Lecturers' Perspectives Regarding AI Competencies for Non-computer Science Students in Undergraduate Education

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Abstract. Artificial intelligence (AI) systems have increasingly been adopted in various fields, including education, healthcare, law, and journalism, due to their ability to save time, reduce costs, and ease human efforts. The growing relevance of AI systems brings a need to prepare undergraduate students from diverse backgrounds to understand and use AI technologies productively and responsibly in their professional careers. However, in order to effectively introduce AI to non-computer science undergraduates, it is essential to investigate the necessary AI competencies these students need to acquire. Therefore, in this work, we have conducted semi-structured interviews with multidisciplinary higher education lecturers with AI knowledge to analyze which AI competencies are relevant to be included in undergraduate curricula for non-computer science students according to their perspectives. This article presents the findings of these interviews as well as the emergent list of competencies. The list covers various aspects of AI, ranging from introductory topics, such as the capabilities of AI systems, to more advanced theoretical knowledge and practical skills in data management and machine learning. Moreover, the list contains competencies related to responsible AI, including the ethical and social implications of AI. Our list extends prior work on AI competencies for non-computer science undergraduates.

Keywords: Computer Science Education · Competency-based Education · Artificial Intelligence · Undergraduate Level

1 Introduction

In recent years, there has been a growing demand for artificial intelligence (AI) education in order to prepare students from different educational levels to develop and use AI-based technologies effectively and responsibly [1–5]. Some research in the artificial intelligence education field has been focusing on investigating which AI competencies different student subgroups should acquire. For

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example, in secondary computer science education, a set of AI-related learning objectives derived from an iterative process with an expert group was presented [6]. For non-technical learners, a set of AI competencies to critically evaluate AI technologies, communicate and collaborate effectively with AI, and apply AI as a tool online, at home, and in the workplace were proposed [7].

Similarly, non-computer science undergraduates need to be prepared to deal with recent AI breakthroughs; they need to be able to effectively use AI technologies in their future workplaces and help with their responsible development [8–10] across domains such as law and journalism [11]. Considering that non-computer science students are a miscellaneous audience, research with a multidisciplinary audience is important to collect different perspectives and investigate adequate AI competencies for these students to ensure that their needs are satisfactorily addressed in undergraduate education. In previous work [12], semi-structured interviews were conducted with professionals working in the intersection of AI and other domains to qualitatively investigate the AI competencies considered suitable for incorporation into the undergraduate education curricula of non-computer science students.

In this work, we aim to extract relevant AI competencies from a different multidisciplinary audience: lecturers with a background in industry and who currently work in a university setting. To that end, we conducted extensive interviews with 19 lecturers from a university of applied sciences, each of whom had at least three years experience in industry and from whom we elicited a diverse set of 27 AI competencies for non-computer science undergraduates.

2 Related Work

Due to the increasing adoption of AI in different domains [13,14], there has been a growing interest in AI education for non-computer science students in undergraduate education over the last few years in order to prepare these future professionals for the changing work landscape. Most of the studies in the field aimed to present or describe AI courses or programs for non-computer science undergraduates [13–26]. For example, AI practices for architecture and design courses using experiential learning and interaction among the students are presented [15]. An interdisciplinary AI course has been designed for liberal arts students [16]. In addition, a curriculum for a graduate-level business course in AI, addressing AI fundamentals as well as the latest developments in the field, was proposed [18].

A smaller amount of work has proposed assisting technologies [27], learning materials [28], or AI educational models [19] or frameworks [29]. In Wang and An [27], a mobile application was proposed to help non-experts understand convolutional neural networks interactively. Takesako and Inoue [28] proposed material for learning basic AI-related knowledge and developing AI easily through a visual programming tool. In Lee and Cho [19], an AI education model that uses teachable machines was proposed. Katznelson and Gerke [29] proposed a framework to study health AI ethics consisting of the following six issues that were considered most pertinent for medical students: informed consent, bias, safety, transparency, patient privacy, and allocation.

3 Methods

3.1 Recruitment and Sampling

In order to further investigate which AI competencies are relevant for non-computer science students in undergraduate education, we conducted semi-structured interviews with a convenience sample of lecturers at the University of Applied Sciences Berlin. In the recruitment process, lecturers were considered eligible if they had at least three years of experience in the industry and were actively teaching in 2022. No other inclusion or exclusion criteria were applied. To recruit participants, invitation emails were sent from April 2022 to July 2022. The sample of invited lecturers was acquired from May 2022 through August 2022. After each interview, we kindly requested recommendations from the interviewee for other professionals who could potentially participate in the study. In the invitation email, we stated the aim of the research, explained the interview procedure, and inquired about the lecturer's availability. We also provided contact information so that the lecturers could reach out to us if they had any queries. Table 1 summarizes the lecturers' domain expertise.

Table 1. Participants' information

ID	Domain expertise
Lect. 1	Communication Design
Lect. 2	Applied Statistics, Machine Learning, Data Science
Lect. 3	Automotive Engineering
Lect. 4	Mechanical Engineering
Lect. 5	Business Information Technology
Lect. 6	Digitization and Workspace Management, Corporate Learning Architecture
Lect. 7	Mechanical Engineering
Lect. 8	Automotive Engineering
Lect. 9	Mechanical Engineering
Lect. 10	Logistics, Production Management
Lect. 11	Business and organizational psychology
Lect. 12	Statistics and Data Science
Lect. 13	Business Information Technology
Lect. 14	Mechanical Engineering
Lect. 15	Mechanical Engineering
Lect. 16	Environmental Computer Science
Lect. 17	Visual Computing
Lect. 18	Mechanical Engineering
Lect. 19	Computer Science in Culture and Health

3.2 Interview Procedure

Interviews were conducted in person, with one or two interviewers depending on availability. The interviewers introduced themselves, specified the goal of the interview, and pointed out its semi-structured nature. The questions were related to the competencies that non-computer science students need to acquire at the undergraduate level. The interviews' duration did not exceed 60 min, and during the interviews, the researchers took notes of the participants' answers.

3.3 Data Analysis

In the first step of the data analysis, the interview notes were qualitatively analyzed using conventional content analysis [30]. In conventional content analysis, researchers immerse themselves in the qualitative data and allow the categories and names for categories to emerge from the data [30]. During the analysis, the first author coded all emerging competencies listed by the interviewees. In the second step, two researchers, through an online meeting, simultaneously analyzed the notes and the initial coding of competencies conducted by the first researcher. In this meeting, when there was a disagreement about the coding, all three researchers discussed and achieved an agreement. The competencies were coded using the list of verbs provided on Bloom's for Computing [31]. The results are detailed in Sect. 4. The entire data analysis process was facilitated by a qualitative analysis tool called MAXQDA [32].

4 Results

In this section, we present the results of the interviews with 19 multidisciplinary higher education lecturers with the objective of collecting the AI competencies that are relevant to non-computer science undergraduate students according to their perspectives. Table 2 lists all the 27 elicited AI competencies from our interviews.

Table 2. Relevant AI competencies according to the interviewees

ID	Competency	Lecturers
	Basics of AI	
CP1	Discuss what AI is	Lect. 4, 7, 10, 14
CP2	Describe different AI approaches	Lect. 2
CP3	Distinguish AI approaches from other computer science approaches	Lect. 2, 4, 6, 7, 11, 12, 14
	AI Capabilities	
CP4	Describe the strengths of AI systems	Lect. 1, 2, 3, 6, 7, 8, 10, 13
CP5	Describe the limitations of AI systems	Lect. 2, 3, 10, 12, 19

(continued)

Table 2. (*continued*)

ID	Competency	Lecturers
CP6	Describe the domain-specific and general benefits and advantages of using AI	Lect. 6, 13
CP7	Describe where and how AI can be used in a specific domain	Lect. 3, 4, 8, 10, 11, 12, 13, 14, 16, 18
CP8	Describe success cases of AI systems	Lect. 1, 2, 11, 14
CP9	Imagine future AI applications	Lect. 1
CP10	Describe which problems AI is appropriate for	Lect. 6, 10, 15, 16, 18
	Data	
CP11	Manage data (prepare the data appropriately based on the problem)	Lect. 16
	Machine Learning (ML)	
CP12	Explain how different machine learning (ML) techniques work	Lect. 2, 17
CP13	Describe what sensors are and recognize their relevance for the ML field	Lect. 15
CP14	Analyze which data and ML techniques are most suitable based on the problem at hand	Lect. 2, 3
CP15	Apply data-driven ML techniques to solve domain-specific problems	Lect. 2
CP16	Evaluate ML model performance	Lect. 2, 11, 12
CP17	Recognize the importance of data quality for the output of ML systems	Lect. 7, 19
CP18	Explain the mathematical background of major ML techniques	Lect. 5, 7, 8, 17
CP19	Recognize that large amounts of data are not always needed in ML	Lect. 7
CP20	Code to apply ML	Lect. 5, 7, 16, 17, 19
CP21	Use no-code tools to apply ML	Lect. 8
CP22	Describe the ML lifecycle and its components	Lect. 10, 12, 13, 16, 18
	Advanced ML	
CP23	Recognize the relevance of big data	Lect. 16
CP24	Describe artificial neural networks and deep learning at a high level	Lect. 7, 8, 17
CP25	Describe how popular AI systems such as recommender and personalized/adaptive systems work	Lect. 5
CP26	Describe the requirements for the development of ML systems, such as infrastructure, data, costs	Lect. 6, 10
	Responsible AI	
CP27	Describe the societal and ethical issues surrounding AI	Lect. 1, 6, 9, 10, 11, 12, 13, 14, 15, 16, 17, 19

4.1 Basics of AI

Some participants highlighted the relevance of students acquiring basic AI competencies, such as discussing what AI is (CP1) and describing different AI approaches (CP2). Moreover, some lecturers also state that it is relevant for students to point out similarities and differences between AI and other CS approaches (CP3), such as statistical methods, big data, and the Internet of Things.

4.2 AI Capabilities

A considerable amount of participants emphasized the importance of non-CS undergraduate students acquiring competencies related to AI capabilities. For example, according to Lect. 1, it is important to demystify AI. Therefore, lecturers point out that students need to learn the strengths of AI systems such as speed, adaptability and automation (CP4), the benefits and advantages (CP6), and limitations of AI (CP5) and imagine what will be possible in the next 5–10 years (CP9). Moreover, according to Lecturers 1, 2, 11, and 14, students need to have an overview of existing AI success cases (CP8), such as generative AI tools (e.g., Dall-e-2). Lecturers also highlight the relevance of students understanding the practical relevance of AI in their domains and understanding how AI is being applied in their fields (e.g., automotive engineering, mechanical engineering, industrial engineering, business, logistics) (CP7). Finally, some lecturers state the relevance of students being able to describe which problems AI is appropriate for (CP10), such as prediction, recommendation and content generation.

4.3 Data

One lecturer emphasized the importance of competencies related to data management. According to Lect. 16, it is important for students to know how to visualize and analyze datasets, for example (CP11).

4.4 Machine Learning (ML)

According to Lect. 2 and 17, it is important to know about the different machine learning (ML) techniques (e.g., reinforcement learning, supervised learning, unsupervised learning) (CP12). Lect. 2 and 3 point out the relevance of students being able to decide which techniques are most suitable based on the problem to be solved (CP14), know how to apply ML methods to solve domain-specific problems (CP15) and evaluate ML model performance using evaluation metrics (CP16). Lect. 15 stated that it is relevant for students to understand what sensor data are (e.g., in robotics) and their relevance for the ML field (C13).

In addition, for Lect. 7 and 19, students need to understand the importance of data in the machine learning context and how it influences the results of ML systems (CP17). Some lecturers state the relevance of understanding the technical side of ML approaches, such as the mathematical background of ML algorithms (e.g., loss functions) (CP18). Lect. 7 highlights that students need to recognize that large amounts of data are not always needed in ML (CP19). Lecturers state the relevance of coding skills for developing ML applications (CP20), including documentation best practices (Lecturer 9). Lect. 8 states the relevance of students being able to use no-code tools to apply their knowledge (CP21). Finally, lecturers pointed out that it is important for students to have an understanding of data and the ML lifecycle (CP22).

4.5 Advanced ML

Lecturers highlighted that students benefit from learning more advanced topics in machine learning. For example, for Lect. 16, it is relevant for students to recognize the relevance of big data in their domains (e.g., environmental computer science) (CP23). Furthermore, lecturers state that it is relevant to learn about artificial neural networks and deep learning (CP24). Furthermore, according to Lect. 5, it is important that students have an understanding of how some popular AI systems work, such as recommender and personalized/adaptive ML systems (such as Instagram and Twitter) (CP25). Finally, Lecturers 6 and 10 highlight that it is relevant for students to understand what is needed for the development of AI systems regarding infrastructure, data, and costs (CP26).

4.6 Responsible AI

Responsible AI was frequently mentioned during the interviews. According to lecturers, students need to be aware of societal and ethical issues surrounding AI (CP27). For example, for Lecturer 1, students need to be aware of data protection. Lecturer 17 also highlighted data security as important, while Lecturer 9 emphasized the importance of topics such as bias, adversarial attacks, and sustainability.

5 Discussion and Conclusion

This article presents the results of 19 semi-structured interviews with higher education lecturers from various fields who have experience with AI. Through these interviews, we have identified a total of 27 AI competencies that these lecturers consider important for non-computer science undergraduate students to acquire. On the one hand, our content analysis can be used by lecturers and researchers to guide content selection for higher education AI teaching for this audience [33]. On the other hand, our results provide a significant milestone toward developing a list of relevant competencies for general AI education in undergraduate education, specifically for non-computer science students.

The competency most cited by the lecturers was related to societal and ethical issues around AI, with the lecturers mainly pointing out issues around data privacy, data security, and algorithmic bias. Another highly cited competency was related to AI capabilities, describing where and how AI can be used in their specific domain, as well as describing the strengths of AI systems. Lecturers also highly cited the relevance of students in distinguishing AI from other computer science approaches, such as statistical methods, big data, or Internet of Things technologies. Moreover, some lecturers also highlighted the relevance of describing the AI lifecycle and its components as well as coding skills to implement AI systems, although some lecturers also mentioned that non-coding tools could be adopted.

We believe that our convenience sample of 19 multidisciplinary university lecturers with at least three years of experience allowed us to elicit AI competencies that can be considered relevant for future professionals to develop and use AI-related technologies effectively and responsibly. However, despite the relevance of the findings, this work presents limitations. The data analyzed in this work were based on researchers' notes taken during interviews, which may be limited by their biases and perspectives. Furthermore, the researcher who conducted the initial coding was not involved in the interviews. As a result, it is possible that the researcher had a limited view of the data. To minimize this limitation, three researchers evaluated the coding schema and achieved agreement in case of divergent interpretations. Moreover, we acknowledge that our participants' sample was formed only by German lecturers from a specific institution, and there was an underrepresentation of participants from other countries and other backgrounds. Therefore, our findings may not sufficiently reflect local knowledge, cultural pluralism, and other viewpoints.

As a future step, our next objective is to merge the list of competencies from interviews with AI professionals working at the intersection of AI and other domains [12], as well as from other competency frameworks for non-technical individuals, in order to achieve a comprehensive list of AI competencies for non-CS undergraduate students.

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