularly, participants saw a wide range of coding abilities and mathematical competencies among students in the study.

Various Backgrounds

A stated that pupils possessed various subject knowledge, abilities, levels of education, and desires. He also noted that meeting so many new individuals was a major benefit of the course for him. B said, "A study group was like playing in a well", but in this course, he was able to meet the professionals whose coding skills were much higher than his. C and E recognized that different students interpret occurrences and ideas based on their backgrounds. They regarded this positively.

Surely, I will have coworking opportunities with people in other fields someday. Before that, I've learned a lot from it because I could see that this is how individuals from this background think, what they care about, how they reason, and what type of outlook they have. (D, male, undergraduate)

Coding Barrier

Most students considered themselves "beginners" with minimal coding skills and were inquisitive about other students' skills. Since the course used Python in Google's collaborative environment for big data analytics, so it was apparent which students could code well. Annotating the web board code forced the students to discuss their coding deficiencies. A and C called another student "the good ones". B also indicated that coding skills facilitated her engagement with big data analytics, which significantly impacted the course as a whole.

I spent even two days trying to solve the problem creatively, using only the for and if statements…… however, at that time, some people were already using AI packages. (E, male, doctoral)

In the course evaluations collected after the semester ended, some students commented that the level of coding required was high even though it was an introductory course. The variation in coding proficiency among the students had a notable influence, particularly in the carrying out team projects. E felt he had nothing to contribute to team project duties because the initiative was often delegated to those with superior coding skills, making him a passive participant. A also noted that in the team activity, decision-making authority tends to accrue to those proficient in coding or research, which he described as "unusual".

Performance vs. Mastery

The diversity of the course's participants led to different opinions on the course's evaluation methods and outcomes. A, C, and G said they did what they could and wanted to do within their abilities without being concerned with grades. They expressed satisfaction with their accomplishments and grades. The instructor gave full marks to assignments demonstrating relative creativity, so learners who could only complete the assignment based on what they learned in class would receive lower marks. E did his best but was disappointed that he could not achieve a high relative score. B was dissatisfied with the grading system, characterizing the course as "No perfect score course".

Closer to Machine Learning

The semantic units were grouped into 5 categories: 'Understanding basic concepts', 'Statistics and mathematics', 'Course showing a forest rather than the trees', 'Difficult but necessary' and 'Outside of the classroom'. At first, participants understood the basic concepts underlying big data and AI through the instructor's explanations and then realized the relationship between AI and statistics/mathematics. Furthermore, they understood the structure of the data science discipline according to the instructor's intentions for the curriculum. Therefore, they realized which areas of the discipline they were particularly lacking in and which areas they wanted to study further. Despite the difficulty of understanding principles, they finally reached a stage where they were able to plan for how they would go about studying on an individual basis in areas of personal interest or need for further study.

Understanding Basic Concepts

Participants said the course introduced them to the basic concepts of big data, AI, and machine learning. C learned how it is actually used, and D described the course as 'dispelling myths' about machine learning. B was able to explain what big data is to others, and E taught his class to high school students based on what he learned in the course.

I realized this is how to teach a machine to learn. I think I have some understanding of the concept. (A, male, undergraduate)

Statistics or Mathematics

As the instructor pursued the student's theoretical comprehension of the big data discipline, he spent considerable time explaining statistical and mathematical concepts. A said that he was able to grasp the fundamental ideas more easily due to the use of mathematics to explain them and that he now sees "machine learning is (essentially a branch of) statistics". B and D said they learned about the close relationship between Bayesian statistics and big data. They realized that it was necessary to recognize the importance of Bayesian statistics.

I honestly only knew the word artificial intelligence and I didn't know the specific principles, but ⋯ now I think it was just a bunch of well-developed math (E, male, doctoral)

Participants also recognized that math skills, as well as statistical knowledge, are required to understand data science data disciplines.

It is necessary to do some math to deal with AI or big data, but⋯ I think it would be a bit difficult to start without knowing math at all. (C, male, graduate)

Course Showing a Forest Rather than Trees

The systematic curriculum covering a wide range of theories related to big data and AI helped the participants understand the structure of the data science discipline. D said that the course, which deals with almost all models used in the field of big data, helped him to develop a schema and identify what he needed to learn more about. B positively perceived the curriculum of the course as helping him to study on his own. A expressed satisfaction with the intensive teaching that covered a lot of material in one lecture.

It was kind of a schema-building course, therefore it covered the fundamental ideas. And I've created a sort of index for when I want to delve further or explain anything to someone. (D, male, undergraduate)

Difficult but Necessary

The course was heavily weighted toward mathematical and statistical solving with a focus on understanding the core principles of big data and AI theory. Students found this course difficult but necessary. In particular, G felt that the course became too difficult towards the end. Some students indicated that the course was challenging. Students tended to attribute the difficulty in understanding the principles to their own lack of competence, stating that “I am not capable of digesting(understanding) everything” and “I couldn’t reach the desired level because of the lack of effort”. B responded, “I didn't understand because I don't know linear algebra”, and she recommended that the class's prerequisites be defined and listed on the syllabus.

The symbols the professor uses are so weird to me. (E, male, doctoral)

Outside of the Classroom

Students said that the curriculum helped them understand the fundamental concepts of AI and big data analytics, as well as their relationship to other disciplines and the structure of the discipline. This cross-disciplinary metacognition enabled them to identify areas where they needed more knowledge. Recognizing their deficiencies also motivated them to seek out other additional learning resources and methods, leading five students to take the initiative to plan their learning outside of the classroom. A wanted to participate in a study group activity to learn how to analyze data related to her research topic. B and D decided to take additional courses in the College of Natural Sciences and the College of Engineering to broaden their knowledge of AI. The other two, C and G, said that taking the introductory AI course gave them a direction for their future studies and that they would be self-taught using books and video materials.

In terms of analyzing online learning, I plan to study learning analytics and participate in a group study to explore it further. (A, male, undergraduate)

As I took these courses, I found that I was not ready to understand everything, and graduate school in data science showed me exactly what I needed to know. (B, female, doctoral)

Learn from Experience

The instructor's objective was to encourage students to use their knowledge in their respective specialized disciplines through practice rather than relying exclusively on the study of theoretical notions. This intention was reflected in a flexible curriculum with two team projects and weekly practical assignments. However, there were also challenges in working on a collaborative project with people of different skill sets and backgrounds, including. From these practical experiences, the semantic units related to the phenomena were categorized as 'the fastest way to learn by getting immediately involved in projects', 'communication and collaboration', 'the weight of being together', 'an opportunity for novel perspective', and 'a desire to expand further. '

The Fastest Way to Learn is by Getting Immediately Involved in Projects

B used an example to describe the course where practical assignments are given: “a lion dropping its cub from a cliff”. D referred to what the teacher said: “Getting involved right in the project is the fastest way to learn”. A said that coding skills improved greatly through team projects ranging from idea presentation to development and presentation, and E said new data analytics skills could be learned.

I feel like I went through the nature of this(big data analyticis). Through big data, I could experience not only a part of the research journey but the entire scale of it. (D, male, undergraduate)

Communication and Collaboration

In the course of engaging in project tasks, research participants encountered communicating and cooperating with individuals from various backgrounds. As there was a large variance in competency between members, the ambience of the class was formed as cooperative by exchanging help rather than competitive. Students were able to learn through interactions with seniors in the team project, and not only did it become an opportunity to practice communication with team members with differences in skills, but also experienced imagination stimulated by exchanging various ideas. B and C expressed satisfaction with being able to get help by asking their colleagues what they don't know. On the other hand, G also said that 'task allocation is essential' because there is a large difference in individual competencies.

If I try it, and it doesn't work out, it's much better to come out and talk about it than to just go looking for it alone. (C, male, graduate)

Weight of 'being Together.'

Participants in this study engaged with individuals possessing diverse backgrounds and competencies. They underwent the process of collaborative learning while simultaneously encountering various hurdles. First of all, the team project was a valuable opportunity to actually implement their ideas, particularly for those students inclined toward big data utilization. However, the inherent characteristics of collaborative projects placed restrictions on the expression of personal preferences. C and E reported encountering challenges in the process of selecting project subjects due to the presence of team members with varied interests. Additionally, G voiced discontentment with the final decision on the chosen project topic.

Even though it was my major area, and I was aware of better ways to address the issue, it seemed like people were belittling my opinions somewhat, regarding them as boring. (E, male, doctoral)

The distribution of diverse duties posed complications due to the significant variation in talents across team members. D, who was a significant contributor to the creation of the program, eventually got tired of the laborious task of explaining every detail to the other team members and decided to stop explaining. In contrast, A expressed a sense of inadequacy in contributing to the team because of his limited comprehension. Furthermore, he expressed the stress that is typically connected with participating in collaborative projects.

An Opportunity For a Novel Perspective

Nevertheless, the application of acquired knowledge in real-world scenarios has the potential to significantly alter students' perceptions. To illustrate, B was presented with a chance to challenge the prevailing frequentist statistical paradigm during the first class through the introduction of Bayesian statistics. D indicated the recognition that enhancing public literacy necessitates a reinforcement of education about Bayesian statistics.

I believe that some of the challenges encountered within the frequentist paradigm can be solved to some extent. In the future, new social science research methods related to these big data research methods would increase the probability. (E, male, doctoral)

C, E, and G found that big data analytics was not that formidable but accessible and learnable, or they gained confidence that they could do it.

It seems to be learnable. I believe I become more interested in it compared to before. (Omitted) It was more enjoyable than I had anticipated. (C, male, graduate)

Meanwhile, B has come to recognize that machine learning tends to be overestimated by the public. Both B and D voiced worries over the potential concentration of advantages from progress in the field of big data on a restricted group of individuals.

So does the Luddite movement. Can people truly return to the past when a new technology emerges? People's lives are altered substantially by this. It has numerous adverse facets, though. (B, female, doctoral)

Planning Big Data Utilization Research

Students also generated new research questions based on their practical experience. Students came to the course because they were interested in research using big data, and after the course, they wanted to conduct research where they could actually apply what they had learned. Some participants engaged in further research on topics that have always been of interest to them. In particular, B and E expressed a desire to conduct field research that would analyze data drawn from the real world.

How can I utilize this big data to overcome the constraints of qualitative research and to use statistical data further? (G, male, doctoral)

Like, if there's an education policy that comes out, what's the difference between people's reactions to it and the ideology that we science educators have. How we're going to implement it in the field... (E, male, doctoral)

Discussion

This study identified several noteworthy phenomena within students' experiences enrolled in an introductory AI course. We found that many students from various majors, including science education, wanted to understand the nature of AI and apply it to various problems. Therefore, students in the introductory AI course have different motivations and backgrounds, and their math and coding skills can vary greatly. In this study, the instructor planned to provide problem-solving experiences in which members with different capabilities could create individualized schemas for learning AI and collaborate with each other. Through these experiences, the instructor assumed that students could acquire the basic knowledge of AI and gain insights into how AI can be used to solve real-world problems. The study results showed that running such an experimental course allowed us to generate arguments that while structured, concept-driven learning is important in AI, problem-solving experiences that connect to real-world problems can be key to AI education.

Although a significant proportion of participants majored in education, particularly in science education, they sought to learn AI and big data analytics to apply in their research and work. Their objectives seemed to be shaped by the increasing demand for AI expertise in society (Stine et al., 2019) and societal pressure to empower teachers with AI-ready skills (Luckin et al., 2022). Most participants with extrinsic motivation perceived AI as a tool for data analysis and career advancement, with only one participant mentioning enjoyment as a reason for learning AI.

The increasing demand for AI professionals has encouraged learners from diverse majors to enroll in the introductory AI course, resulting in greater learner diversity. One of the themes 'Collaborative learning in a diverse group' presented students with new challenges. They expanded their networks and acquired new knowledge or skills by collaborating with people from different majors. However, some students encountered coding barriers while working on these collaborative projects. Students proficient in coding performed better on assignments and team projects in these courses. This disparity led to feelings of inadequacy among students with limited coding skills, reducing their engagement and fostering passive participation in team tasks. Although programming is a highly effective tool for transforming ideas into reality, students often struggle to develop programming skills due to its stringent syntax rules and the abstract thinking required by programming languages (Choi & Lee, 2014).

Divergent views exist on the level of programming proficiency that a student in a big data course needs to possess. According to Long and Magerko (2022), understanding how to program can help students understand AI, but not everyone needs to know how to program to interact with AI in their daily lives. Therefore, computational literacy is not necessarily a prerequisite for AI literacy. Gil (2016) suggested that not every learner is inclined to invest the time and effort. On the other hand, according to Han (2020), learners who perceived themselves to be better at coding showed significant positive changes in all attitudinal factors examined after working on the AI project. Lee and Perret (2022) found that some teachers who understand computer science concepts and specialized programming languages had an advantage over others in a program designed to prepare high school teachers with AI content knowledge. These show that while coding skills are not essential for learning AI and big data analysis, they benefit teachers and students.

Based on the findings from the team project in this study, we identified the potential of team project tasks as an effective strategy to address the diversity of learner proficiencies for successful AI education. Previous research on inclusion and diversity in computer science education has also advocated for the adoption of project- and team-based learning approaches to engage low-achieving students (Dahlberg et al., 2010; Xia et al., 2022). In this study, some students perceived solving real-world problems collaboratively with peers from other disciplines as an opportunity to broaden their perspectives and enhance their communication skills. Project-based activities that encourage students to identify problems in real-world scenarios and apply AI techniques to solve them promote problem-solving and computational thinking skills (Kim et al., 2021; Torrey, 2012) while fostering data literacy (Wolff et al., 2016). Certain learners with limited coding skills reported feelings of isolation and helplessness during team projects. However, complex real-world problems are not resolved solely through coding skills but require diverse background knowledge and problem-definition skills. Therefore, instructors should guide team members in assigning roles that align with their strengths, enabling all participants to contribute effectively to the project.

Based on the analysis and discussion of the collected results, we propose an individual problem-solving assignment with distinct topics and levels of difficulty tailored to four identified learner types, as depicted in Figure 1. In this study, learners with low motivation and skill, such as participant E, struggled with coding and mathematics. These learners, falling into Area A, would find problems that can be addressed using basic programming skills within their respective fields appropriate. Concurrently, the utilization of elementary data analytics tasks through block-based AI model-building tools, such as KNIME and Orange3, can facilitate the acquisition of computational thinking skills, obviating the necessity for coding. Conversely, for learners in Area B, exhibiting low motivation yet high skills, more advanced problems within their major field would be more suitable. In this study, a low-motivated and high skilled learner, such as C, expressed a desire to analyze education-related data using AI. Given their high skills, beyond merely inserting existing code, challenging assignments that require modifying the code structure to suit their problems can enhance their motivation.

Learners demonstrating high motivation and low skills, such as B, showed high curiosity and wanted to experience diverse problems from a wide range of fields in the course. For learners in Area C, various social problems utilizing AI would be appropriate. Providing them with opportunities to apply AI models to solve diverse real-world problems could be handled adequately. Such experiences facilitate learners' comprehension of the utility of these models and encourage more enduring motivation for ongoing learning about AI. Conversely, learners demonstrating both high motivation and high skill, such as participant D, were satisfied with learning about a range of AI theories. For learners in Area D, various problems requiring modification of AI models based on the understanding of AI theories would be appropriate. It is anticipated that the customization of problem-solving tasks considering these learner characteristics will positively impact engagement and motivation.

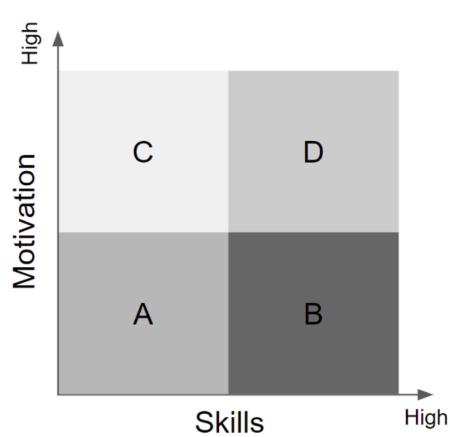

Fig. 1. Grouping learners by motivation and skills

Conclusion

This study employed a phenomenological approach to investigate the experiences of learners who enrolled in an introductory AI course specifically designed to introduce basic knowledge of big data and AI. We explored the six participants' lived experiences in an introductory AI course and understood their achievements and challenges during this experience. The following conclusions, summarized here into four distinct categories, offer insights into the characteristics of the introductory AI course that can inform the design of the curriculum and the instructional methods.

Firstly, although the majority of participants in the study were science education majors, they demonstrated motivation to explore AI-related careers. Lin et al. (2021) argued that cultivating future AI specialists requires developing strategies to enhance students' career motivation in the field of AI. To improve the satisfaction of learners with diverse motivations and achievement goals, it is essential to design a curriculum that not only introduces computing concepts but also includes skills for personal development and career advancement (Sanusi et al., 2022). We identified that learners with career motivation and a desire to develop career-related skills expressed satisfaction in AI courses by enhancing their competency in analytics tools, which they could utilize in future research or professional work.

Secondly, it was observed that for certain learners, coding and mathematics posed challenges in learning AI. While some participants improved their coding abilities through task performance, others experienced a significant burden associated with these tasks. To address these issues, we proposed in the discussion section that problem-solving assignments should be assigned in a variety of topics and levels of difficulty based on learners' individual motivations and skills

Thirdly, an effective approach to enhancing learners' comprehension of concepts and theories, as well as their ability to apply acquired knowledge, involves facilitating collaborative team projects that engage learners with diverse backgrounds and skills. Through the projects, learners gained insights from different perspectives and cultivate their communication skills while engaging in real-world problem-solving. Instructors should emphasize the importance of assigning team roles based on individual strengths, particularly considering students with limited coding skills.

Finally, implementing a curriculum that incorporates a range of theoretical frameworks has enabled learners to dispel preconceived notions that once rendered AI incomprehensible and inaccessible. Learners began with fundamental knowledge, but by the end of the course, they identified their weaknesses or areas of interest and planned to deepen their learning based on this course experience. Although machine learning is currently a significant focus in AI research and education (Yang et al., 2023), there is limited work on machine learning education, particularly in teaching non-majors (Sulmont et al., 2019). From this perspective, this study contributes by suggesting pedagogical strategies and curricula to effectively teach machine learning to non-major students.

This study is subject to a limitation in generalizing the research findings due to examining experiences from a restricted sample of only six participants. In addition, the preponderance of physics majors among the participants may have biased the identification of the central phenomenon. To address this limitation, future research should include learners from diverse academic disciplines to capture a broader spectrum of experiences and phenomena in introductory AI courses. Nonetheless, its significance lies in providing valuable data for instructors aiming to design introductory AI courses, as it highlights the observed phenomena and characteristics of learners' experiences taking the course.

Data Availability Statement

Due to confidentiality and ethical considerations, the raw data for this qualitative study is not publicly available. Summarized findings and anonymized excerpts may be provided upon request and approval from the Institutional Review Board (IRB) or ethics committee.

Conflicts of Interest

The author(s) declared no conflicts of interest.

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