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AI Competencies for Non-computer Science Students in Undergraduate Education: Towards a Competency Framework

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ABSTRACT

Artificial Intelligence (AI) has been increasingly applied in various societal areas such as medicine, education, and science. For example, through the generation of more accurate medical diagnoses to support patients' treatment, more content personalization to provide adaptive learning for students and more accurate predictions for future climate changes. Consequently, there is an increasing demand for professionals from different fields with AI competencies. These future professionals need preparation during their undergraduate education to deal with the remarkable AI breakthroughs in their domains and to understand, use, and help with the responsible development of these technologies. However, to address AI to non-computer science students in undergraduate education, it is necessary to thoroughly investigate the core AI competencies essential to these students acquire in order to prepare them effectively. Based on this, the objective of the research is to develop a framework with core AI competencies that can be adopted in future work to inform AI education for this target audience. Therefore, towards the AI competency framework for non-computer science students in undergraduate education, as an initial part of the process, we conducted semi-structured interviews with professionals working in the intersection of AI and other domains. The objective of the interviews was to qualitatively investigate the AI competencies considered suitable for incorporation into the undergraduate education curricula of non-computer science students from these professionals' points of view. In this work, we present the results of these interviews and the list of core AI competencies for non-computer science students in undergraduate education according to these professionals. In summary, this list encompasses different perspectives, varying from basic AI competencies related to AI definition, history, and capabilities to more complex theoretical knowledge and practical skills regarding data and machine learning. The list also includes responsible AI competencies, covering AI's social, ethical, and legal aspects.

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CCS CONCEPTS

• **Social and professional topics** → **Adult education**; • **Computing methodologies** → *Artificial intelligence*; • **Applied computing** → Computers in other domains.

KEYWORDS

AI education, undergraduate education, competency-based education, interviews

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1 INTRODUCTION

Artificial intelligence (AI) systems have become a leading technology in diverse areas, such as medicine, education, law, and journalism [37]. These systems, developed using machine learning and/or logic- and knowledge-based approaches, can, for a given set of human-defined objectives, generate outputs such as content, predictions, recommendations, or decisions, influencing the environments they interact with [14]. Consequently, AI systems are saving time and are reducing costs and human efforts to perform certain tasks [15]. For example, they support the detection and diagnosis of diseases [6], provide adaptive and individualized instruction and experience [9, 26], perform automated lawsuit classification [1], produce news stories, carry out content summarization, and translate challenging texts [16].

Due to the increasing adoption of AI systems in different domains [37], there is a growing demand in the labor market for professionals with AI skills across different areas who can use AI to lead to innovative and enhanced outcomes in their fields [2]. Based on this, in recent years, there has been a rising interest in the field of AI literacy for non-computer science students in undergraduate education to prepare these future professionals for this evolving workplace. Currently, the majority of studies in the field aim to present or describe an AI course/program for non-computer science students in undergraduate education institutions [3, 7, 8, 11–13, 18, 20, 23, 27, 29, 30, 38, 45, 46]. Other works propose an educational technology [42] or learning material [39] or an AI educational model [29]. Nonetheless, additional theoretical contributions that list AI competencies and can guide future works in the field in order to prepare this audience effectively are highly needed for the maturity of the field.

Moreover, although there are theoretical contributions in the broader AI education research field that have proposed AI competencies for different audiences, their target is different, such as K-12 and general non-technical audiences [24, 32, 33, 41]. Non-computer science students in undergraduate education specifically may present different needs regarding AI competencies. For example, since these systems may pose a range of risks such as bias perpetuation, privacy and copyright violations, misinformation dissemination, manipulation facilitation, and security concerns [5, 43], researchers are also advocating the importance of these future professionals' education about how to safely, critically, and ethically interact with AI in their jobs [19]. Moreover, for example, researchers are also pointing out the importance of multidisciplinary actors developing AI systems [19] since AI is an interdisciplinary field that can benefit from the broad spectrum of domain knowledge for its development [25].

Considering this, universities need to address this growing demand for AI education by equipping students with core AI competencies that prepare them for the AI-based workplace and also provide a solid basis for future subject-specific AI education. Therefore, to do it effectively, it is highly important to specifically investigate which core AI competencies are relevant to be included in the undergraduate education curricula of general non-computer science students and propose theoretical contributions that can guide the implementation of future works. Based on it, this research aims to answer the following questions: (RQ1) What are the reasons why AI should be taught to undergraduate non-computer science students from the perspective of professionals working in the intersection of AI and other domains?; (RQ2) What are the core AI competencies considered suitable for incorporation into undergraduate education curricula of non-computer science students at the undergraduate level according to professionals working in the intersection of AI and other domains? To answer these research questions, we conducted semi-structured interviews with professionals working at the intersection of AI and other domains. As non-computer science students are from various fields, it is important to gather qualitative insights from professionals with working experience at the intersection of AI and other domains. Based on the research questions outcomes, we provide a list of competencies that non-computer science students in undergraduate education need to acquire according to these professionals' perspectives. Following a bottom-up approach, this is a step toward developing a framework with core AI competencies for non-computer science students in undergraduate education that can guide future works in the field.

2 RELATED WORKS

As AI systems become more integrated into society's everyday life, more efforts in the AI literacy research field have been made to investigate which AI competencies different groups of society should acquire. In this section, we aim to present these related works that have been proposing AI competencies for K-12 teachers, broader non-technical and specific professional audiences. Consequently, we situate our work in the field and highlight its novelty and relevance. For K-12, Michaeli et al. [33], following an iterative process with an expert group, propose learning objectives for AI in secondary computing education. Touretzky et al. [40], through collaboration with AI experts and K-12 teachers, present guidelines for AI to K-12, which are based on five "Big Ideas". Huang [24], reached from the basic definition of DeSeCo's key competencies [35], presents the key competencies that Chinese students in the fundamental education stage should have.

For teachers, Directorate-General for Education [17] presents emerging competencies that educators and school leaders should acquire to understand the potential benefits and challenges of using AI systems in education, as well as enable them to leverage AI to improve teaching, learning, and assessment practices. In Ng et al. [34], a new AI competency framework for teachers is proposed based on existing contributions. The objective of the new framework is to include technological-related competency to incorporate non-technical skill sets, such as life and career skills, multidisciplinary skills, as well as learning and innovation skills in order to equip the teachers with the necessary AI competencies for better teaching and learning.

For a broader non-technical audience, Long and Magerko [32], based on an exploratory review of interdisciplinary literature, proposes a set of AI competencies for non-technical learners to enable them to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as an online tool, at home, and in the workplace. Laupichler et al. [28], through a Delphi study, propose an item set in order to assess the competencies of AI of non-experts, derived from the AI definition proposed in [32]. The Digital Competence Framework for Citizen (DigComp) [41], based on a validation online survey with a diverse audience, proposed a set of competencies for citizens in order to help them to engage confidently, critically, and safely with digital technologies (including artificial intelligence).

Furthermore, there are also works investigating which AI competencies are suitable for specific professions to be acquired in undergraduate education. In Çalışkan et al. [47], through a Delphi study, a list of AI competencies has been proposed to be incorporated into the medical education curriculum. The aim here is to equip medical professionals with the necessary skills to effectively utilize artificial intelligence technologies and their potential applications in the field of medicine. Similarly, Liaw et al. [31] propose competencies to be included in medical education and training for the effective deployment of AI-based tools in primary care. Likewise, Russell et al. [36], based on expert interviews, propose AI-related clinical competencies to guide future teaching and learning programs of healthcare professionals to optimize the potential benefits of AI-based tools while minimizing any potential harm. For engineering and technical education students, through a Delphi study, Chen et al. [10] propose a list of competencies for artificial intelligence in finite element analysis to support a training and development plan.

As seen, there are a considerable number of contributions regarding AI competencies for different society groups. Most of them focus on a specific audience (e.g., K-12 students and teachers, health students, engineering students) or concentrate on a broader non-technical audience. Non-computer science students in undergraduate education, in particular, may have specific needs regarding AI competencies since these future professionals need to be prepared to possibly use AI methods or AI systems to lead to positive benefits (new/improved outcomes) in their field domains, analyzing these technologies critically when applying or developing them in their future jobs, and/or collaborating in an interdisciplinary group of AI professionals.

Therefore, to support universities in addressing AI education for non-computer science students, a core of AI competencies for this diverse audience should be investigated in order to prepare them effectively for the AI-based workplace and also provide a solid basis for future subject-specific AI education. Since non-computer science students in undergraduate education are a diverse audience and to propose adequate core AI competencies for these students accordingly, research with interdisciplinary experts who work with AI from these different fields is relevant in order to ensure that the needs of these students are satisfactorily addressed in undergraduate education. Based on this, following a bottom-up approach, in this work, we conducted interviews with multidisciplinary professionals with AI experience about the topic of AI competencies for non-computer science students in undergraduate education. This is a first step towards proposing a competency framework with core AI competencies for general AI education for this audience.

3 METHOD

In order to answer the two research questions stated in 1, we conducted semi-structured interviews with professionals working at the intersection of AI and other domains. In this section, we aim to describe how the study was conducted.

3.1 Recruitment and Sampling

Our aim was to sample a varied group of participants with different levels of experience in different domains intersecting with AI who were willing and knowledgeable to discuss and share their thoughts on AI competencies for non-computer science students in undergraduate education. Therefore, in the recruitment processes, the criteria used to select the participants was that they should be professionals (researchers, university professors, practitioners) who actively work or have experience in the intersection of AI with other domains (e.g., physics, journalism, psychology). For example, a university professor who works in the field of AI applied to the Education field or a data scientist whose Ph.D. thesis was in the application of AI methods in the Political Science domain. No other inclusion or exclusion criteria were applied. To recruit participants, an email was sent to different professionals. The list of invited professionals contained names of professionals retrieved from AI articles, AI companies, social networks (Twitter, ResearchGate, LinkedIn), and university websites. Another part of the sample of invited professionals was acquired using snowball sampling. After each interview, we kindly requested recommendations from the interviewee of other candidates who could potentially participate in the study.

In the invitation email, we presented ourselves, depicted the objective of the interview, explained the relevance of the participation of the professional, elucidated the expected duration time, and listed the topics that we were going to address in the interview. At the end of the email, they were asked to choose a day and hour for the conduction of the interview based on their time availability through a scheduling platform called Calendly. In total, we recruited 17 professionals. Based on preliminary data analysis, there is a possible saturation after the 15th participant. Hence, recruitment was stopped at 17 after no new information emerged. Table 1 summarizes the participants' information, including country of residence, years of work experience that the interviewed professionals have in the intersection of AI and their application domain, their educational degree, their current job position, and their application domain of AI. Most of the participants currently live in Germany (11), followed by residents from Brazil (4), the United States (1), and the Netherlands (1). Most of the participants hold a doctorate degree (11), followed by a master's degree (4). Moreover, most of the participants currently work in Academia.

3.2 Interview Procedure

The first author of this work conducted the interviews in a one-on-one semi-structured manner between November 2022 and June 2023. The interviewer is a computer science education researcher working in the AI literacy field. The interviews were conducted remotely using a university Webex account, from which only the meeting audio was recorded. The interviews lasted between 40 and 80 minutes. We conducted one pilot interview not only to ensure that our interview procedure was clear but also that the questions were suitable to achieve our objective and that our scheduled interview would not exceed the scheduled time.

The first phase of the interview consisted of a presentation about the research objective and the involved researchers. Afterward, there was an explanation about how the interviews were going to be conducted. This includes information about the topics addressed in the interviews, the expected duration time, and the interview procedure. Moreover, during this first phase, participants read the consent form and were encouraged to ask questions concerning any information that was not clear about the research. The information and declaration consent form contained information about the research project, data use and publishing, confidentiality, data protection and storage, data subject rights (based on GDPR), and the researchers' contact. After reading the form and agreeing with the interviews, the interviewer started the audio recording. The interviewees were asked to explicitly declare their consent to the recording. All the participants explicitly consented to use the recorded data for research purposes, as explained in the form.

The second phase of the interview consisted of inquiring about the participants' experiences in the AI field and its intersection with the application domains. The third phase consisted of warm-up questions to encourage participants to think about the use of AI in their application domains, preparing them to discuss AI competencies later. The fourth phase consisted of inquiring about the main questions concerning the relevance of teaching AI for non-computer science students in undergraduate education and the competencies this audience should acquire from the interviewed professionals' point of view. Finally, the last phase of the interview consisted of investigating the closing questions regarding recommendations about research or practical work of AI in their application domain and training already existing for the investigated target audience. The interview questions were supplied as supplemental material and can be seen in Appendix A. In order to enable the participants to answer the competency-related questions with more confidence and precision, we asked them to answer these questions thinking

Table 1: Participants' information

ID	Country of Residence	Years of experience	Educational Degree	Current work position	Application domain of AI
P1	Brazil	8 years	Doctorate	University Professor and AI developer	Education
P2	Germany	4 years	Doctorate	Data Scientist	Political Science
P3	Germany	4 years	Master	Research assistant and PhD student	Business
P4	Brazil	4 years	Doctorate	University Professor and researcher	Law
P5	Germany	5 years	Master	PhD Candidate	Medicine
P6	Netherlands	7 years	Doctorate	Postdoctoral researcher	Journalism
P7	Germany	3,5 years	Master	Research Assistant	Anthropology
P8	Germany	5 years	Master	Research Assistant and PhD student	Linguistics
P9	Germany	4 years	Bachelor	Master's student	Psychology
P10	Germany	8 years	Doctorate	University Professor and researcher	Philology
P11	Germany	6 years	Bachelor	Sound artist and AI researcher	Arts
P12	Germany	6 years	Doctorate	Data Scientist	Sociology
P13	Germany	6 years	Doctorate	University Professor and researcher	Physics
P14	Germany	7 years	Doctorate	Data Scientist	Political Science
P15	United States	8 years	Doctorate	PhD Candidate	Arts
P16	Brazil	10 years	Doctorate	University Professor and researcher	Education
P17	Brazil	10 years	Doctorate	University Professor and researcher	Education

about the students from their application domain of AI since they are more familiar with their needs.

3.3 Data Analysis

Before the data analysis, all audio recordings were transcribed (sixteen automatically and one manually because one participant did not agree with the use of the tool). The automatic transcriptions of the interviews were supported by an automated speech-to-text service called Konch AI, which complies with GDPR. The use of this tool was stated on the consent form. In the first step of the data analysis, the first author listened to the audio recordings and simultaneously manually reviewed the transcripts afterward since an automated speech-to-text service was used, and some words were mistranscribed. This step also helped the first author to get familiar with the data. In the second step of the data analysis, the first author qualitatively analyzed the interview transcripts regarding the competency-related questions (fourth phase of the interview) using the conventional content analysis method [22]. In conventional content analysis, researchers immerse themselves in the qualitative data and allow the categories and names for categories to emerge from the data [22]. Based on this, during the analysis, the first author coded all emerging reasons and competencies listed by the interviewees. The competencies were coded using the list of verbs provided on Bloom's for Computing [4]. After the competencies were coded, they were grouped into themes based on their topic similarity. The results are detailed in Section 4. The entire data analysis process was facilitated by a qualitative analysis tool called MAXQDA [44].

4 RESULTS

In this section, we aim to state the research outcomes of the two questions posed in Section 1. In subsection 4.1, we aim to answer RQ1: "What are the reasons why AI should be taught to undergraduate non-computer science students from the perspective of professionals working in the intersection of AI and other domains?" In subsection 4.2, we aim to answer RQ2: "What are the core AI competencies considered suitable for incorporation into undergraduate education curricula of non-computer science students according to professionals working in the intersection of AI and other domains?". Moreover, in this section, we refer to our participants as P1, . . . , P17, as shown in Table 1.

4.1 Reasons why AI should be taught to Non-CS students in undergraduate education

All the participants acknowledge that AI competencies are relevant to be acquired by non-computer science students from different domains in undergraduate education. The participants stated different reasons that support the relevance of non-computer science students acquiring AI competencies in undergraduate education. At the end of the subsection, we list the main reasons, which are referred to as R1, . . . , R5, in Table 2.

4.1.1 R1 (Use AI systems effectively and critically). Non-computer science students in undergraduate education need to be prepared to (R1) effectively and critically use general but also domain-specific AI systems in their future studies or workplaces, as emphasized by most participants. For example, in the journalism context, journalists will report on these systems, so students need to have a critical understanding of AI, such as what it is, how it works, and the risks (P6). In the law field, AI is becoming increasingly used, and students need to understand how this technology works and the impact AI systems bring to the law regulation scenario (such as AI regulation) and to daily practice (such as the use of this technology to classify law documents) (P4). In the psychology domain, students also need to learn AI since they may encounter AI systems in workplaces where AI is increasingly being adopted, such as human resources or human factor sectors (P9). In the medical context, students also must be prepared to work in the increasingly AI-driven environment. For example, pathologists benefit from AI competencies since they need to be prepared in case automatic analyzers are integrated into their workspaces and their whole work process might change (P5).

4.1.2 R2 (Apply AI methods effectively and critically). The AI methods have been increasingly becoming part of a set of research methods in different fields, and this is bringing benefits, as pointed out by a relevant number of participants. Therefore, AI competencies are relevant for these students so they can (R2) effectively and critically apply different AI methods to generate innovative and enhanced outcomes in their future studies or workplaces. For example, there are some fields in philology with so many materials to be analyzed that techniques such as distant reading and automatic digitization are required to have an overview of this whole corpus. Therefore, it is out of necessity (P10). Moreover, philology students will benefit from AI knowledge and skills since they can apply a plurality of methods and compare if the results generate the same conclusions (P10). Similarly, sociology students can significantly enhance their scientific capabilities since AI methods allow for a broader range of research methods and possibilities (P12). For journalist students, AI education is essential since they could use some AI methods to conduct investigative journalism, and then they need AI education to create or talk with specialists developing these AI systems (P6).

4.1.3 R3 (Study AI and its perspectives effectively and critically). In some fields, such as Anthropology and Sociology, AI is one of the objects of study, as highlighted by two participants. Consequently, students in these fields need AI competencies so they can (R3) effectively and critically study AI and its perspectives. For example, since anthropologists have been studying human relations with digital culture for a long time, and AI is already a part of many domains, anthropology students need to learn about AI to conduct thorough analyses (P7). For example, if they are researching immigration, they need to understand that AI is an integral part of the topic as it plays a role in current border controls. Thus, understanding how AI works is essential (P7). Moreover, AI competencies are also valuable for sociology students if they want to study how people work with AI since there are new fields in sociology that study if people trust machine learning, for example. Therefore, AI competencies become essential (P12).

4.1.4 R4 (Collaborate in AI development interdisciplinary groups). Some domain knowledge (e.g., linguistic, law, psychology knowledge) is essential for AI development, as pointed out by one participant. Therefore, non-computer science students from these fields need to acquire AI competencies so they can (R4) effectively use their domain knowledge to collaborate in AI development interdisciplinary groups. For example, linguistics professionals with domain knowledge in linguistics, computational skills, and AI knowledge are essential to work jointly with other computer scientists or mathematicians professionals to develop tools with more domain-specific understanding (P8).

4.1.5 R5 (Increase employability chances). There is an increasing demand for professionals with AI competencies, as pointed out by one participant. Then, AI competencies can be relevant for these students so they can (R5) increase their employability chances after finishing their studies at the university (P2).

4.2 AI competencies for non-computer science students in undergraduate education

The following subsections and Table 3 summarize our main findings grouped in themes.

4.2.1 Computing. According to some participants, it is relevant that students first acquire basic computing competencies in order to be prepared to acquire AI competencies effectively. For instance, for P7, it is crucial to understand what algorithms, data structures, and code are and how they differ (C1). Moreover, P7 also highlights the importance of students understanding how the code is compiled/interpreted and executed by a computer (C4) and having an overall understanding of the computer architecture (C2).

According to P4, for students to understand how AI works, they need to understand programming logic first (C3). Similarly, P1 also points out that although the teachers are not directly connected to the IT field, they require problem resolution as a skill (C3). According to P14, another relevant computing skill is being able to use distributed version control systems such as Git since this is a tool that enables peer collaboration and makes the code transparent and could be a powerful tool to support the learning process (C5). P8 also mentions that it is also relevant for students to understand machine-readable text formats such as CSV and XML (C6).

4.2.2 Basics of AI. Some participants highlighted the relevance of students acquiring basic AI competencies, such as defining what AI is and explaining the history of AI. According to P6 and P16, students must first have theoretical knowledge of AI and what AI is (C7). Similarly, P9 highlights the relevance of defining AI and compares it with human intelligence (C7).

According to P11, art students need to understand the history of artificial intelligence, and more specifically, neural networks since these have been massively used nowadays, and also consider the history of generative art and computing, like creative computing (C8).

Moreover, according to P6, students must first understand the different types of AI (e.g., knowledge-based AI and ML) and their differences (C9). For P4, it is also relevant for law students to know how to classify typical AI applications (such as Netflix and autonomous cars) according to the AI techniques used (C10).

4.2.3 AI Capabilities. Some participants pointed out competencies related to AI capabilities. A considerable number of participants mentioned the relevance of students knowing the limitations and strengths of AI techniques and algorithms for certain problems. For example, P16 highlights the relevance of students to understanding the strengths and limitations of AI (i.e., understanding what is possible and what is not possible to solve with AI) (C11). In complement, P1 also highlighted the relevance of knowing the limitations and strengths of AI techniques and algorithms based on the problem to be solved (C11).

Participants also mentioned students' relevance in knowing how AI can be used in their domains. For example, P5 states that medical students need to have an understanding of how AI systems can be introduced in their work (e.g., in which tasks AI systems can

Table 2: Reasons for teaching AI to non-computer science students in undergraduate education according to professionals working in the intersection of AI and other domains

ID	Reason	Participants
R1	Use AI systems effectively and critically	P1, P3, P4, P5, P6, P9, P10, P11, P13, P14, P15, P16, P17
R2	Apply AI methods effectively and critically	P2, P6, P10, P12, P13, P14
R3	Study AI and its perspectives effectively and critically	P7, P12
R4	Collaborate in AI development interdisciplinary groups	P8
R5	Increase employability chances	P2

support, such as detection and diagnosis of diseases) (C12). P3 also highlights that business students also need to be aware of the potential of AI in their domain (C12), such as supporting business that develops drugs against diseases. Similarly, for P14, students need to recognize the power of data and AI for research purposes in their fields (C12).

Consequently, participants also highlighted that it is important that students know AI success cases in their domains or in general. For example, P8 highlights the relevance of students knowing successful and practical AI applications that can be used daily to support their learning and work, such as Grammarly (C13).

4.2.4 Multidisciplinary AI. P9 highlighted the relevance of students understanding how their domain knowledge can help in the AI development field. The participant expresses that it is relevant for students to know how their psychology knowledge can contribute to AI development, such as by helping make AI more human-centered (C14).

4.2.5 Data. Participants frequently mentioned data-related competencies as relevant competencies to non-computer science students at the undergraduate level. For example, for P4, it is suitable for law students to learn about data and datasets (C15). Similarly, P7 also states that it is appropriate for anthropologist students to know what data is (C15). Furthermore, according to P10 and P14, another relevant data-related competency for students is learning about the data pipeline and what it consists of (C16).

Moreover, a relevant number of participants also mentioned the relevance of students to know how to collect or find data for their purposes (C17). For example, P1 states that student teachers should know how to collect data and how to conduct it ethically to avoid negative concerns (such as using consent forms, knowing well the data source, and following data protection laws such as GDPR). P8 also highlights that it is important that linguistics students know where to find suitable datasets. Additionally, P12 stated that sociology students need to understand the data-generating process of the dataset they are using (C18). If they did not collect the data themselves, they need to comprehend the process that led to the data's outcome. Complementing, P7 also mentions that it is relevant for students to analyze and get a reflective and critical view of the data (understand the assumptions and worldviews) (C18). Furthermore, according to P3, it is also relevant that business students have an understanding of how to label data (C19).

Another highly mentioned data-related competency was regarding managing data (C20). For example, for P1, student teachers should be able to manage data ("be able to do data management so that they reshape and eliminate what is unnecessary for the ML algorithm they chose based on the type of problem") (C20). P1 also highlights the relevance of students being able to manage data (C20), such as data collection, cleaning, analysis, and visualization. P1 also highlights the relevance of managing data and feature engineering (C20).

Competency related to statistics was also highly mentioned (P2, P8, P10, P12). For example, according to P2, political science students need to learn about the basics of statistics first, such as measures of central tendency, dispersion, and association (C21). Another data-related competency mentioned in the interviews was regarding programming using query languages. According to P2, it could be relevant if political science students are introduced to query languages such as SQL if they need to work on large-scale data projects where they need to organize data in databases (C22).

4.2.6 Machine Learning. A considerable amount of the participants pointed out some specific ML competencies important for non-computer science students to acquire in undergraduate education. Most participants stated that students need to learn how ML techniques and their main algorithms work (C24). Moreover, P10 and P11 highlight the relevance of students' understanding of these ML algorithms' basic mathematical background (C25), such as activation and loss functions. Furthermore, according to P12, causal relationships are often analyzed in sociology. Therefore, sociology students must also critically describe the difference between correlation and causation and the possible impact of not well-founded correlations in predictive models (C26).

Furthermore, some participants state the relevance of students learning about the ML lifecycle and its components (C23). According to P3, it is relevant that business students have an understanding of the whole process, from collecting/acquiring data and labeling data to training and evaluating a model (C23). P6 also states the relevance of students understanding the software development process (C23), such as understanding what a requirement is and the different stakeholders of the system, so they can effectively communicate with a technologist and report what they need if they need an AI tool to be developed.

Besides, some participants also highlighted the relevance of acquiring skills that allow them to develop ML systems. For example, P1, P3, and P4 state that students benefit from being able to analyze which problems that can be solved by ML in their domains (C27). Complementary, some participants also highlight the relevance of students in identifying which data and ML techniques are most suitable based on the problems to be solved. According to P1, it is important that students can identify ML techniques they could use to solve the problems (C28), such as ML learning techniques such as supervised learning (regression, classification) and unsupervised learning (clustering, association). Similarly, P14 highlights that it is very important that students have the skill to "identify appropriate ML methods based on the question they have" (C28). P1 also states that philology students need to understand how neural networks work and know what type of neural network architecture to use depending on the problem (C28). Moreover, P10 states that it is important for students to understand the hardware requirements (computing power) they need to develop their projects (C29).

Consequently, participants also point out the relevance of students applying data and ML techniques to solve problems in their domains (C30), including conducting hyperparameter tuning, according to P13. So, according to P17, in case they have "data from the students, and they want to extract some kind of information," they can apply ML techniques. Some participants stated that students can use no-code tools (C31), while others said that students can use programming languages to apply ML (C32). P1 points out that since teachers are not directly connected to the IT field, he suggests they need to be able to use tools such as Orange and Teachable Machine that do not require coding skills (C31). Similarly, according to P4, since law students usually do not have a programming background, low-code or no-code tools such as OutSystems, Grasshopper, and Scratch that only require logic are sufficient to support this learning process (C31). On the opposite, according to P8, it is important that linguistics students acquire fundamental programming skills using some programming language such as Python (C32). P2, similarly to P12, also highlights the relevance of students learning programming languages such as R or Python in order to apply their acquired knowledge to address real-world problems (C32). P1 also states that developing programming skills to apply ML is important for physics students, as well as having some library knowledge (C32). Participants also highlighted the importance of students evaluating the performance of their models using evaluation metrics (C33). P7 also states that it is relevant that the students learn how these systems can be shaped and adapted after the deployment through user and environment interaction (C34).

4.2.7 Advanced Machine Learning. Participants highlighted that students also benefit from learning more advanced topics of Machine Learning. For example, P8 and P10 highlight that it is important that students have a basic understanding of neural networks and deep learning and how it works (C35). Moreover, P2 also highlights that since deep learning has been increasingly adopted in the political science domain (e.g., for text analysis and classification), students can also be introduced to this content in undergraduate education (C35).

P12 also states that students need an introduction to what is and the capabilities of Computer Vision (CV) and Natural Language Processing fields (NLP) (C36). Moreover, according to P7, it is also relevant that students understand how the latest AI systems are being built using earlier models (i.e., using transfer learning) and how this process happens (C37). P8 and P11 also highlight the relevance of students learning about how transformers and generative models work (C38).

4.2.8 Human-AI Interaction. Some participants also highlighted that students should acquire competencies that prepare them to interact with AI systems effectively and critically in the work environment. For P5, medical students need to have an understanding of how AI systems can be introduced in their work and distinguish their responsibilities and the machine's responsibilities (C39).

Moreover, according to P5, since medicine is a highly sensitive field and requires that AI systems have higher performance (e.g., regarding the sensitivity and specificity) in their outcomes, students need to have an understanding of how evaluations of adopted AI systems are conducted and evaluate if the performance outcomes are adequate for the medical area (C40).

4.2.9 Responsible AI. Competencies related to Responsible AI were frequently mentioned during the interviews. Participants often cited the relevance of students being able to know AI-related ethical issues. For example, P7 states that it is essential that students understand all ethical problems that could be raised throughout the AI lifecycle (C41). Extending, P6 states that journalist students need to understand the AI ethical concerns, what responsible AI is, and its ethical principles, such as explainability, fairness, transparency, accountability, privacy, inclusion, and reliability (C41), so they can have a critical view of AI and better report about this technology or better propose an AI technology. Some participants highlight some AI ethical challenges in particular. According to P3, business students need to be able to discuss how AI is impacting society surveillance and the critical problems concerning this (C41). For P2, it is relevant that political science classes learn about bias in AI since *"machine learning models or statistical models can discriminate because sometimes you have certain groups that are overrepresented"* (C41). Moreover, P17 also stated the relevance of student teachers to knowing about bias and its consequences in education, e.g., that could generate gender stereotypes and consequently decrease students' motivation and engagement (C42). P3 highlights that business students should be able to discuss the consequences and dangers of biased data for AI applications and how it can perpetuate societal bias and discrimination (C42). Additionally, P11 highlights the relevance of students knowing the leading group of people revealing these problems to society (C43).

Besides pointing out the relevance of students knowing the AI-related ethical issues and their consequences and dangers, some participants also point out the relevance of them to learn the ways that these problems can be mitigated (C44). For example, P3 points out the relevance of discussing which actions are being taken in the political sphere to avoid the negative effects of AI surveillance (C44) and discussing how procedures could be taken to not generate AI-biased applications (C44). P1 also points out that students need to comprehend how to handle imbalanced datasets and understand the relevance of this step to avoid negative effects in the models they are creating (C44). Some participants also highlighted the relevance of applying procedures when developing AI tools that can mitigate ethical problems. For example, P1 points out that in case student teachers apply ML algorithms, it is relevant that they evaluate their models regarding fairness (C44, C45) in order to mitigate bias. P2 also highlights that it is important for political science students to know how to deal with these possible challenges regarding AI bias (C45). For P13, if it is not a black box model, students need to be able to explain the outcomes of their AI systems (C45). Similarly, P12 states that students need to be able to explain the outcomes of their systems (Explainable AI) (C45).

Moreover, another competency cited was regarding relevance to assessing the possible negative impact of AI systems in their domains and society. For example, according to P16, students need to be able to evaluate if an AI system is appropriate to be used depending on the context, such as if the possible bias in the system can prejudice a certain group in a specific educational context (C46). Similarly, P17 states that students need to be able to assess AI technologies regarding their possible negative effects on education (C46). For example, P1 pointed out the relevance of teachers evaluating the impact of AI tools (such as essay generators as ChatGPT) in education and society (C46). P4 also highlights the relevance of students understanding the possible impacts of AI systems in the law field (such as the possibility of AI replacing lawyers who perform repetitive tasks) (C46). P9 also says that students need to discuss the drawbacks of applying AI systems (such as AI chatbots) in some psychological contexts (C46), for example, some AI use cases, such as Eliza. Similarly, P9 also says that students need to discuss AI systems' benefits (C47) for their domain. As well, P17 stated that educational actors, from a motivational perspective, also benefit from knowing the positive effects of AI in the field, for example, regarding learning, motivation, and engagement (C47).

In addition, another Responsible AI-related competency mentioned was to know famous unethical AI applications and their effects in their domains (P3, P8, P9). For example, P3 states the relevance of business students to discussing famous unethical AI applications (C48), such as the Lensa app that raises gender bias. Moreover, other highly mentioned competencies were about the legal aspects of AI. Some participants noted the relevance of students knowing about data protection laws such as GDPR (C49) and the current status of the AI regulations (C50). For example, P11 states that students need to be aware of data privacy and their rights (C49). For example, they need to think if they want to publish their work online and have the risk of their works being used as part of a training dataset of an AI system without consent. P9 also highlights the relevance of understanding AI's current state regarding legal concerns, specifically, the GDPR (C49) and the AI regulations (C50).

4.2.10 Miscellaneous. Participants also mentioned that some not AI-related competencies are relevant to acquire along with AI competencies. P1 also highlights the relevance of students knowing how to communicate their results properly, for example, through data storytelling (C51). P1 mentions that students also need to have knowledge about good sources where they can find resources to learn or develop AI projects (C52) since AI is constantly evolving and they need to keep updated.

5 DISCUSSION

As previously stated in Section 1, researchers state different reasons in the literature to support the importance of non-computer science students acquiring AI competencies during their undergraduate education. In complement, in this work, we investigated the perspective of various professionals skilled in AI and other fields on the significance of teaching AI to non-computer science students at the undergraduate level and the reasons behind it. According to the participants, there are different reasons, including students need to (R1) effectively and critically use general but also domain-specific AI systems in their future studies or workplaces, (R2) effectively and critically apply different AI methods to generate innovative and enhanced outcomes in their future studies or workplaces, (R3) effectively and critically study AI and its perspectives, (R4) effectively use their domain knowledge to collaborate in AI development interdisciplinary groups and (R5) increase their employability chances after finishing their studies at the university. Therefore, these reasons will shed light on the literature regarding the relevance of teaching AI to non-computer science students and can be used to motivate future research works and initiatives in the field.

Moreover, the main contribution of this work is a list of core AI competencies that non-computer science students need to acquire in undergraduate education, according to professionals with experience in AI and other domains. The core AI competencies provided in the list, as seen in Table 3, encompass different AI perspectives. Some participants pointed out that general computing-related competencies, not necessarily related to AI and data competencies, are relevant. This may indicate that since this audience is not from a technical area, they need to acquire some fundamental computing competencies before acquiring AI competencies. Besides, data competencies were highly cited as relevant. This is an expected outcome since research indicates that certain data competencies overlap with AI competencies [32]. Data competencies are also mentioned in the other AI competencies contributions for non-technical audiences, listed in Section 2. However, not all these contributions point out data higher-order competencies as relevant. In our results, not only theoretical knowledge but also practical skills regarding data were pointed out as relevant, such as the most cited data-related competency, manage data (C20).

In addition, as other contributions in Section 2, the participants have raised the significance of introducing ML competencies to non-computer science students in their undergraduate education. Among the mentioned ML-related competencies, the most cited competency was C24. Most participants highlighted the importance of students understanding how ML techniques and their main algorithms work. However, there were differing opinions regarding the level of knowledge necessary for this competency. Certain professors believe that understanding the mathematical background (C25) is pertinent, while others do not share this view. Moreover, there is also no agreement regarding which ML techniques these students should learn. Some professors point out that the students should be introduced to mainly supervised and/or unsupervised learning. In contrast, other participants point out that students need to learn how all ML techniques work.

Furthermore, over fifty percent of the participants emphasized the importance of students not only acquiring ML theoretical knowledge but also applying it to solve problems in their respective domains. Regarding tools to apply data and ML techniques, some were in favor of using programming languages (particularly Python, followed by R) (C32), while others preferred the use of no-code tools (C31). The current literature has contrasting results regarding code and no-code tools for AI education for non-computer science students at the undergraduate level. For example, some studies successfully adopted programming languages to enable students to learn AI in practice [45], and other studies faced problems, such as [23]. Other studies successfully adopted non-coding tools to

Table 3: AI competencies for non-computer science students in undergraduate education according to professionals working in the intersection of AI and other domains

ID	Competency	Participants
	Computing	
C1	Describe what algorithms, data structures, and code are and how they differ from each other	P7
C2	Explain the computer architecture	P7
C3	Demonstrate logic programming language / problem resolution understanding	P1, P4
C4	Summarize how the code is compiled/interpreted and executed by a computer	P7
C5	Operate distributed version control systems	P14
C6	Describe and use different machine-readable text formats	P8
	Basics of AI	
C7	Discuss what AI is	P6, P9, P16
C8	Explain the history of AI	P11
C9	Describe the different types of AI, and compare them	P6
C10	Classify AI technologies according to the used AI techniques	P4
	AI Capabilities	
C11	Describe limitations and strengths of AI techniques and algorithms for certain problems	P1, P5, P6, P9, P11, P12, P14, P16
C12	Describe how AI can be used in their domains	P3, P5, P14, P11
C13	Describe AI success cases in their domains or in general	P1, P8
	Multidisciplinary AI	
C14	Describe how domain knowledge can help in the AI development field	P9
	Data	
C15	Describe what data and datasets are	P4, P7
C16	Describe what a data pipeline is and what it consists of	P10, P14
C17	Describe forms of collecting or finding data	P1, P2, P3, P8, P9
C18	Describe the data-generating process of the used dataset and interpret the assumption and worldviews part of it	P7, P12
C19	Describe how the labeling of data could be performed	P3, P4
C20	Manage data	P1, P4, P8, P11, P12, P13, P14
C21	Describe, interpret, and apply basic statistics in datasets	P2, P8, P10, P12
C22	Perform queries on data	P2
	Machine Learning	
C23	Describe the ML software development process/lifecycle and its components	P3, P6, P7, P13, P14
C24	Explain how ML techniques and their main algorithms work	P1, P2, P3, P4, P5, P8, P9, P10, P11, P12, P13, P15, P16, P17
C25	Explain the mathematical background of ML algorithms	P10, P11
C26	Explain the difference between correlation and causation	P12
C27	Analyze problems that can be solved by ML in their domains	P1, P3, P4
C28	Identify which data and ML techniques are most suitable based on the problems to be solved	P1, P2, P10, P12, P14, P16
C29	Decide the hardware requirements needed to develop a specific ML project	P10
C30	Apply data and ML techniques to solve problems in their domains and conduct hyper-parameter tuning	P1, P3, P4, P12, P13, P14, P15, P17
C31	Use no-code tools to apply ML	P1, P3, P4, P17
C32	Acquire programming skills and use programming languages to apply ML	P2, P8, P10, P11, P12, P15, P16
C33	Evaluate the performance of their models using evaluation metrics	P1, P11, P13, P14
C34	Explain how ML systems can adapt through user and environmental interaction post-deployment	P7
	Advanced Machine Learning	
C35	Describe Neural Networks / Deep Learning introductorily	P2, P8, P9, P10, P12
C36	Describe introductory what is and the capabilities of CV and NLP fields	P12
C37	Explain how the latest AI systems are being built using transfer learning	P7
C38	Describe how generative models and transformer architecture works	P8, P11
	Human-AI Interaction	
C39	Describe the human's responsibilities and the machine's responsibilities in the work environment	P5, P15
C40	Describe different evaluation metrics and evaluate if AI systems are adequate to be used in their area based on them	P5
	Responsible AI	
C41	Describe AI-related ethical issues	P2, P3, P5, P6, P7, P8, P9, P11, P13, P15, P16, P17
C42	Discuss the consequences and dangers of the ethical concerns of AI	P3, P8
C43	Reference the main people that are revealing the AI problems to society	P11
C44	Explain ways to counter the problems resulting from AI-related ethical issues	P1, P3, P9
C45	Apply procedures when developing AI tools that can mitigate ethical problems	P1, P2, P12, P13
C46	Assess the possible negative impact of their developed or adopted AI systems in their domain and the society	P1, P4, P6, P9, P12, P13, P15, P16, P17
C47	Assess the possible positive effects of their developed or adopted AI systems in their domain and the society	P9, P17
C48	Discuss famous unethical AI applications and about the effects in their domains	P3, P8, P9
C49	Describe the main points in data protection laws such as GDPR	P1, P5, P9, P11, P12
C50	Discuss the current status of the AI regulations	P5, P9, P12, P14
	Miscellaneous	
C51	Make presentations to communicate the results properly	P14
C52	Name sources that provide resources with content and tools for learning and developing AI projects	P15

enable students to understand AI concepts or build their custom models without programming [7, 42], but in other studies, such as [3], students mentioned that they would like to spend more time on programming projects. Therefore, professors and course developers of AI courses for this audience may choose tools that align more with the students' pre-competencies and needs. As an alternative, since the audience of non-computer science students is diverse and with different backgrounds and interests, a possible solution for future contributions to overcome this problem is to provide these different learning tools jointly (e.g., no-code tools and code tools) for these students and not constraining them to specific learning tools.

Advanced ML-related competencies were also pointed out as relevant for the participants. In addition to the relevance of learning about neural networks / deep learning, CV, and NLP, participants also pointed out that it is relevant for students to learn about the latest AI advances, such as transfer learning, generative AI, and transformer architecture. This is an expected outcome since these latest advances in AI have recently achieved great success and become a milestone in the AI field [21]. In addition, participants also pointed out the relevance of these future professionals acquiring an understanding of the difference between human responsibilities and machine responsibilities in the work environment. This was also similarly proposed in Long and Magerko [32], Michaeli et al. [33].

In addition, during the interviews, a significant number of participants made repeated references to the competencies that are related to responsible AI. Regarding responsible AI-related competencies, the most frequently mentioned competency was C41. According to most participants, it is highly relevant that these students describe AI-related ethical issues (e.g., bias, privacy, accountability, transparency, social-economical and environmental impact). In addition, over fifty percent of the participants emphasized that these students need to have the skill of assessing the impact of the AI tools in their domains and society based on responsible AI principles (C46). Moreover, the participants highlighted not only the ethical aspects of AI but also the legal aspects. Competencies regarding data protection laws such as GDPR (C49) and AI regulations (C50) were highly pointed out as relevant by the participants.

6 CONCLUSION, LIMITATIONS AND FUTURE WORKS

This article presents the results of semi-structured interviews conducted with professionals working at the intersection of AI and other domains. Through these interviews, we have identified a total of 52 core AI competencies that these interviewed professionals consider important non-computer science undergraduate students acquire at the undergraduate level. As a next step, we aim to merge this acquired list of competencies with competencies acquired through other methods, and then we aim to conduct a Delphi study with different experts to reach a consensus on the core AI competencies this target audience should acquire.

Regarding the limitations of this study, we acknowledge that our participants' sample was skewed toward European participants, and participants from other continents were under-represented. Therefore, our findings may neglect local knowledge and cultural pluralism. In addition, the participants' list of AI application domains is not exhaustive (e.g., there was a lack of participants with expertise in the intersection of AI with chemistry, biology, and economics). Consequently, our findings may also neglect the perspectives of professionals working in these other domains, which could differ from our current sample. Despite these limitations, our study provides a significant milestone toward developing a framework with core AI competencies for general AI education in undergraduate education, specifically for non-computer science students.

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A INTERVIEW QUESTIONS

In this section of the Appendix, we depict the questions we asked the participants during the interviews.

- Introduction of Participants: (1) How many years of experience in the AI field?; (2) What is your current role?; (3) What is your background in the AI field (e.g., the projects that you worked on involving AI)?"
- Warm-up Questions: (1) How is AI being used in your application domain (in practice and/or research)?; (2) What are the AI tools mostly used in your application domain?; (3) What AI methods are most used in your application domain?; (4) What are the effects of AI in your application domain?
- Competencies-related questions: (1) Do you think it is relevant for future professionals from your application domain to learn AI? If yes, why?; (2) What AI-related competencies are relevant for students from your application domain in undergraduate education to acquire?
- Closing questions: (1) Which important research or practical work do you know on AI in your application domain?; (2) Which training already exists for AI for non-computer science students in undergraduate education?; (3) Do you have a recommendation for another person to participate in this research?