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FAAI:
The Future is in Applied Artificial Intelligence
Erasmus+ project 2022-1-PL01-KA220-HED-000088359

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A3.3 Artificial Intelligence Learning Requirements: **WP3**

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Summary: The consortium of The Future is in Applied Artificial Intelligence Project designed the first competency-based applied artificial intelligence curriculum at the high-education institution level. The development was based on advanced system research of existing artificial intelligence-related resources and surveying target groups of teachers, information technologies students, and employers which should enhance the performance of implementing artificial intelligence education. A review of applied artificial intelligence was prepared in the form of keyword clustering. The initial data was collected with the help of surveying, gathering job offers, existing artificial intelligence training courses, scientific projects, and real cases. Synthetic analysis of the textual information from the studies was using the word clouds technique. Tensor-based approach was used for the presentation of the competence-based course. The specific numerical requirements for the course in the form of priorities follow from the solution of decision-making problems using the analytic hierarchy process technique. Based on the comprehensive study of the surveys, educational experience, scientific projects, and business requirements, a meta-analysis of the recent references, we specified the criteria for a training course in the form of a tensor-based representation of competencies in relation to the content and educational modules.

Keywords: Analytic hierarchy process, applied artificial intelligence, competency-based curriculum, tensor-based approach, word clouds

I. INTRODUCTION

For the successful application of Artificial Intelligence (AI) in the real world, a comprehensive approach is needed, including robust data collection and preprocessing, effective algorithm design and training, ethical considerations, continuous evaluation and improvement, interdisciplinary collaboration, and careful integration into existing systems and workflows. Innovative training courses play a pivotal role in the successful implementation of AI models in the real world by equipping learners with practical knowledge, hands-on experience, and the ability to navigate complex challenges, thereby enabling effective AI model development, deployment, and adaptation to real-world scenarios.

The general requirements for an effective training course on AI include a comprehensive curriculum covering fundamental AI concepts, practical hands-on exercises and projects, real-world case studies, access to relevant datasets and tools, experienced instructors, and a focus on ethical considerations and industry applications.

The *objective* of the work is to develop the comprehensive approach for designing the training course on applied artificial intelligence (AAI), which, being based on the system research of business requirements corresponds to the principle of competency-based education and innovative pedagogy.

PROJECT FAAI

The given work was implemented within the framework of Erasmus+ project 2022-1-PL01-KA220-HED-000088359 entitled "The Future is in Applied Artificial Intelligence" (FAAI) by a consortium including the University of BielskoBiala (Poland), University of Library Study and Informations Technologies (Bulgaria), University of Ss Cyril and Methodius in Trnava (Slovakia), University of Nis

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(Serbia), University of Montenegro (Montenegro) and co-founded by the European Union. The project aims to bring together universities and businesses in order to provide innovative solutions to develop artificial intelligence experts [1].

The term AAI refers to the practical implementation and utilization of AI techniques and technologies to solve real-world problems and achieve specific goals in various domains. It has become widely adopted and used in the AI community and industry to distinguish the practical application of AI from theoretical research and development. The term highlights the emphasis on using AI in practical settings and leveraging its capabilities to address specific challenges and deliver tangible outcomes.

One of the project goals is dealing with designing the training course on AAI which reflects real-world needs and should be competency-based. Throughout the project, system research was conducted which was based on the studies of the existing AI courses, scientific projects, real cases, the AI job market, IT students, lecturers, and employers.

A. RELATED PAPERS ON AAI

When preparing the survey of the related papers we have selected 10K of the references from WoS library as a result of the query "applied artificial intelligence". With the help of CiteSpace [2] the obtained set of works was divided into 12 the most significant clusters with the respect to keywords as depicted in Fig. 1.

The list of the obtained keywords include "artificial neural network", "artificial intelligence", "deep learning", "lung cancer", "explainable artificial intelligence", "COVID-19 patient", "IoT device", "reinforcement learning", "drug discovery", "wireless communication", "aqueous solution", which shows the most significant AI models as well as applications. The most cited papers throught out the clusters are [3] (cluster #0) related to artificial intelligence solutions for thyroid pathologies, [4] (clusters #1, #3, #4, #5) related to supporting the model decision in a context that a human can readily interpret (explainable AI), [5] (cluster #2) [6] (cluster #6) on AI/ML technique for COVID-19 outbreaks, [7] (cluster #7) devoted to AI and DL technology facilitating data analytics of IoT systems, [8] (cluster #8) on reinforcement learning application in different fields, [9] (cluster #9) about AI application for drug discovery, [10] (cluster #10) on AI-based network communication, [11] (cluster #11) on AI for environmental studies.

The "bursting" works throughout this analysis are related to good practice and real cases; they are listed below:

- [12] introduced "deep learning" terminology
- [13] made available two best-performing ConvNet models for further research of deep visual representations in computer vision
- [14] on Human-level control through deep reinforcement learning
- [15] is the Deep Learning textbook intended to help students and

practitioners enter the field of machine learning in general and deep learning in particular

- [14] introduced the new trend considering learning complex motifs using large data sets. Considered deep artificial neural networks use multiple layers to discover patterns (more complex with each layer) and structure of large data sets. The approach can be used for DNA, RNA and application in medicine.
- [16] reviewed deep supervised learning, unsupervised learning, reinforcement learning and evolutionary computation.
- [17] presented the ImageNet, a benchmark in object category classification and detection on hundreds of object categories and millions of images
- [18] presented the training of large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes.
- [19] presented a new approach to computer Go that uses deep neural networks trained by a novel combination of supervised learning from human expert games, and reinforcement learning from games of self-play.

II. THE BACKGROUND OF A STUDY

A. COMPETENCY-BASED EDUCATION

Competence-based education (CBE) was gaining momentum as an educational approach that focuses on developing specific skills and abilities, rather than solely emphasizing knowledge acquisition. CBE aims to prepare students for real-world challenges by providing them with the necessary competencies to succeed in their chosen fields. Below are some key features and elements commonly associated with state-of-the-art competence-based education focusing on IT education.

CBE relies on clearly defined *competency frameworks* that outline the specific skills and knowledge students should acquire. These frameworks typically break down competencies into measurable learning outcomes [20].

CBE often promotes *personalized learning* experiences tailored to individual students' needs and interests. It allows learners to progress at their own pace and provides flexibility in terms of content, learning activities, and assessment methods [21].

In CBE, assessments focus on evaluating students' demonstrated competencies rather than relying solely on traditional exams or standardized tests. *Authentic assessments* [22] may include projects, portfolios, presentations, simulations, or real-world tasks that showcase students' abilities in real-life contexts.

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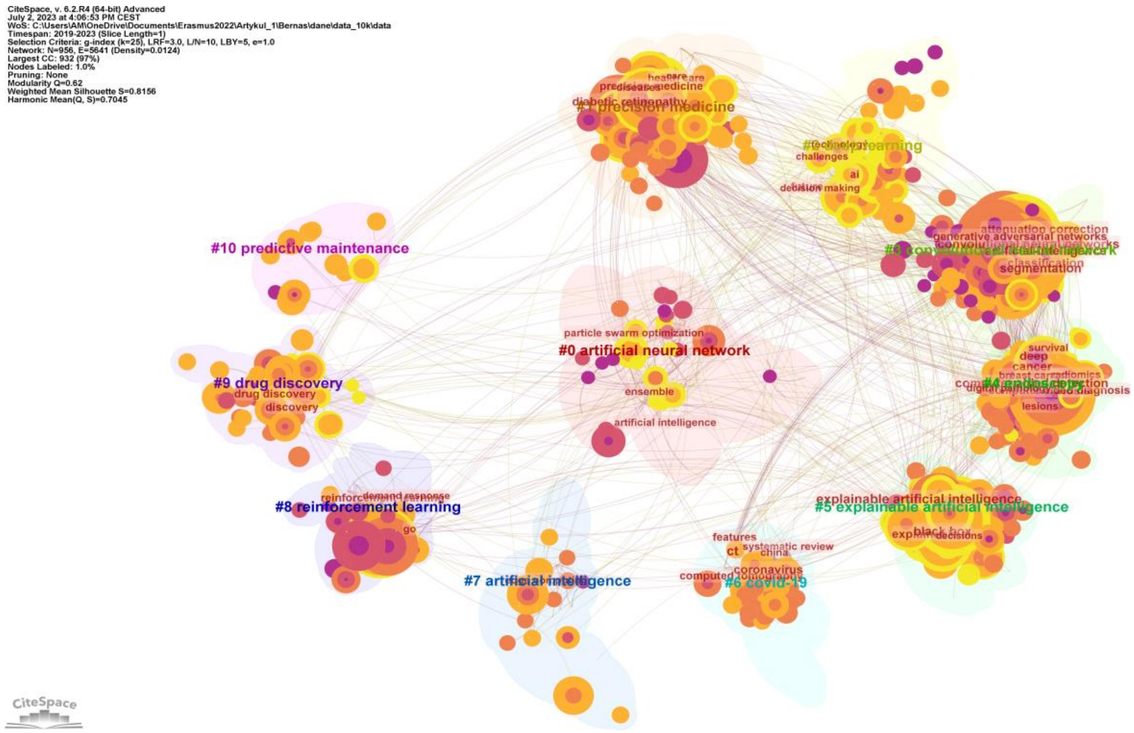

FIGURE 1. Cluster plot for WoS publications throughout 10 last years in response to a query concerning applied artificial intelligence

Instruction in CBE is designed due to learning paths to develop and reinforce the identified competencies. It often involves active and experiential learning methods, such as project-based learning, problem-solving activities, collaborative work, and hands-on experiences [23].

State-of-the-art CBE often leverages *technology integration* to enhance learning experiences. This may include the use of online platforms, adaptive learning systems, educational apps, virtual reality (VR), and augmented reality (AR) tools, which can provide personalized feedback, simulations, and interactive content [24].

CBE advocates for recognizing and awarding *credentials* based on demonstrated competencies [25]. This can involve issuing digital badges, certificates, or even degrees that highlight specific skills and abilities attained by learners.

CBE extends beyond formal education settings and emphasizes the importance of *lifelong learning and ongoing professional development* [26]. It aims to foster a mindset of continuous improvement and adaptability to meet the evolving demands of the workforce.

B. IT EDUCATION

The state-of-the-art in IT education encompassed several key areas.

Blended learning combines traditional classroom instruction with online resources and activities. It leverages technology to provide a more interactive and personalized learning experience. This approach allows students to access course materials, collaborate with peers, and engage in hands-on exercises through digital platforms.

Project-based learning focuses on practical applications of IT skills. Students work on real-world projects, individually or in teams, to solve problems, design software, or create innovative solutions. This approach promotes critical thinking, problem-solving, and collaboration, while giving students hands-on experience.

Adaptive learning systems utilize technology to personalize the learning experience based on individual student needs and performance. These systems analyze data on students' strengths, weaknesses, and learning styles to provide customized content, pacing, and feedback. By adapting to each student's requirements, adaptive learning enhances engagement and improves learning outcomes.

Recognizing the growing importance of coding skills, many educational institutions emphasize *coding and computational thinking* in their IT curricula. Students learn programming languages, algorithms, data structures, and problem-solving techniques. This focus equips them with the foundational skills required for software development, data analysis, and other IT fields.

Given the escalating importance of *cybersecurity*, IT education often incorporates cybersecurity principles and practices. Students learn about securing networks, protecting data, identifying vulnerabilities, and responding to cyber threats. Institutions may offer specialized courses or degree programs in cybersecurity to meet the demand for skilled professionals in this field.

The proliferation of data in various industries has led to increased emphasis on *data science and analytics* education. Students learn statistical analysis, data visualization, machine learning, and data mining techniques. Educational programs often include hands-on experience with data analysis tools and programming languages commonly used in the field, such as Python or R.

State-of-the-art IT education also emphasizes the *ethical and social implications* of technology. Students explore topics such as privacy, security, digital ethics, algorithmic bias, and the impact of technology on society. This focus encourages students to consider the broader consequences of their work and develop responsible and inclusive approaches to IT. Many educational institutions establish partnerships with industry leaders and offer *internships or cooperative education* programs. These collaborations provide students with opportunities to gain practical experience, work on real-world projects, and develop professional networks. Such industry engagement helps bridge the gap between academia and industry, ensuring that graduates are better prepared for the workforce.

C. DEFINITION OF AAI

AAI refers to the utilization of AI techniques and technologies to solve real-world problems and address practical challenges in various domains, aiming to augment human capabilities, enhance decision-making processes, and automate complex processes.

Applied AI encompasses a wide range of fields, including but not limited to healthcare, finance, transportation (e.g., autonomous vehicles), manufacturing, cybersecurity, and customer service like personalized recommendation systems. Cutting-edge applications leverage techniques such as machine learning, deep neural networks, natural language processing for language understanding and generation, computer vision for image and video analysis, and robotics for physical task automation. Expert systems are also still significant for knowledge-intensive decision support.

In applied AI, the focus is on developing practical solutions that can be integrated into existing systems or workflows to achieve tangible outcomes. This often involves collecting and preprocessing data, analyzing, and interpreting complex data sets, extracting meaningful patterns and insights, training AI models using appropriate algorithms, validating and finetuning the models, and deploying them in real-world scenarios. Through iterative learning and refinement, AI models are continuously improved to achieve higher accuracy, robustness, and adaptability.

Furthermore, applied AI takes into consideration ethical, legal, and societal implications, ensuring that the deployed systems are transparent, fair, secure, and accountable.

D. SCOPE OF PROBLEMS AND AREAS OF AAI

The scope of artificial intelligence problems is broad and diverse. AI can be applied to a wide range of domains and can address various types of problems. Some areas where AI can be leveraged are as follows: automation, decision support,

TABLE 1. Scope of AI problems according to the decreasing order of significance

Scope	Percentage
healthcare	17,60%
ecology	9,74%
cybersecurity	8,99%
manufacturing	7,49%
data processing	5,24%
robotics	4,87%
smart grid	3,75%
finance	3,75%
energetics	3,75%
recommendation systems	3,00%
agriculture	3,00%
photo and video	2,62%
face and body recognition	2,25%
culture	2,25%
chatbots	2,25%
business intelligence	2,25%
automotive	2,25%
voice recognition	1,87%
video processing	1,87%
geolocation	1,87%
education	1,87%
road traffic	1,50%
object detection	1,50%
transport	1,12%
search and recommendation	1,12%
library	0,75%
aviation and ocean transport	0,75%
social network analytics	0,37%
military	0,37%

Natural Language Processing, Image and Video Analysis, healthcare, robotics and autonomous systems, gaming and entertainment, cybersecurity, smart cities, and environmental monitoring. These examples represent just a fraction of the scope of AI problems. AI continues to advance and find applications in various industries and sectors, creating new opportunities for solving complex challenges and improving efficiency and decision-making processes. A whole variety of AI real cases should be taken into account when designing a competency-based course on AI.

Within the framework of FAAI project, 267 real cases based on AAI solutions were studied. Table 1 shows areas of the tasks together with their significance.

E. AAI SCIENTIFIC PROJECTS

A part of the research under the FAAI Erasmus + program involved a questionnaire about scientific projects in applied AI. The questions were aimed to research the needs and expectations of scientific projects to aid to train specialists in the field of Applied AI. The questionnaires about 63 projects collected by partner organizations from the 5 countries were collected and analyzed. The project coordinators were from 19 countries, 34 came from universities, 6 from academies of science, and 24 from other organizations or companies. Since the questionnaires primarily focused on ongoing projects, the

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obtained results can be considered current and up-to-date. Most projects have 1-6 participants; however, one project has 50 participants.

Among the more interesting results belongs the finding,

that more than half of the projects concerned deep neural networks learning modules, and most machine learning tasks which were solved, were image processing, classification, regression, clusterization and natural language processing. From the number of 63 questionnaires 55 were concerned with the following ML tasks. Knowledge representation and reasoning, planning and search strategies, expert systems, and fuzzy logic were not mentioned in the projects. Most of the cases use open software libraries. Among the used AI libraries dominated TensorFlow, Keras, scikit-learn and CUDA. The programming languages were Python and C++.

F. AI EDUCATION

AI Education is rapidly gaining importance in today's technology-driven world. An entire review of AI teaching and learning throughout the last 20 years is presented in [27]. As AI continues to find its application in various industries and aspects of our lives, there is an increasing need for individuals with a solid understanding of AAI concepts and techniques. Artificial intelligence and automation are likely to be adopted by even more companies to improve efficiency and productivity. These technologies can be used to automate repetitive tasks, process large amounts of data, and make more accurate predictions. Therefore, a need for a good and unified approach to AI Education is necessary.

At the secondary school level in [28] they developed and evaluated an AI curriculum.

In [29] they evidenced that the best practices in AI teaching and learning in Higher Education constitute from key factors such as confidence, mathematics anxiety, and differences in student educational background.

However, competency-based learning paradigms being particularly effective in developing practical skills and preparing individuals for real-world applications of AI, fall to be outside consideration. AI courses should focus on the acquisition of specific competencies and offer hands-on training with real-world problems, enabling learners to develop the necessary skills and knowledge to become successful AI practitioners.

For a learner, it is essential to choose training courses that align with their specific needs and goals, taking into account the latest innovations in the field. Vice versa, when developing a course curriculum, it is also necessary to define clear and specific course goals and follow the latest advancements in the field.

III. MATERIALS AND METHODS

We offered an approach for developing an AAI training course by using the outcomes of various surveys, standards for competences and topics, data processing, and decision-making based on multicriteria optimization (see Fig. 2 for its generalized view). It includes the following steps.

Beginning by determining the overall objectives of the training course. We identify the desired outcomes, competencies, and knowledge areas that need to be covered.

We carry out surveys and assessments to gather data on the needs and preferences of the target audience. This can include surveys on existing knowledge, skill gaps, learning preferences, and desired topics.

We identify the standards or benchmarks for competences that participants should achieve upon completion of the training. These standards come from [30] and will help define the required knowledge, skills, and abilities in AAI.

Based on the survey data and competence standards, we determine the specific topics that need to be covered in the AAI training course. We consider the relevance, importance, and priority of each topic.

Multisource Data Analytics Toolbox includes processing and analyzing the survey and study data to extract meaningful insights. This may involve statistical analysis, data visualization, and summarization techniques (like word clouds, CiteSpace graphs, AHP) to identify patterns, trends, and correlations among the survey responses and multisource data.

Based on the identified topics, competencies, and survey outcomes, we determine individual educational modules that address specific aspects of the training course. Each module should have clear learning objectives and content that aligns with the desired outcomes.

We create cross-matrices that illustrate the relationships between topics, competencies, and educational modules. This matrix helps visualize how each module contributes to the development of specific competencies and how different topics are interconnected with modules and between themselves.

We combine the individual educational modules and cross-matrices to form a 3D tensor representation. This tensor captures the interdependencies between topics, competencies, and educational modules in a structured and organized manner.

We apply multicriteria optimization techniques[1] to make informed decisions based on the data gathered. Considering multiple factors such as the importance of each topic and the preferences of the target audience will optimize the design and delivery of the AAI training course.

We integrate any specific requirements that arise from the decision-making process. This could include modifications to the content, delivery methods, assessment strategies, or sequencing of modules based on the optimization results.

A. MATERIALS

The work is based on a series of data gathered as a result of the project FAAI study of the good practice in field of AAI. Namely, we have analyzed

- 74 offers gathered from the job market;
- 63 scientific projects in AI;
- 92 existing AI training courses;
- 27 good practice solutions;

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- 279 real cases on AI solutions;
- surveys filled in (80 academics, 1054 IT students, 38 employers)

[1]AHP method is described further

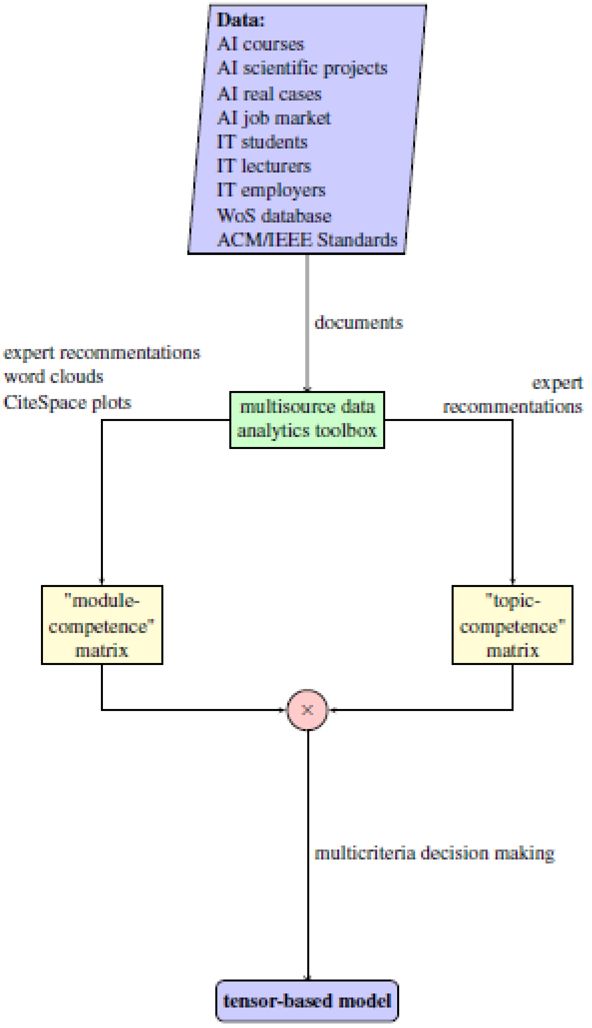

FIGURE 2. Flowchart for determining AAI course requirements

B. WORDCLOUDS

Word clouds, also referred to as wordle diagrams or tag clouds, are captivating data visualizations that portray the most significant words or phrases in a graphical format. This innovative technique visually highlights the relative frequency of words in a given text [31], resulting in an aesthetically-pleasing and easily understandable representation.

The concept of word clouds emerged in the early 1990s,accompanied by initial instances of visualizing word frequencies. The accessibility of computer-based text analysis tools and web applications further popularized their utilization. Presently, many online platforms and software effortlessly-enable users to generate word clouds from text data. The creation of word clouds follows a straightforward procedure [32]. Initially, a text is examined to extract unique words or phrases, and their occurrence frequency is determined. The size or prominence of aword in theword cloud is proportional to its frequency in the text. Words of greater significance are typically displayed in larger fonts or positioned closer to the center, while less relevant words are smaller or positioned-toward the periphery. Word clouds find extensive applications across various domains [32], [33]. In the business realm, they facilitate sentiment analysis, trend identification, and exploration of keywords within customer feedback or product descriptions. In the field of education, they serve as tools for visualizing key concepts or themes, aiding in comprehension and retention of knowledge. Additionally, they are utilized in social research, content analysis, and opinion mining, offering valuable insights into vast collections of textual data.

C. CLUSTER ANALYSIS OF KEYWORDS

To perform cluster analysis of references from Web of Science (WoS) using CiteSpace software [2], we export 10K reference data from WoS in plain text format. CiteSpace will process the data and create a citation network. Once the citation network is created, CiteSpace offers various visualization and analysis options. We explored the different settings and parameters to generate meaningful clusters regarding the keywords. Corresponding labeling allows us to indicate leading authors and institutions. Bursting works can be also determined.

D. AHP

The AHP method is used to address decision-making problems that involve multiple criteria and alternatives. It is particularly effective when faced with complex decisions where subjective judgments and trade-offs between hierarchy-structured criteria need to be considered [34]. In the given work, the AHP method will be applied in the context of designing an AAI educational course to prioritize and make decisions regarding various aspects of the

course, namely, learning Objectives, course content, assessment methods, teaching strategies, resource allocation, technology integration, evaluation, and feedback. By conducting pairwise comparisons we can assess the relative importance or preference of each criterion and alternative. For example, we can compare the relevance of content

against the job market requirements. Pay attention that a few decision-makers can be taken into account, e.g., academics,

students, employers, etc. Calculating the priority or weight of each criterion and alternative based on the pairwise comparison values involves applying mathematical calculations, such as normalizing the comparison values and calculating the

eigenvalue and eigenvector. The result is a set of priority values that indicate the relative importance of each criterion and alternative.
Using the calculated priorities we make informed decisions about the training course design. The priorities help us to
identify the most critical criteria and the most suitable alternatives based on their relative importance. This allows us to focus on aspects that have a higher impact on achieving the desired competencies.

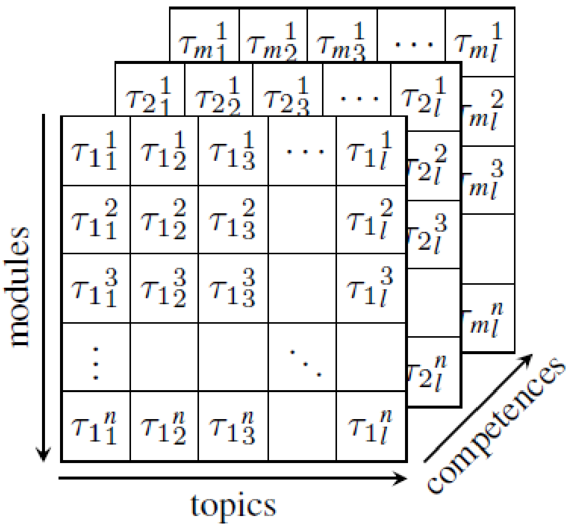

FIGURE 3. Tensor mapping the relation "competence-topic-module"

By applying the AHP method to these aspects of course design, educators and curriculum developers can make informed decisions that promote effective teaching and learning experiences, align with educational goals, and meet the needs of learners.

E. TENSOR APPROACH FOR RELATIONS

This method represents a three-dimensional tensor (Fig. 3) composed of topic and competence using tensor-based depiction, which is a way to represent each module. To construct a 3D tensor with binary elements τ_i using the vectors $C \in \mathbb{R}^m$, $T \in \mathbb{R}^l$, and $M \in \mathbb{R}^n$ as directions (Fig.3), along with two matrices A_{MC}, A_{CT} showing the Boolean relations between vectors *M and C, and C and T* , we can use the following expressions:

$$\mathbf{A}_{MC} = \begin{bmatrix} \mathbf{A}_{MC}[1,1] & \mathbf{A}_{MC}[1,2] & \dots & \mathbf{A}_{MC}[1,m] \\ \mathbf{A}_{MC}[2,1] & \mathbf{A}_{MC}[2,2] & \dots & \mathbf{A}_{MC}[2,m] \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{A}_{MC}[n,1] & \mathbf{A}_{MC}[n,2] & \dots & \mathbf{A}_{MC}[n,m] \end{bmatrix}$$

$$\mathbf{A}_{CT} = \begin{bmatrix} \mathbf{A}_{CT}[1,1] & \mathbf{A}_{CT}[1,2] & \dots & \mathbf{A}_{CT}[1,l] \\ \mathbf{A}_{CT}[2,1] & \mathbf{A}_{CT}[2,2] & \dots & \mathbf{A}_{CT}[2,l] \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{A}_{CT}[m,1] & \mathbf{A}_{CT}[n,2] & \dots & \mathbf{A}_{CT}[m,l] \end{bmatrix}$$

$$\mathbf{T} = [\tau_{ij}^k]_{i=\overline{1,m},j=\overline{1,l},k=\overline{1,n}}, \quad \text{where } \tau_{ij}^k := \mathbf{A}_{MC}[k,i] \cdot \mathbf{A}_{CT}[i,j]$$

where · is the logical AND operator. The tensor T can be also constructed using the Kronecker

product (⊗) of the two matrices.

IV. RESULTS

A. STUDIES OF JOB MARKET

AAI is a very important field when it comes to the labor-market. We can see that there are a lot of possibilities that

AI can be used in this area. AI is an important technology that helps businesses improve efficiency, reduce costs and

make better decisions. We see that improvements in AI are also connected with creating new opportunities and creating

TABLE 2. Positions offered.

Position	Percentage
Data Engineer	25.68%
Data Scientist	22.97%
Data Analyst	10.81%
AI Engineer	10.81%
Other positions	29.73%

TABLE 3. Machine learning problem

Type	Percentage
Classic ML	77.03%
Deep ML	63.51%
SciML	28.38%
Other	5.41%

new jobs for industries. These are particularly important inthe fields of data science, machine learning, and robotics.

1) Positions offered on the job market

Regarding the positions in the job market in the field of AAI,

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there are various dominant positions offered. These positions are distributed all over the EU, which implies that the AAI
field is widespread over the world. Based on the job market research shown on Table 2, the most dominant positions offered on the market are Data Engineer and Data Scientist positions, with 25.68% and 22.97% respectively. While data engineers are specialized in designing, building and maintaining the infrastructure of the systems required for handling data-processing, data scientists are responsible for extracting insights and knowledge from the data. Data Analysts and AI Engineers both share the same percentage of 10.81%. This shows that a significant portion of positions require focus on interpreting and analyzing the data,
with strong visualization skills. Together with strong ability to develop and deploy AI systems and algorithms.
Amongst other positions, there is no specific position that is occurring more dominantly than the others. It varies from dev ops engineers to software engineers or web developer positions.

2) Machine learning problem

One of the most important pieces of information relevant to the job market is a kind of machine learning problem that
needs to be solved. This can point towards which competencies may be the most important for working in AAI. The
results are shown in Table 3. Based on the results, it is evident that the biggest portion of machine learning problems is concentrated on classical ML problems and Deep ML problems. This implies that the traditional machine learning techniques that include algorithms like decision trees, support vector machines, and random forests are needed to be competent in applied AI.
The second most important set of ML problems being solved represents Deep ML problems. Deep ML has gained significant popularity over the last several years and has

TABLE 4. Models being developed

Model	Percentage
Multilayer neural networks - MLP	67.57%
Rules (Classification, Associating)	55.41%
Decision tree	50%
Convolutional neural networks - CNN	45.95%
Recurrent neural networks - RNN	36.49%
Random forest	35.14%
Encoder-decoder networks	13.51%
U-NET	10.81%
GRU	4.05%
LSTM	2.7%

become one of the most used ML in areas such as computer vision or natural language processing.
The results also show that it is necessary to obtain scientific domain knowledge and incorporate it with the machine learning

process. Therefore, it can be concluded that the applied AI has a significant application in models that are oriented to physics-based models, simulations, or differential equations [35].

3) Models being developed

As a machine learning engineer, one of the most important tasks is to develop a model that will be used in the algorithm for the real-world problem. There are various possible models being developed, and their distribution is shown in Table 4.

Table 4 represents the distribution of different models being developed on the job market. MLPs, as feedforward neural networks with multiple layers are widely used for tasks such as classification, regression, and pattern recognition, due to their ability to capture complex patterns from data [36].

The results show that one of the most important competencies while working in applied AI are creating logical rules based on conditions predefined from the real-world problem. These techniques can be used for making predictions and discovering correlation between data with various success.

It is shown that neural networks represent the biggest portion of models being developed on the job market. Both convolutional and recurrent neural networks can be used for many domains, like image or visual data processing.

Overall, the data shows the dominance of MLPs and rule-based approaches in the context of models being developed. Significant shares have decision trees and convolutional and recurrent neural networks. It's worth noting the presence of specific architectures like encoder-decoder networks, U-NET, GRU, and LSTM, with smaller percentages, indicating their relevance in certain specialized applications within the field of machine learning.

4) Machine Learning tasks to be solved/

In the job market of applied AI, there are various machine learning tasks that businesses seek to solve using AI techniques. These tasks span across different domains and industries, and require several skills in machine learning to address them effectively.

TABLE 5. Machine learning tasks to be solved

Task	Percentage
Classification	68.92%
Regression	58.11%
Clusterization	35.14%
Image classification	28.38%
Image captioning	22.97%
Natural language processing	22.97%
Image segmentation	22.97%
Speech recognition	12.16%

Table 5 shows distribution of machine learning tasks that need to be solved. Overall, the data highlights the prevalence of classification and regression tasks, which are fundamental tasks in machine learning, and their application is wide.

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It also indicates the importance of having skills in image and natural language processing, as well as speech recognition. Clusterization, image segmentation and captioning demonstrate specific challenges and applications in the job market. Furthermore, the distribution of tasks reveals the significance of image processing, natural language processing and speech recognition as important techniques to be known and
learned across AI courses.

Understanding the distribution of machine learning tasks is valuable to businesses that are seeking to apply AI techniques to solve problems in various domains. With these insights, businesses that apply AI techniques in diverse domains allow them to prioritize and focus their efforts based on significance of different tasks.

B. STUDIES OF EMPLOYERS

The survey gathered responses from 38 companies to explore their needs and expectations regarding the training of specialists in applied AI. Most respondents (86.84%) represent private organizations, with only 13.16% indicating their affiliation with public organizations. In terms of organization size, more than half of the respondents (52.63%) classify their companies as small, around 26.32% of the respondents categorize their companies as medium-sized, and 21.05% of the respondents classify their companies as large, indicating that they have over 250 employees. The largest proportion of respondents (36.84%) work in the IT service segment. Other significant segments include other product startups (15.79%) and miscellaneous categories (15.79%). IT outsourcing, computer technics sales, hybrid software development, IT outstaffing, offshore programming, and game technologies are also represented. Some companies are product startups operating in domains such as administrative activities and MES, software development and IT outsourcing, research and technology (IT area), IT services, IT financing, and research and education.

The primary fields of activities declared by the organizations vary, with manufacturing and development (47.37%), design (39.47%), consulting (44.74%), customer service (42.11%), and research (39.47%) being the main domains. The applications and solutions of these companies span various sectors, including education, public services, sales, marketing, finance, security, healthcare, transportation, and others. Regarding the usage of AI in business activities, most of the organizations (86.64%) indicate that they currently utilize AI, while, a small portion (13.16%) state that they have intentions to do so in the future.

Regarding AI-related job positions, Data Engineer has the highest percentage of job offerings (58.33%), followed by Data Analyst (55.56%) and Data Scientist (44.44%). Other positions such as Technical Recruiter, Security Engineer, and Database Manager have lower percentages of job offerings. In terms of experience requirements, 41.67% of job positions do not require any experience in AI. The majority of positions require experience ranging from short practice up to one year (25%) to from 1 to 3 years (27.78%). Only a small percentage of job positions require experience over 5 years (5.56%). The survey also examined the general competencies needed for AI-related roles. The highest percentage (60%) is attributed to the competency of recognizing problems related to algorithmic and data bias, privacy, and data integrity. Other highly rated competencies include describing major areas of AI and its applications, recognizing the utility of machine learning methods, and identifying appropriate performance metrics for evaluating machine learning algorithms. Competencies such as representing information in logic and probabilistic formalisms and debating the effects of decisions arising from machine learning conclusions have lower percentages. When it comes to the dispositions required for AI and data science employees, respondents emphasize the importance of respecting the history and limitations of AI, being adaptable in algorithm design, utilizing machine learning ethically and responsibly, and being thorough and ethical in presenting results. Other important dispositions include algorithm selection and evaluation, accurate and ethical evaluation approaches, attention to detail in unsupervised learning techniques, and considering context-specific challenges. The survey examined the types of machine learning problems being solved by companies. The majority of companies (68.57%) are using classic and deep machine learning techniques, while a smaller percentage used SciML methods (8.57%). In terms of developed or studied models, decision trees and Multilayer Perceptrons (MLPs) are the most mentioned, followed by rules, Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs). The use of neural networks, both traditional and deep learning, are prevalent within companies. The most common AI and ML tasks solved or studied by companies include classification, regression, image classification, clusterization, and natural language processing. Tasks such as image captioning, speech recognition, and image segmentation have lower percentages of responses. Python is the most commonly required programming language (85.71%), followed by C++ (45.71%), Java (42.86%), R (37.14%), and C# (22.86%). Other languages like JavaScript and Matlab are required less frequently. Regarding AI libraries (frameworks), TensorFlow is the most commonly used (78.79%), followed by Keras (48.48%) and scikit-learn (42.42%). Other frameworks such as PyTorch, Apache TVM, AMD HIP, OpenAI, and Matlab toolboxes are also used, but to a lesser extent. The most used ecosystem is Anaconda (54.55%), followed by Apache Hadoop (39.39%), Matlab (39.39%), and R Studio (33.33%). For academic/analytical employees, competences such as carrying out feasibility studies, innovating and modifying methods, and applying modern methods of psychology and pedagogy are rated highly. Competences related to simulations, statistical verification, and copyright protection are rated relatively lower. The required soft skills include critical thinking, communication, working with tools and technology, planning and organizing, and business fundamentals. Collaboration, customer focus, dynamic re-skilling, and professional networking are also valued but to a lesser extent. According to the survey results, companies value additional competences including the ability to select appropriate data structures and algorithms, as well as visualizing the results of AI analysis. Additionally, companies prioritize competences related to implementing cloud computing-based solutions. On the other hand, competences such as analyzing threats to real-time applications, developing and operating large-scale data storage, and using a wide range of Big Data analytics platforms are considered less important. Companies also require employees to have the ability to implement tasks at both the unit level and the general/universal problem level, showcasing their versatility and problem-solving skills.

The survey results provide valuable insights into the opinions and satisfaction levels of employers regarding specialists graduating with a training degree in AI and IT. Employers express concerns about the shortage of AI specialists in the job market and the lack of practical experience among graduates. The practical application of machine learning experience is seen as an area that needs improvement. Additionally, some employers mention high salary expectations from AI specialists, making it challenging to find suitable candidates locally. Regarding IT specialists, opinions are mixed. While some employers appreciate their good background and technical proficiency, others find their practical skills lacking. Collaboration and creativity are identified as essential skills for IT specialists, and there seems to be an adequate pool of junior talent available. However, the situation becomes more challenging when searching for mid or senior-level specialists. The need for AI specialists is a topic of debate among employers, with some stating there is no need while others observe a significant gap in the job market. The satisfaction of employers with the level of preparation of Master's graduates in the area of AI is moderate overall, with the majority expressing moderate satisfaction. This indicates that improvements are needed to better align the skills of graduates with employer expectations. While the supply of AI specialists on the job market satisfies most companies, a considerable proportion is not satisfied, suggesting a need for more skilled professionals. Companies generally hold positive views towards raising the qualification of their current employees through AI master's level studies, indicating a willingness to invest in education and training. When it comes to university graduates' competencies in AI, companies have a neutral to positive perception. Graduates are generally considered to have high theoretical knowledge, but opinions vary regarding the practical application of that knowledge. Basic knowledge in business management, economics, and law is seen as good, as is the understanding of the latest international standards. Personal attributes such as innovation, work ethics, personal ambition, and self-assessment receive mixed responses. These survey findings highlight the need for improving the practical skills and experience of AI graduates, aligning educational programs with industry requirements, and bridging the gap between theoretical knowledge and its practical application. Employers are eager to hire qualified AI specialists and are willing to invest in the education and training of their current employees. The results also emphasize the importance of collaboration between educational institutions and industry stakeholders to ensure the preparedness of graduates for the dynamic AI job market.

The survey results provide insights into the opinions of employers regarding project activities related to AI research and their willingness to participate. Building a website to present AI research results by a local university is considered moderately important by most companies, with 20% being neutral and a smaller percentage considering it very important. None of the companies rate the idea as unimportant. This indicates a general interest in showcasing AI research outcomes through a dedicated website. Regarding communication and engagement, a significant number of companies, 63.89%, express their desire to receive a newsletter about the progress of the project.

However, a notable minority, 36.11%, show no interest in such newsletters. For active participation in the project's development through training and use-cases, 44.74% of companies respond positively, while 55.26% decline. This suggests that a considerable proportion of employers are open to involvement in the project activities. Regarding the presentation of project results, a majority of companies (60.53%) express interest in being invited to a multiplier event. This demonstrates the companies' eagerness to stay informed about the project's outcomes and stay updated with the latest developments in the AI and Data Science fields. While there is a general interest in a website presenting AI research results and receiving progress updates, the willingness to actively participate in the project's development and attend a multiplier event is more mixed. Understanding and accommodating the preferences and needs of employers is crucial for the successful implementation and dissemination of the FAAI project.

C. STUDY OF STUDENTS

The questionnaire for IT students, masters, and alumni in Information Systems and Technologies was filled out by 1052 persons in total, showing great interest in AAI topics inside the student population. The first group of three questions in the survey (questions 1-3) was of general purpose, with the aim to find out the basic information about surveyed –

their nationality, age, and student status. As expected, students mostly originated in the participant countries of the project: Poland 13.88%, Serbia 15.11%, Bulgaria 34.98%, Montenegro 19.68%, and Slovakia 10.55%. There are also 61 persons (5.8%) of other nationalities. Respondents are in large majority younger than 24 years 72.34% and still students 89.45% (64.83% first level of studies and 24.62% second level of studies). Only 11.55% are graduates.

The following set of ten questions (questions 4-13) was intended only for students. First, they were asked to state what education degree they are learning for. Most of the respondents are from Bachelor Studies 72.81% or Master Studies 22.15% (71.96% in the first two years of studies) with specialization in some variations in the field of IT (Information Technology 28.69%, Computer Science 25.82%). When asked whether they know any Applied Artificial Intelligence courses offered at their university, students in large majority chose answers No (54.03%) and Yes, I know only a few (39.25%) while only 6.72% chose the

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answer Yes, I know a lot of them. Activities, mostly preferred by students, to extend their knowledge in AAI are Projects (59.22%), Lectures (44.49%) or Laboratories (38.21%). Creating a website to showcase the findings of AAI research conducted by the local university staff is important or very important for almost 82% of respondents. One other significant inquiry was whether the students were acquainted with AAI matters where only 9.7% answered No, I have not heard about it and I am not interested in such access. At the end of this section of questions, students were asked whether they would like to take part in AAI courses and large majority (90.02%) answered neutrally or positively (Neutral– 35.36%, Somewhat agree – 29.47%, Agree – 25.19%).

Third group of questions named Participation in Applied Artificial Intelligence training consists of only two questions (14 and 15) related to the AAI context and the previous courses in AAI area. Only 212 respondents (20.15%) already participated in classes based on AAI. Most of the students showed interest for collecting data from different sources (web, social networks etc.) (44.3%) or doing AAI analytics/machine learning (47.34%).

Next set of questions was about working experience (questions 16-19). Almost half of surveyed persons are currently working 519/1052 (49.33%), meaning that a large number of them are both studying and working. The rest of the questions in this section aim to gather information on the duration and nature of the respondents' employment. Out of 519 workers, 347 of them work in the private sector, 157 in public sector, while 11 work in non-profit organizations. As expected (respondents are in majority younger than 24 years), surveyed mostly have less than 3 years of experience (356 out of 519 employed) and they work in IT industry (311 out of 519).

These workers in IT industry answered the group of questions (20-23). Questions were formulated in such a way to better describe the job position, requirements and experience of the IT workers. Survey showed that most of the IT workers work as Software developers (17.4%), in Support (4.75%), as Administrators (3.61%) and in Network construction and service (3.33%). More than a half of the IT workers stated that for an appointment to their position Bachelor diploma was needed. Out of 1052 respondents in total, only 136 had some experience with work in Applied Artificial Intelligence field and they use it on their work.

Maybe the most important set of questions for the realization of FAAI project was related to Important competencies necessary for Applied Artificial Intelligence (questions 2429). Respondents had the opportunity to choose which soft skills they consider most important for employment in the organization in which they are working from the list of more than 30 options. Few skills stand out in the sense that large majority of the workers find them more important than others: Ability to work in a team (66.73%), Ability to plan and manage time (62.55%), Ability to communicate in a second (foreign) language (60.27%). The following skills were also popular:

Ability to identify, propose and resolve problems (55.8%), Capacity to learn and stay up-to-date with learning (51.14%), Ability to apply knowledge in practical situations (50.38%), Capacity to generate new ideas (creativity) (48.95%). Other competences were chosen less frequently and the following competences were recognized as the least important: Commitment to conservation of the environment (11.88%), Ability to show awareness of equal opportunities and gender issues (12.36%), Ability to take the initiative and to foster the spirit of entrepreneurship and intellectual curiosity (13.5%).

When asked which competencies should have a specialist in AAI, respondents mostly chose answers: Using appropriate training and testing methodologies when deploying machine learning algorithms, Recognizing the breadth and utility of machine learning methods, Selecting appropriate (classes of) machine learning methods for specific problems, Comparing and contrasting machine learning methods. Most valued related competence which a specialist in AAI should have and which should be taught during AAI trainings is Effectively use variety of data analytics techniques (Machine Learning, Data Mining, Prescriptive and Predictive Analytics). Most popular AAI tools to be used to assist theoretical lectures tend to be: Applied Artificial Intelligence Analytics platforms (Hadoop, Spark, Data Lakes), Applied Artificial Intelligence and distributed computing tools (Spark, MapReduce, Hadoop, Mahout, Lucene, NLTK, Pregel), and Google Colab. Least popular are: Anaconda ecosystem, R Studio, and Mathcad.

D. STUDY OF ACADEMICS

Assessment of Applied Artificial Intelligence Education: A Survey of Academics' Perspectives This research study conducted an extensive survey to evaluate the current state of applied artificial intelligence (AI) education among academics. The survey, conducted under the FAAI Erasmus+ program, collected and analyzed questionnaires from 80 lecturers across five countries. The findings provide valuable insights into the teaching practices, competencies, and areas for improvement in applied AI education.

Results revealed that a significant number of respondents were beginners in the field of applied AI, while most of the responders claimed intermediate-level skills. Advanced level proficiency was reported by 23.75% of participants, with only 7.50% considering themselves experts. Therefore, the survey presents a comprehensive overview rather than a narrow expert perspective.

One noteworthy finding was that more than half of the teachers were self-taught in artificial intelligence, followed by those who received AI lessons during their university degree. Only less than a fifth underwent specialized AI courses. Regarding preferred activities for knowledge expansion, thematic courses were the most popular choice, while participation in conferences was half as popular. Commercial projects, open-source projects, engagement with public scientific groups, and getting to know the results of research conducted at the universities garnered similar levels of support (about 50 percent).

The study highlighted that a significant number of teachers lacked experience in teaching AI and had limited publication and research participation in applied AI (nearly forty percent had never published an article on applied AI matter, and

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only half participated on applied AI research). This emphasizes the need to involve more colleagues in AI projects, considering their evident interest. However, more than 50% of the teachers had at least one year of teaching experience, and almost one-fifth possessed over five years of teaching experience, positioning them as experts. Merely 15% of teachers expressed disinterest in AI teaching.

Interestingly, the majority of teachers had not participated in commercial AI projects but expressed a positive inclination toward involving external AI experts from industry (Somewhat agree 37.50%, Agree 42.50%, no one was against the experts from industry). There was strong consensus among respondents regarding the importance of including applied AI competencies in the curriculum, such as major AI areas including the context of applications, recognizing breath and utility of machine learning (ML)methods, and their practical implementation. It includes the need to compare ML methods and select appropriate one together with its training and testing. However, advanced topics like overfitting, the curse of dimensionality, performance metrics, algorithmic and data bias were considered less critical.

The significance of discussing the potential ramifications of decision-making arising from machine learning (ML) received relatively limited attention from the respondents, suggesting it was not considered highly crucial. Similar results were observed regarding ethical considerations surrounding AI systems. It is likely that the teachers perceived the acquisition of comprehensive knowledge in the methods themselves as the primary focus for students, as the debate surrounding usage and ethics would be futile without a solid understanding of the functioning of these methods. Furthermore, the importance of logic and probabilistic formalism, along with their reasoning, was also deemed relatively less significant.

To promote AI education, respondents emphasized the significance of establishing a website showcasing local university research on applied AI and creating open-source projects dedicated to AI problem-solving. They also emphasized the importance of oral presentations, student scientific groups, as well as webinars, but fostering collaboration with experts from AI companies is considered most important to better understand Applied AI matters. For students, the job market requirements are considered important, but to gain critical practical AI knowledge, collaboration with AI companies is required.

From the teacher recommendations can be selected the following advice for the curriculum:

- Focus more on the free versions.
- Select proper computing language and libraries first
- Attention on Computer Vision, Explainable AI, HumanAI interaction
- Add more doing by examples activities
- Solving real AI cases at classes

The fact that neither the university courses, nor specialized courses are major skill resource even among educators shows the necessity for improving both university courses as well as specialized ones. The study revealed the need to improve university courses and specialized training programs for applied AI. The majority of teachers expressed a desire to participate in sponsored AI courses to enhance their knowledge. While most teachers occasionally investigated the latest AI trends, nearly a fifth acknowledged to possess only basic knowledge. When questioned about familiarity with the newest applied artificial intelligence trends, technics, solutions, most people answered that they are occasionally investigating the area, and. The questionnaires unsurprisingly reveal that there is a need for teachers to improve their skills in teaching and promoting applied AI. Obstacles to enhancing applied AI education were identified, including problems with the study program, formal barriers to new teaching methods, and inadequate equipment. Addressing these challenges requires comprehensive improvements encompassing study programs, teaching methodologies, and access to appropriate resources. The desired competences include teaching, promoting, and improving knowledge in the field of AI. The hard skills required for effective teaching and learning of applied AI include machine learning, selected programming languages and libraries, data analysis and visualization, algorithm design and optimization, deep learning, and natural language processing. The study emphasized the importance of incorporating ethical considerations as a core part of the AI curriculum, an aspect that teachers did not currently prioritize. Additionally, the development of soft skills such as communication, collaboration, adaptability, creativity, problemsolving, and leadership were deemed crucial for effective applied AI education. Active participation in AI communities and engagement with field experts were strongly encouraged to remain up to date with the latest advancements and industry trends. Overall, this survey provides valuable insights into

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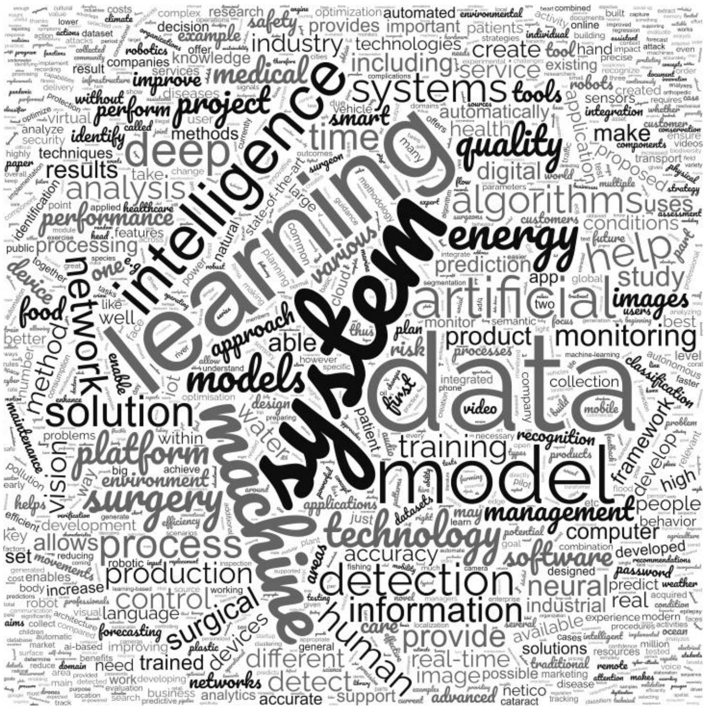

FIGURE 4. Job Responsibilities Word Cloud

the current landscape of applied AI education among academics, highlighting areas of strengths and opportunities for improvement. The findings contribute to the ongoing efforts to enhance the quality and relevance of applied AI education in academic institutions.

E. SYNTHETIC ANALYSIS OF SURVEYS

Job offers, project proposals, and applied AI surveys included open text fields, provided respondents with the opportunity to express their thoughts and opinions. These open-ended responses were analyzed using word clouds tool to gain insights into the most frequently mentioned words or themes in the data. The data was pre-processed. The stop words and word case were ignored. Additionally, the tenses support words were also removed. In the first survey, job responsibilities were examined to analyze the main responsibilities and obligations associated with the work position. A total of 57 responsibility descriptions were analyzed to gain insights into the key tasks and duties involved in the job. The result was presented in Fig. 4.

Regarding job responsibilities, the word cloud analysis highlighted a prominent group of words centered around "data" and "system," emphasizing the importance of obtaining valuable information for a specific business domain using machine learning and artificial intelligence techniques for training. The term "deep learning" also received strong emphasis in the text. Additionally, concepts such as "energy," "quality," "management," and "human solutions" emerged as significant. On the other hand, less frequently appearing words included "application" as "network", "medicine" and "food industry." The collected surveys about the projects

FIGURE 5. Project goals Word Cloud

were further analyzed to extract valuable insights and gain a deeper understanding of their characteristics, objectives, and outcomes. Figure 5 presents a word cloud analysis of project goals, while Figure 6 showcases the word cloud visualization of project results, providing insights into the primary objectives and targets as well as the significant outcomes and achievements of the analyzed projects. The discrepancy in the number of results analyzed, with 63 results in comparison to 52, can be attributed to the fact that some projects are still ongoing and therefore have yet to produce final outcomes.

Two word clouds depict the underlying focus on creating a "project" that involves the development of a "system" using “learning methods”, resulting in the creation of a "model" as a viable solution. In terms of application areas, the dominance of "video" solutions is evident. From a technological standpoint, "behavioural," "deep," and "neural" applications emerge as the most popular. Furthermore, the preference lies in achieving "efficient" and "significant" results. Finally, the objective of the real case study of AAI was analysed, involving research on 276 examples. The findings were presented in Figure 7.

Similar to the analysis of job offer responsibilities, the word cloud image reveals that the key focus lies in the requirement of "systems" built upon "data," where a "model" is generated through "machine" and "artificial" "intelligence" "learning." Additionally, emphasis is placed on "energy" utilization, while "image" based solutions are prominently featured. "Deep" solutions are favoured, and the application fields of "network," "medicine," "business," and "maintenance" are frequently mentioned.

FIGURE 6. Project results Word Cloud

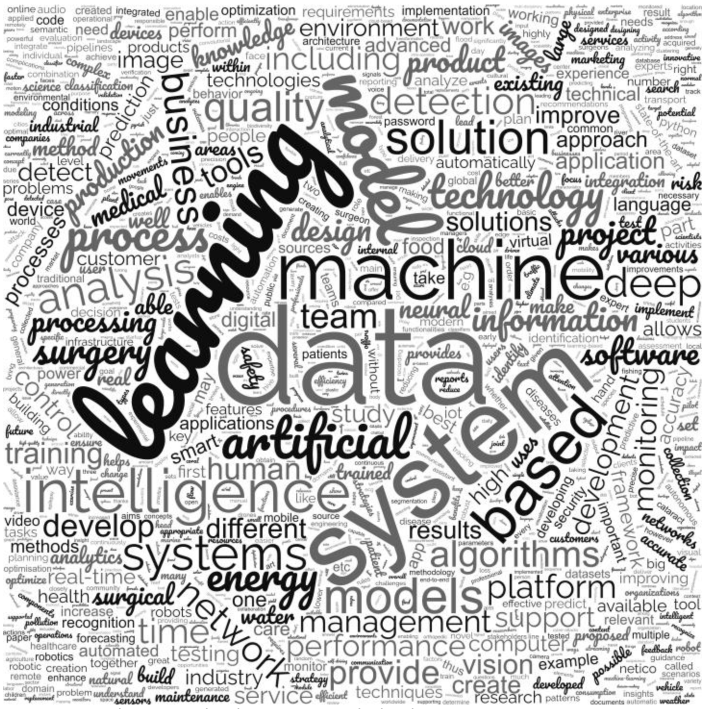

FIGURE 7. Real case study objectives Word Cloud

F. DECISION-MAKING PROBLEMS BASED ON AHP ANALYSIS

The results of the surveying that were presented in Sections II-D, II-E, II-F, IV-A, IV-B, IV-C, IV-D were used as the statistics to determine the attributes of the alternatives within a series of decision-making problems, which will be described in the ongoing subsections. Multiple decision-makers coming from different surveys will be considered (job market, academics, students, employers, good practice).

We have used the AHP scale (1 to 5) to assign values representing the relative importance or preference. Pairwise comparisons of alternatives have been conducted with the help of calculating either pairwise preferences or using pairwise functions like:

```
pairwiseFunction: function(a1, a2) min(5,
      max(1/5, a1$attribute/a2$attribute))
```

Here `a1`, `a2` are alternatives to be compared relative to `attribute`.

1) Priorities of competencies from the point of view of AI ML In the given decision-making problem, Figure 8 presents the model of the decision-making process. The problem involves 12 competences related to AI and ML. The decision-makers include job market representatives, academics, students, and employers.

Figures 9-13 display the priorities for specific groups of criteria from the

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viewpoint of the corresponding decisionmakers. These figures represent the relative importance assigned by each group to the different competences. The priorities are determined through a pairwise comparison process, where decision-makers compare each competence against others based on their significance.

2) Programming languages relative to the dedicated server and cloud solution

The choice of programming language is indeed important when studying AI, as it can significantly impact the ability to develop AI systems effectively. The criteria when choosing language include libraries and frameworks supported, vibrant community and resources, flexible and expressive code, performance and efficiency, integration and deployment, and industry trends.

Here in the context of determining programming language priorities for AI training course, AHP was utilized to incorporate the viewpoints of decision-makers such as the job market, employers, and good practice solutions (see model on Fig. 14).

The priorities obtained from each decision-maker are aggregated to generate a comprehensive set of priorities for the programming languages in AI training courses (see Fig. 1518). This was achieved by calculating weighted averages of the decision-makers' priority vectors.

3) Artificial intelligence models within the framework of Classic ML and Deep ML

From the viewpoint of Classic ML, decision-makers should focus on studying well-established machine learning algorithms, such as linear regression, decision trees, and support vector machines, which have been widely used and tested in the job market, favored by employers, and considered good practice in AI. From the viewpoint of Deep ML, decisionmakers should prioritize studying deep neural networks, convolutional neural networks, and recurrent neural networks, as these models have shown remarkable performance in various AI applications, are in high demand in the job market, sought after by employers, and reflect current best practices in the AI field.

When trying to solve the given decision-making problem numerically, Figure 19 presents the flowchart of the decision-making process. The problem involves 10 models related to classic and DL. The decision-makers include job market representatives, employers, and good practice solutions.

Figures 20-23 display the priorities for specific groups of criteria from the viewpoint of the corresponding decisionmakers. These figures represent the relative importance assigned by each group to the different AI models. The priorities are determined through a pairwise comparison process, where decision-makers compare each competence against others based on their significance.

G. TENSOR-BASED COURSE REPRESENTATION

Basing on the previous studies we have determined the vectors C (Table 6), T (Table 7), M (Table 8). Moreover, matrices $\mathbf{A}_{MC}$ and $\mathbf{A}_{TC}$ are presented in Table 10 and Table 9 respectively. Multiplying corresponding entries we get tensor τ_{ij}^{k}.

The generation of abstracted module models is now possible thanks to tensor decomposition. Each tensor is made up of three relationships, or "competence-topic-module" relations. Each tensor is then a trait made up of a weighted sum of rankone tensors obtained by multiplying three-factor vectors.

Such an approach allowed us to get a series of matrices for relations "module-topic" according to different competencies. Figure 3 shows the tensor, whose components are: topics, modules, and competencies. The formation of the desired competence can be achieved by realizing both specific topics and modules.

Table 9 shows the cross matrix "topic-competence" for 12 key competencies in AI higher education which can be obtained by realizing selected from the 12 topics listed in Table 7. Thus, for example, the competence named: "Recognize the breath and utility of machine learning methods" can be achieved by realizing the following topics : Rule-based expert systems; Machine learning I; Machine learning II; Deep neutral networkbasics; Deep neutral networkadvanced topics; Deep reinforcement learning; Natural language processing; Robotics.

In order to strengthen the quality of education while ensuring high standards of education, we propose to reinforce this competence through the implementation of specific modules.

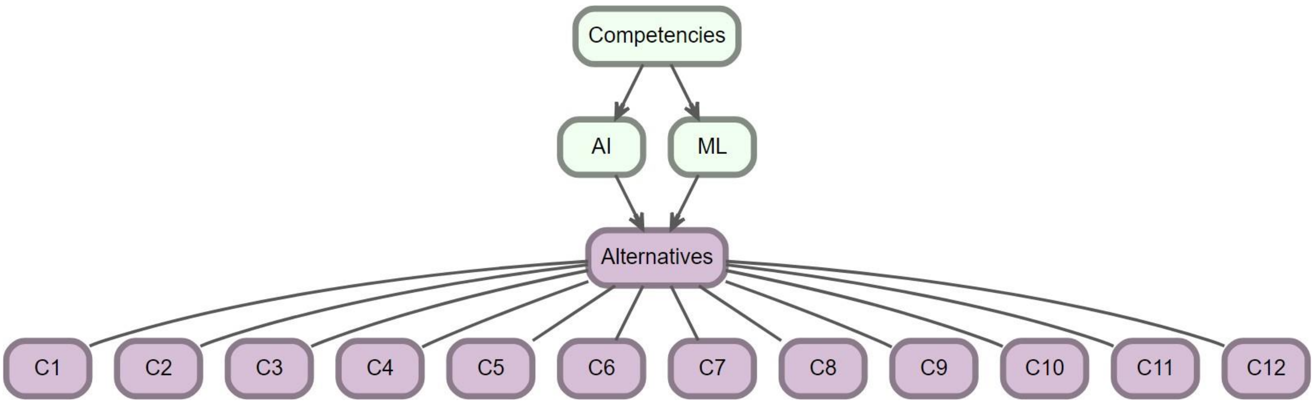

FIGURE 8. Model for decision making on the competencies as affected by AI and ML

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	Weight	C1	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C2	Inconsistency
Competencies	100.0%	23.0%	7.0%	7.0%	7.0%	7.0%	7.0%	7.0%	7.0%	7.0%	7.0%	7.0%	7.0%	0.0%
ML	78.3%	18.0%	5.5%	5.5%	5.5%	5.5%	5.5%	5.5%	5.5%	5.5%	5.5%	5.5%	5.5%	0.0%
AI	21.7%	5.0%	1.5%	1.5%	1.5%	1.5%	1.5%	1.5%	1.5%	1.5%	1.5%	1.5%	1.5%	0.0%

FIGURE 9. Priorities for competencies as affected by AI and ML: total result

	Weight	C1	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C2	Inconsistency
Competencies	100.0%	45.0%	5.0%	5.0%	5.0%	5.0%	5.0%	5.0%	5.0%	5.0%	5.0%	5.0%	5.0%	0.0%
ML	83.3%	37.5%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	0.0%
AI	16.7%	7.5%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.0%

FIGURE 10. Priorities for competencies as affected by AI and ML: job market as the decision maker

	Weight	C1	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C2	Inconsistency
Competencies	100.0%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	0.0%
AI	50.0%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	0.0%
ML	50.0%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	0.0%

FIGURE 11. Priorities for competencies as affected by AI and ML: academics as the decision maker

	Weight	C1	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C2	Inconsistency
Competencies	100.0%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	0.0%
ML	75.0%	6.3%	6.3%	6.3%	6.3%	6.3%	6.3%	6.3%	6.3%	6.3%	6.3%	6.3%	6.2%	0.0%
AI	25.0%	2.1%	2.1%	2.1%	2.1%	2.1%	2.1%	2.1%	2.1%	2.1%	2.1%	2.1%	2.1%	0.0%

FIGURE 12. Priorities for competencies as affected by AI and ML: students as the decision maker

	Weight	C1	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C2	Inconsistency
Competencies	100.0%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	8.3%	0.0%
ML	87.5%	7.3%	7.3%	7.3%	7.3%	7.3%	7.3%	7.3%	7.3%	7.3%	7.3%	7.3%	7.3%	0.0%
AI	12.5%	1.0%	1.0%	1.0%	1.0%	1.0%	1.0%	1.0%	1.0%	1.0%	1.0%	1.0%	1.0%	0.0%

FIGURE 13. Priorities for competencies as affected by AI and ML: employers as the decision maker

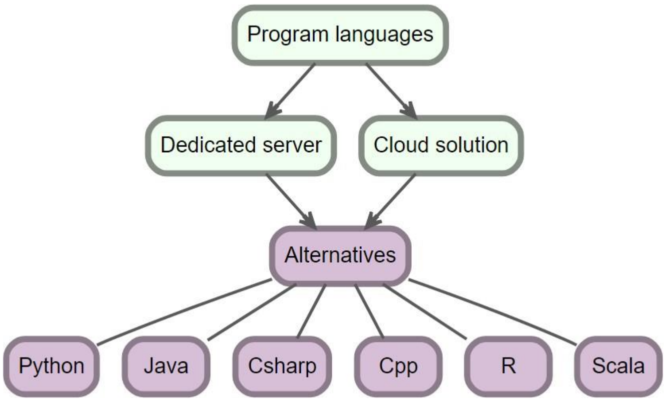

FIGURE 14. Model for decision making on the programming languages relative to dedicated server or cloud solutions

TABLE 6. Competencies from AI and ML to be covered by the proposed course on applied AI

denotation	competence
C_1	Describe major areas of AI as well as contexts in which AI methods may be applied.
C_2	Represent information in a logic formalism and apply relevant reasoning methods.
C_3	Represent information in a probabilistic formalism and apply relevant reasoning methods.
C_4	Be aware of the wide range of ethical considerations around AI systems, as well as mechanisms to mitigate problems.
C_5	Recognize the breadth and utility of machine learning methods
C_6	Compare and contrast machine learning methods.
C_7	Select appropriate (classes of) machine learning methods for specific problems.
C_8	Use appropriate training and testing methodologies when deploying machine learning algorithms.
C_9	Explain methods to mitigate the effects of overfitting and course of dimensionality in the context of machine learning algorithms.
C_{10}	Identify an appropriate performance metric for evaluating machine learning algorithms/ tools for a given problem.
C_{11}	Recognize problems related to algorithmic and data bias, as well as privacy and integrity of data.
C_{12}	Debate the possible effects – both positive and negative – of decisions arising from machine learning conclusions.

TABLE 7. Topics from AI and ML to be covered by the proposed course on applied AI

denotation	topic
T_1	Artificial intelligence – history and logic-based models
T_2	Knowledge Representation and Reasoning (Probabilitybased)
T_3	AI-Planning and Search Strategies
T_4	Fuzzy logic, fuzzy control systems
T_5	Rule-based expert systems
T_6	Machine learning I (overview and supervised learning)
T_7	Machine learning II (unsupervised learning)
T_8	Deep neural networks – basics
T_9	Deep neural networks – advanced topics

T_{10}	Deep reinforcement learning
T_{11}	Natural language processing
T_{12}	Robotics

TABLE 8. Modules of the proposed course on AAI

M_1	Basic principles of the application of AI in science and in modern business solutions
M_2	Embeddable modules from IBM, Microsoft, Google, AWS, etc.
M_3	Conducting research related to the practical application of artificial intelligence
M_4	Building software applications using AI
M_5	Implementation of external AI modules in software applications
M_6	AI-based solutions for Ecology
M_7	AI-based solutions for Agriculture
M_8	AI-based solutions for HealthCare
M_9	AI-based solutions for Smart City
M_{10}	AI-based solutions for Industry
M_{11}	AI-based solutions in Robotics
M_{12}	Application of other AI modules

TABLE 9. Cross-matrix for the relation "competence-topic" for AAI course

	T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	T_{10}	T_{11}	T_{12}
C_1	1	0	0	0	0	0	0	0	0	0	0	0
C_2	1	1	0	0	0	0	0	0	0	0	0	0
C_3	0	1	0	0	0	0	0	1	0	0	0	0
C_4	1	1	1	1	1	1	1	0	1	1	1	1
C_5	0	0	0	0	0	1	1	1	1	1	1	1
C_6	0	0	0	0	0	1	1	1	1	1	1	1
C_7	0	0	0	0	0	1	1	1	1	0	1	1
C_8	0	0	0	0	0	1	1	1	1	1	0	0
C_9	0	0	0	0	0	1	1	0	1	1	0	0
C_{10}	0	0	0	0	0	1	1	1	1	0	0	0
C_{11}	1	1	1	1	1	1	1	0	1	1	1	1
C_{12}	0	0	0	0	0	1	1	0	1	1	1	1

Table 10, shows the "module competence" cross matrix. From this, it can be seen that the education of the desired competencies was reinforced by the realization of certain modules. Thus, for example, the education of the previously selected competence "Recognize the breath and utility of machine learning methods" was reinforced by the realization of the following modules: M1 (Basics principles of application of AI in science and in modern business solutions) and M3 (Conducting research related to the principle application of artificial intelligence). Thus, each competency can be obtained by completing specific topics and modules. Tables 13 24 show the cross matrix " modules topics" for each of the 12 competencies. These tables contain the value "1"

TABLE 10. Cross-matrix for the relation "competence-module" to be implemented in the designed AAI course

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	M_{11}	M_{12}
C_1	1	1	1	0	1	0	0	0	0	0	0	1
C_2	0	1	0	0	1	0	0	0	0	0	0	1
C_3	0	1	0	0	1	0	0	0	0	0	0	1
C_4	0	1	1	0	1	0	0	0	0	0	0	1
C_5	1	0	1	0	0	0	0	0	0	0	0	0
C_6	0	1	0	1	1	1	1	1	1	1	1	1
C_7	1	0	1	0	0	1	1	1	1	1	1	0
C_8	1	0	0	1	0	1	1	1	1	1	1	0
C_9	0	0	0	1	0	1	1	1	1	1	1	0
C_{10}	0	0	0	1	0	1	1	1	1	1	1	0
C_{11}	0	0	0	0	0	1	1	1	1	1	1	0
C_{12}	0	0	0	0	0	1	1	1	1	1	1	0

	Weight	Python	Java	Csharp	Cpp	R	Scala	Inconsistency
Program languages	100.0%	40.7%	18.6%	11.1%	11.1%	9.6%	9.0%	0.0%
Cloud solution	51.8%	22.2%	11.4%	7.1%	2.7%	2.7%	5.6%	4.4%
Dedicated server	48.2%	18.5%	7.2%	4.0%	8.3%	6.9%	3.3%	2.8%

FIGURE 15. Priorities for program languages relative to dedicated server or cloud solution: total decision

	Weight	Python	Java	Csharp	Cpp	R	Scala	Inconsistency
Program languages	100.0%	44.5%	12.0%	14.2%	10.5%	11.3%	7.4%	0.0%
Dedicated server	50.0%	20.7%	4.4%	5.2%	8.0%	8.8%	2.8%	0.6%
Cloud solution	50.0%	23.8%	7.6%	9.0%	2.5%	2.5%	4.6%	4.4%

FIGURE 16. Priorities for program languages relative to dedicated server or cloud solution: decision from viewpoint of job market

	Weight	Python	Java	Csharp	Cpp	R	Scala	Inconsistency
Program languages	100.0%	34.7%	21.8%	16.1%	12.0%	10.8%	4.5%	0.0%
Dedicated server	50.0%	15.8%	8.9%	5.9%	9.4%	8.1%	1.9%	1.7%
Cloud solution	50.0%	18.9%	12.9%	10.2%	2.6%	2.6%	2.6%	2.9%

FIGURE 17. Priorities for program languages relative to dedicated server or cloud solution: decision from viewpoint of employers

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	Weight	Python	Java	Csharp	Cpp	R	Scala	Inconsistency
Program languages	100.0%	42.3%	21.0%	4.8%	10.8%	7.6%	13.5%	0.0%
Cloud solution	54.5%	23.6%	13.2%	3.0%	3.0%	3.0%	8.9%	4.0%
Dedicated server	45.5%	18.7%	7.8%	1.8%	7.8%	4.7%	4.7%	2.8%

FIGURE 18. Priorities for program languages relative to dedicated server or cloud solution: decision from viewpoint of good practice in AAI

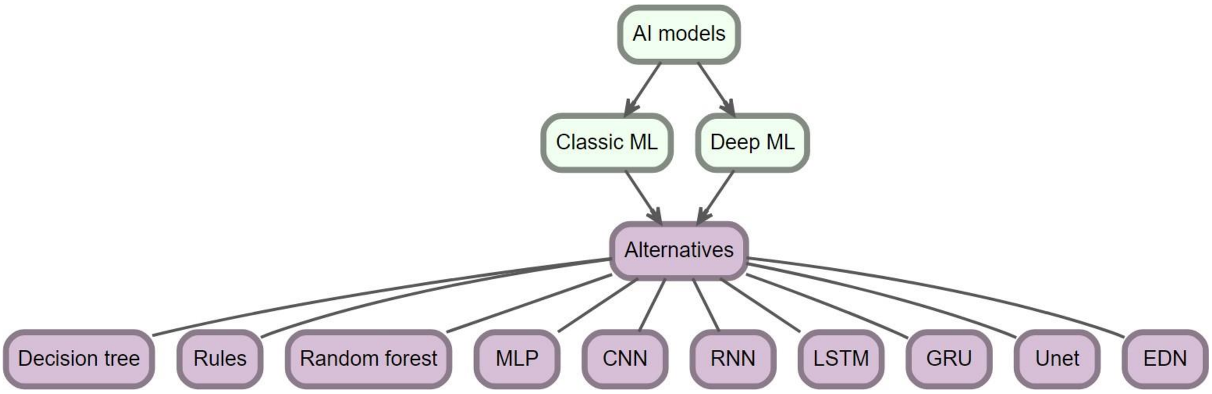

FIGURE 19. Model for decision making on AI model relative to classic or deep ML

	Weight	CNN	RNN	MLP	Decision tree	Random forest	Rules	EDN	Unet	LSTM	GRU	Inconsistency
AI models	100.0%	18.2%	13.9%	11.2%	11.0%	10.4%	8.1%	8.0%	6.8%	6.4%	6.0%	0.0%
Deep ML	59.7%	16.6%	12.2%	2.6%	2.6%	2.6%	2.6%	6.3%	5.2%	4.7%	4.4%	1.4%
Classic ML	40.3%	1.7%	1.7%	8.6%	8.4%	7.8%	5.5%	1.7%	1.7%	1.7%	1.7%	0.3%

FIGURE 20. Model for decision making on AI model relative to classic or deep ML: total decision

	Weight	CNN	RNN	MLP	Decision tree	Random forest	Rules	EDN	Unet	LSTM	GRU	Inconsistency
AI models	100.0%	13.9%	12.7%	13.4%	12.1%	11.0%	12.5%	8.1%	7.0%	4.4%	5.0%	0.0%
Classic ML	54.8%	2.1%	2.1%	11.7%	10.4%	9.3%	10.8%	2.1%	2.1%	2.1%	2.1%	0.3%
Deep ML	45.2%	11.8%	10.6%	1.7%	1.7%	1.7%	1.7%	6.0%	4.9%	2.3%	2.9%	1.2%

FIGURE 21. Model for decision making on AI model relative to classic or deep ML: decision due to job market requirement

	Weight	CNN	RNN	MLP	Decision tree	Random forest	Rules	EDN	Unet	LSTM	GRU	Inconsistency
AI models	100.0%	13.1%	10.5%	11.3%	11.7%	10.2%	11.3%	9.2%	7.1%	8.7%	7.1%	0.0%
Classic ML	50.0%	1.9%	1.9%	9.8%	10.2%	8.7%	9.8%	1.9%	1.9%	1.9%	1.9%	0.2%
Deep ML	50.0%	11.2%	8.6%	1.5%	1.5%	1.5%	1.5%	7.3%	5.2%	6.8%	5.2%	1.4%

FIGURE 22. Model for decision making on AI model relative to classic or deep ML: employer as a decision maker

	Weight	CNN	RNN	MLP	Decision tree	Random forest	Rules	EDN	Unet	LSTM	GRU	Inconsistency
AI models	100.0%	26.7%	17.2%	9.5%	9.5%	9.5%	5.5%	5.5%	5.5%	5.5%	5.5%	0.0%
Deep ML	77.8%	25.7%	16.2%	4.5%	4.5%	4.5%	4.5%	4.5%	4.5%	4.5%	4.5%	0.6%
Classic ML	22.2%	1.0%	1.0%	5.1%	5.1%	5.1%	1.0%	1.0%	1.0%	1.0%	1.0%	0.0%

FIGURE 23. Model for decision making on AI model relative to classic or deep ML: decision from viewpoint of good practice requirements

when the education of a given competency will be possible by realizing both the selected module and the selected topic,
and "0" when the realization of a given topic is not suitable for the realization of a certain selected module. Tables
13 24 presented here are matrices formed by multiplying topics through a vector of modules For example, for Table
13: Competencies: Describing the main areas of AI and the contexts in which AI methods can be applied will be possible
through the completion of topic 1 (T_1Artificial intelligence history and logic-based models) and modules (M_1 Basic
principles of applying artificial intelligence in science and modern business solutions; M_2 Embedded modules of IBM,
Microsoft, Google, AWS, etc.; M_3 Conducting research related to the practical application of artificial intelligence;
M_{12} Application of other AI modules). An analogous interpretation can be made by analyzing the remaining tables.

IV. DISCUSSION

A. REQUIREMENTS FROM JOB MARKET

The job market for applied AI is dynamic and evolving. From various programming skills to knowing design patterns or having a specific educational requirement. The following chapters show distribution and info about necessary requirements needed for an individual to have in order to be competent in the field of AAI.

1) Required programming languages

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Knowing programming skill comes connected to a specific programming language needed in applied AI techniques. Table 11 gives information about which programming languages are most needed in applied AI.

TABLE 11. Required programming languages

Language	Percentage
Python	79.73%
R	28.38%
C++	25.68%
C#	14.86%
Java	12.16%

As expected, Python is the programming language that is needed the most in the fields of applied AI. This shows that most of the courses should focus on delivering a detailed curriculum on Python programming language and libraries that are suitable for this field. This percentage stems from Python's simplicity and a huge ecosystem that can be used for various domains.

The rest of the programming languages are on a pretty similar scale, with R programming language selected at 28.38%, which shows us that a significant portion of competencies are oriented towards statistical computing and analysis and visualization due to its extensive collection of statistical libraries and packages.

Results also show that other programming languages required are Java, C#, and C++.

2) Educational Requirements

Table 12 shows data about which educational requirements are necessary to have, in order to work in AAI.

Educational requirements in applied AI typically involve a strong foundation in mathematics, more specifically statistics and statistical analysis, and computer science. The data shows that a bachelor's degree in computer science is often

TABLE 12. Educational requirements

Degree	Percentage
Bachelor degree computer science-related field	33.78%
Master degree computer science-related field	29.73%
No education level, skills only	27.03%

Other	9.46%

a minimum requirement, accompanied by a master's degree, both of degrees in computer-science related fields.

Although PhD in these fields provides deeper knowledge and specialization, study shows that in general PhD is not a necessary level of education. More important is having skills, which means that both learners and courses should force continuous learning, and certifications, and stay updated in the field of AAI.

3) Required Competencies

One of the most important knowledge sets on the job market is focusing on the necessary competencies needed for applied AI. Competency in general refers to knowledge, skills, and abilities that an expert needs to have in order to work in the applied AI field.

The study shows that selecting appropriate classes of machine learning methods and applying them to specific problems is the most dominant competency required, with a score of 59.46%. This is expected, considering the fact that one of the most important tasks is to find out the best processing of the data given. This shows that the experts need to have a comprehensive understanding of major areas in AI and the contexts it can be applied to.

With the score of 48.65% and 41.89% respectively, comparing machine learning methods and representing information in a logic formalism are the next two most important competencies. We may conclude that comparing ML methods is directly connected to selecting the appropriate method for the specific problem, so it's not surprising that this competency is very needed. The ability to represent information using logic or probabilistic formalisms and apply relevant methods enables experts to effectively model and manipulate knowledge.

Competencies that have a significant impact are using appropriate training and testing methodologies when deploying machine learning algorithms, together with recognizing the breadth and utility of machine learning methods at around 40

Knowing the required competencies in the field of applied AI is a very important study. It gives many useful information that can be oriented toward curriculum development, skill development or career preparation. In the area of curriculum development, understanding required competencies helps institutions to design and develop up-to-date programs. Aligning competencies with the curriculum is a necessary step toward succeeding in a chosen field.

B. EQUIREMENTS FROM EMPLOYERS

The findings of the survey, which explore the needs and expectations of employers in the field of Applied AI, highlight several important conclusions regarding the required hard skills, soft skills, and university education in applied AI, Machine Learning (ML), Data Science, and Big Data. In terms of hard skills, the competency most valued by employers is the ability to recognize problems related to algorithmic

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and data bias, as well as privacy and data integrity. Additionally, companies emphasize the importance of competencies such as describing major areas of AI, identifying performance metrics for evaluating ML algorithms and recognizing the breadth and utility of ML methods. To address these requirements, companies should focus on providing training and development opportunities to enhance the skills and abilities of individuals who exhibit weaker competencies. It is crucial for AI and data science employees to respect the field's history and understand the benefits and limitations of both logic-based and probability-based representations of knowledge. They should also demonstrate commitment to applying machine learning as part of a goal-oriented process for clients and be meticulous in comparing learned models. Algorithm selection and evaluation are deemed crucial for ensuring the quality of learned models, and ethical evaluation approaches with high confidence are essential. Attention to detail is emphasized in unsupervised learning techniques for data exploration, understanding, summarization, and visualization. Regarding the use of ML models, classic ML and deep ML techniques are widely employed by companies. While traditional ML models like decision trees and multilayer perceptrons (MLPs) are commonly used and studied, deep learning models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are very popular choices. The survey also reveals the most common AI and ML tasks within companies, with classification and regression ranking the highest. Image classification, clusterization, and image captioning are also prevalent, while tasks like speech recognition and image segmentation receive considerable response rates. In terms of programming languages, Python is the most required language for AI and ML work, followed by C++. Java, R, and C# also hold significance in the field. TensorFlow is the most widely used AI framework, followed by Keras and scikitlearn. Other frameworks like PyTorch, Apache TVM, AMD HIP, OpenAI, and Matlab toolboxes are used to a lesser extent. The Anaconda, Apache Hadoop, and Matlab are popular ecosystems, indicating a focus on comprehensive ML tools, large datasets, and complex algorithms. Employers prioritize competences related to innovation, adaptation, feasibility studies, and modern methods of psychology and pedagogy for academic/analytical employees. Critical thinking, communication, and proficiency with tools and technology are highly valued soft skills. Planning and organizing, business fundamentals, and collaboration skills are also considered essential. Moreover, employers emphasize the importance of competences such as selecting appropriate data structuresand algorithms, visualizing AI analysis, and implementing cloud computing-based solutions. The findings demonstrate that technical skills in AI and data science are crucial but not sufficient for success in the field. Employers value additional competences, including problem-solving skills, practical experience, software architecture, presentation skills, critical thinking, adaptability, and domain-specific knowledge in some cases. Effective communication, both with customers and within internal teams, is deemed essential. The survey indicates that the competences required by companies in the AI and Data

Science field are diverse, reflecting the interdisciplinary nature of the field. While theoretical knowledge of AI specialists is generally good, practical skills often need improvement. Understanding business requirements, estimating practical aspects of development, and the ability to work on problems of different scales are crucial competences. Employers have mixed opinions on the quality of IT graduates, but they appreciate their technical proficiency and solid background. Practical skills and creativity are considered crucial, while collaboration skills are essential for teamwork. While the job market for junior IT specialists is deemed sufficient, finding mid or senior-level specialists can be challenging. Opinions on the need for AI specialists are divided, with some employers indicating a significant gap in the job market. Most companies are moderately satisfied with the level of preparation of Master's graduates in the area of AI, indicating room for improvement. Companies generally have a positive view towards raising the qualification of their current employees by allowing them to study AI at a master's level. In conclusion, the survey provides valuable insights into the needs and expectations of employers in the field of Applied AI. It emphasizes the importance of a broad range of competences, including hard skills, soft skills, and interdisciplinary knowledge. Continuous learning, practical experience, effective communication, and problem-solving abilities are key to success in this rapidly evolving field.

Overall, the survey shed light on the employer requirements regarding skills and competences in applied AI and Data Science. The findings can help to improve the training and educational programs to meet the needs of employers in the field of Applied AI.

C. REQUIREMENTS FROM STUDENTS

The great response of IT Students, Masters, and Alumni in Information Systems and Technologies (over 1000 participants in the online survey), mostly from the partners' countries, demonstrates the huge interest of these target groups in Applied Artificial Intelligence. Young students think that AAI content will be important for their further careers and demonstrate the clear need for adequate courses.

The majority of students were interested in the survey on AAI, but not knowing about any relevant course at their university, demonstrates the good foundation of the FAAI project and the growing need for courses dealing with AAI. It is clearly stated that the developing course should lean heavily on practical implementation with laboratory work, student projects, and internships. Higher education institutions should focus on implementing AAI content into study programs by either innovating existing courses or introducing completely new courses. Improving material components (equipment, laboratories) is secondary, but also important factor. Creating a website to present research in the scope of AAI should be another priority for partner universities. It is an efficient way to disseminate findings and engage students and other target audiences in AAI topics. The fact that nearly all IT students expressed interest or were neutral towards studying an AAI course aligns with the project's assumption that there is a deficiency in AAI and other digital skills in the European region. Therefore, it emphasizes the need for new initiatives to adequately incorporate these skills into the curriculum, teacher development, assessment practices, and learning content.

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Designed AAI courses must be heavily oriented toward Software developers because they are making the vast majority of the target group for developing digital competencies and skills in the area of Applied Artificial Intelligence. Employers in the IT sector mostly demand Bachelor's degrees from their employees, so the most logical choice to place AAI courses would be at Bachelor's studies or as part of some specialization programs. On the other side, we must have in mind that these courses usually demand some already gained knowledge from the field, while more basic courses are obviously desired by the target population.

Developing soft skills becomes more and more important in today's work environment. Young people recognize their importance as well as their employers. Any designed training should also focus on developing soft skills, especially those related to Teamwork, Communication, and Time management. Creativity, Resolving problems, Capacity to learn and apply obtained knowledge should also be highly valued during course creation. The most valuable competencies for a specialist in AAI are: Using appropriate training and testing methodologies when deploying machine learning algorithms, Recognizing the breadth and utility of machine learning methods, Selecting appropriate (classes of) machine learning methods for specific problems, and Comparing and contrasting machine learning methods.

FAAI training and guidelines for their design also have to take into account desirable future professions for respondents (in accordance with the list of the European framework of IT competences) and to be tailored specifically around the most popular ones, like Software Development, Project Manager, Systems Administrator, and Database Administrator.

D. REQUIREMENTS TO ACADEMICS

The competence of educators plays a crucial role in equipping them with the skills and knowledge needed to effectively teach and promote AAI. As the field rapidly evolves, it becomes essential to identify and prioritize the competences required to keep educators up-to-date and provide valuable instruction to students. The key competences that should be

emphasized among academics in relation to AAI include the following.

It is imperative for educators to incorporate *ethical* considerations into the curriculum as AI becomes increasingly integrated into various domains. Educators must equip students with the ability to critically evaluate the ethical implications and potential consequences of AI decision-making. This involves fostering discussions on bias, fairness, transparency, accountability, and the broader social and ethical dimensions of AI technologies.

Academics should possess a solid understanding of core *technical concepts and methodologies* in applied AI. This encompasses knowledge of machine learning algorithms, statistical modeling, data preprocessing and analysis, programming languages, and commonly used libraries in AI development. Additionally, proficiency in areas such as computer vision, natural language processing, and deep learning is crucial, as they are fundamental components of applied AI.

AI is a *multidisciplinary field* that intersects with various domains such as computer science, mathematics, cognitive science, and ethics. Academics should be encouraged to adopt an interdisciplinary approach to AI education, bridging the gap between technical knowledge and its application in real-world contexts. This involves fostering collaboration and incorporating diverse perspectives from other disciplines, enabling students to tackle complex AI challenges holistically. Developing students' *critical thinking and problem-solving* skills is vital in applied AI education. Academics should emphasize the ability to analyze and evaluate AI models and algorithms, identify limitations and potential biases, and propose innovative solutions to address AI-related problems. By nurturing students' analytical and logical reasoning abilities, educators enable them to become effective AI practitioners
and researchers.

Effective *communication and collaboration* skills are essential for educators in the field of applied AI. Academics should be able to articulate complex AI concepts in a clear and accessible manner, fostering engagement and understanding among students with varying levels of technical background. Moreover, promoting collaboration within and outside the academic community, such as through industry partnerships, encourages knowledge sharing, networking, and exposure to real-world AI applications.

Given the rapid advancements in AI technologies, academics should possess *adaptability and a commitment to lifelong learning*. They should stay updated with the latest developments, emerging trends, and best practices in the field. This involves engaging in continuous professional development, attending conferences and workshops, participating in AI communities, and seeking guidance from industry experts. By embracing a growth mindset, academics can effectively prepare students for the ever-evolving landscape of applied AI.

Academics have a responsibility to foster *ethical leadership* and serve as role models for their students. By demonstrating ethical behavior, promoting integrity, and upholding

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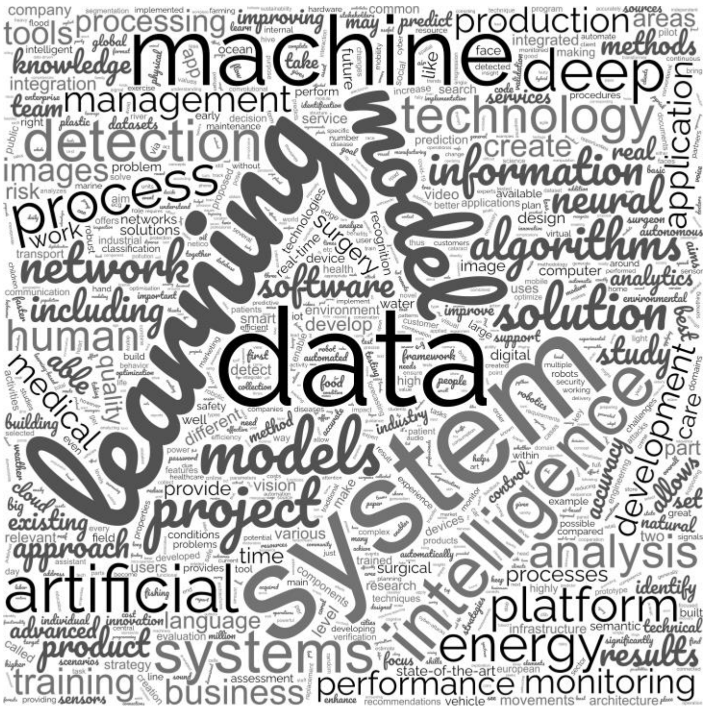

FIGURE 24. Word cloud for data from multiple surveys

professional standards, educators inspire students to adopt ethical practices in their AI endeavors. Educators should instill a sense of social responsibility, emphasizing the importance of AI for the betterment of society and encouraging students to leverage AI for a positive impact.

In summary, the competences required for academics in the field of applied AI go beyond technical proficiency. Emphasizing ethical considerations, adopting an interdisciplinary approach, nurturing critical thinking and problem-solving skills, fostering effective communication and collaboration, embracing adaptability and lifelong learning, and promoting ethical leadership can empower educators to provide comprehensive and impactful AI education. By cultivating these competences among academics, we can ensure that future generations are equipped with the knowledge and skills to navigate the ethical, technical, and societal complexities of applied AI.

E. SYNTHETIC ANALYSIS OF SURVEYS

In summary, the word cloud analysis of job responsibilities, project goals, project results, and the objectives of the real case study of AAI revealed consistent themes. The join word cloud was presented in Figure 24.

The importance of "systems" based on "data" and the generation of "models" through "machine" and "artificial" "intelligence" and "learning" were prevalent across all word clouds. Additionally, emphasis was placed on "energy" utilization and "deep" solutions. Application fields such as "network," "medicine," "business," and "maintenance" were commonly mentioned. In analyzing the word cloud, it is evident that the ideal system to be created should possess distinguishing char-

acteristics such as "performance," "quality," and "accuracy." Moreover, it is imperative that certain solutions enhance the existing ones. Finally, “management” and “monitoring” are also important keywords from the analyzed system. Thus, the lifecycle of the created solution should be presented. The findings presented insights into the main responsibilities and obligations in job positions, project objectives and outcomes, and the objectives of the real case study.

F. AHP ANALYSIS OF TENSOR RELATION "COMPETENCE-CONTENT-MODULE"

As it was shown, AHP can be used for training course design in competence-based education by helping to prioritize and make decisions regarding various aspects of the course. Applying AHP in this context helped us to do the following. When defining the goal, we establish the ultimate goal of the training course. This could be developing specific
competencies in AAI.

Identifying criteria that contribute to the achievement of the goal, in competence-based education, these criteria could include factors such as the relevance of the content to the desired competencies, the clarity and effectiveness of instructional methods, the assessment strategies used to measure competency attainment, the alignment with industry standards or job requirements.

With the help of generating alternatives, we determine the different alternatives or options for designing the training course on AAI. These alternatives could include different instructional approaches, teaching methodologies, assessment methods, sequencing of topics, duration of the course, or incorporation of practical exercises or real cases.

By applying AHP in the AAI training course design, we can systematically evaluate and prioritize different factors, consider multiple perspectives, and make more informed decisions that align with the goals and requirements of CBE.

1) Priorities of competencies point of view of AI ML

The Analytic Hierarchy Process (AHP) method can be applied to determine priorities among the competences related to AI and ML in the context of the job market, academics, students, and employers as decision-makers. AHP is a structured approach that helps decision-makers compare and prioritize different criteria based on their relative importance.

Using the AHP method, decision-makers can systematically evaluate and assign weights to the competences. The results from Figures 9-13 can then be used to guide decisionmaking processes related to AI and ML competences, such as curriculum

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development, hiring decisions, or educational programs, taking into account the perspectives of job market representatives, academics, students, and employers.

2) Programming languages for AAI training course

Different programming languages have varying support for AI libraries and frameworks, such as Python with TensorFlow and PyTorch, which greatly simplify AI development. Languages like Python and R have vibrant AI communities, offering abundant resources for learning and troubleshooting. Some languages offer flexibility and expressiveness, like Python's simplicity and readability, while others, like Lisp or Haskell, have built-in support for functional programming, advantageous for certain AI techniques. The choice of programming language may depend on performance requirements, with languages like C++ or Java offering better performance than interpreted languages. Integration and deployment needs can also influence the choice of language, such as using JavaScript for web applications. Python's popularity in the AI community makes it widely used in industry, academia, and research.

It's important to note that the specific priorities of programming languages related to AI training courses can vary depending on the context, technological advancements, and the evolving needs of the job market and employers (see Fig. 15-18). Therefore, the most up-to-date and comprehensive results would be obtained from recent studies or surveys conducted by AI experts, research institutions, or industry organizations that specialize in AI and programming languages. The criteria that are important for assessing the programming languages' suitability for AI training courses could include factors such as performance, scalability, community support, libraries and frameworks, ease of use, ecosystem, industry adoption, and compatibility with server-dedicated and cloud solutions.

3) AI models within the framework of Classic ML and Deep ML

From the viewpoint of Classic ML, decision-makers should prioritize studying fundamental models like linear regression, logistic regression, and decision trees, as these are widely used in the job market, sought after by employers, and represent good practice in AI. From the viewpoint of Deep ML, decision-makers should focus on studying deep neural networks, convolutional neural networks (CNNs), and recurrent neural networks (RNNs), as these models have gained significant prominence in the job market, are highly valued by employers, and are considered essential for keeping up with the current best practices in AI.

G. TENSOR-BASED COURSE REPRESENTATION

Through the analysis of the table containing the cross-matrix topic-competence, it can be seen that the competence formed through the implementation of the largest number of topics is competence C_4. In order to develop it, it is necessary to implement almost all topics (T_1-T_{12}) except for topic T_8.

Considering the cross-matrix modules-competence, it can be seen that the strengthening of C_6 competence should be done through the realization of almost all modules (M_1-M_{12}) except M_1 and M_3.

Based on the analysis presented in Tables 13-24, it is evident that the modules and topics have a significant relationship. The findings indicate the following connections between competencies and educational components (topics):

- Competency C_1 can be developed by implementing T_1 along with modules M_1, M_2, M_3, and M_{12}.
- To cultivate competency C_2, it is recommended to implement T_1 in conjunction with modules M_2, M_5, and M_{12}.
- For the education of competency C_3, it is advisable to undertake T_1, T_5, T_{12}, and utilize modules M_2 and M_8.
- Competency C_4 can be effectively taught through the realization of T_2, T_3, T_4, T_{12}, and the majority of modules, except for M_8.
- To acquire competency C_5, it is necessary to engage in T_1, T_3, and utilize modules M_6 through M_{12}.
- The development of competency C_6 requires the implementation of T_2, T_4 through T_{12}, as well as the utilization of modules M_6 through M_{12}.
- Competency C_7 can be effectively trained through the realization of T_1, T_3, T_6 through T_{11}, and by utilizing modules M_6 through M_{12}.
- For the education of competency C_8, it is recommended to undertake T_1, T_3, T_4, T_6 through T_{11}, and utilize modules M_6 through M_{12}.
- Competency C_9 can be acquired by undertaking T_4, T_6 through T_{11}, and utilizing modules M_6 through M_{12}.
- To develop competency C_{10}, it is advised to undertake T_4, T_6 through T_{11}, and utilize modules M_6 through M_{12}.
- The development of competency C_{11} necessitates the implementation of T_6 through T_{11}, and utilizing most modules, except for M_8.
- For the education of competency C_{12}, it is recommended to implement T_6 through T_{11}, and utilize modules M_6, M_7, and M_9 through M_{12}.

V. CONCLUSION

The study successfully developed a comprehensive approach for designing a training course on AAI in the higher education context. This approach is based on evidence-based pedagogical approaches and follows the principles of competencybased education and innovative pedagogy.

The research conducted a thorough review of AAI through keyword clustering, incorporating data from surveys, job offers, existing AI training courses, scientific projects, and real cases. The analysis of textual information using word clouds provided valuable insights.

The study employed a tensor-based approach to present the competence-based AAI course, ensuring a holistic representation of competencies in relation to the course content and educational modules. This approach allows for a structured and comprehensive understanding of the required skills and knowledge in AAI.

Through the solution of decision-making problems using AHP technique, the

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research identified specific numerical requirements and priorities for the course, further enhancing the course's design and effectiveness.

The findings of the study emphasize the importance of aligning the training course with the needs and preferences of the target audience. By incorporating insights from surveys, educational experience, scientific projects, and business requirements, the developed training course on applied artificial intelligence ensures the achievement of desired competencies and learning outcomes.

The implications of this research are significant for higher education institutions seeking to design effective training courses on AAI. The approach presented in this study provides a framework for developing courses that meet the demands of the rapidly evolving field of artificial intelligence, while also catering to the specific needs of students and industry requirements.

Overall, this work contributes to the advancement of evidence-based pedagogical approaches in the field of artificial intelligence education, specifically in the context of higher education. The developed training course on applied artificial intelligence offers a comprehensive and competency-based learning experience, fostering the acquisition of relevant skills and knowledge needed to tackle real-world AI problems.

APPENDIX A

COMPETENCIES CROSS-MATRICES

Tables 13-24 present the relation "topic-module" from the viewpoint of the corresponding competencies.

TABLE 13. Cross-matrix for the relation "topic-module" according to the competence C_1

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	M_{11}	M_{12}
T_1	1	1	1	0	0	0	0	0	0	0	0	1
T_2	0	0	0	0	0	0	0	0	0	0	0	0
T_3	0	0	0	0	0	0	0	0	0	0	0	0
T_4	0	0	0	0	0	0	0	0	0	0	0	0
T_5	0	0	0	0	0	0	0	0	0	0	0	0
T_6	0	0	0	0	0	0	0	0	0	0	0	0
T_7	0	0	0	0	0	0	0	0	0	0	0	0
T_8	0	0	0	0	0	0	0	0	0	0	0	0
T_9	0	0	0	0	0	0	0	0	0	0	0	0
T_{10}	0	0	0	0	0	0	0	0	0	0	0	0
T_{11}	0	0	0	0	0	0	0	0	0	0	0	0
T_{12}	0	0	0	0	0	0	0	0	0	0	0	0

TABLE 14. Cross-matrix for the relation "topic-module" according to the competence C_2

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	M_{11}	M_{12}
T_1	0	1	0	0	1	0	0	0	0	0	0	1
T_2	0	1	0	0	1	0	0	0	0	0	0	1
T_3	0	0	0	0	0	0	0	0	0	0	0	0
T_4	0	0	0	0	0	0	0	0	0	0	0	0
T_5	0	0	0	0	0	0	0	0	0	0	0	0
T_6	0	0	0	0	0	0	0	0	0	0	0	0
T_7	0	0	0	0	0	0	0	0	0	0	0	0
T_8	0	0	0	0	0	0	0	0	0	0	0	0
T_9	0	0	0	0	0	0	0	0	0	0	0	0
T_{10}	0	0	0	0	0	0	0	0	0	0	0	0
T_{11}	0	0	0	0	0	0	0	0	0	0	0	0
T_{12}	0	0	0	0	0	0	0	0	0	0	0	0

TABLE 15. Cross-matrix for the relation "topic-module" according to the competence C_3

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	M_{11}	M_{12}
T_1	0	0	0	0	0	0	0	0	0	0	0	0
T_2	0	1	0	0	0	0	0	1	0	0	0	0
T_3	0	0	0	0	0	0	0	0	0	0	0	0
T_4	0	0	0	0	0	0	0	0	0	0	0	0
T_5	0	1	0	0	0	0	0	1	0	0	0	0
T_6	0	0	0	0	0	0	0	0	0	0	0	0
T_7	0	0	0	0	0	0	0	0	0	0	0	0
T_8	0	0	0	0	0	0	0	0	0	0	0	0
T_9	0	0	0	0	0	0	0	0	0	0	0	0
T_{10}	0	0	0	0	0	0	0	0	0	0	0	0
T_{11}	0	0	0	0	0	0	0	0	0	0	0	0
T_{12}	0	1	0	0	0	0	0	1	0	0	0	0

TABLE 16. Cross-matrix for the relation "topic-module" according to the competence C_4

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	M_{11}	M_{12}
T_1	0	0	0	0	0	0	0	0	0	0	0	0
T_2	1	1	1	1	1	1	1	0	1	1	1	1
T_3	1	1	1	1	1	1	1	0	1	1	1	1
T_4	1	1	1	1	1	1	1	0	1	1	1	1
T_5	0	0	0	0	0	0	0	0	0	0	0	0
T_6	0	0	0	0	0	0	0	0	0	0	0	0
T_7	0	0	0	0	0	0	0	0	0	0	0	0
T_8	0	0	0	0	0	0	0	0	0	0	0	0
T_9	0	0	0	0	0	0	0	0	0	0	0	0
T_{10}	0	0	0	0	0	0	0	0	0	0	0	0
T_{11}	0	0	0	0	0	0	0	0	0	0	0	0
T_{12}	1	1	1	1	1	1	1	0	1	1	1	1

TABLE 17. Cross-matrix for the relation "topic-module" according to the competence C_5

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	M_{11}	M_{12}
T_1	0	0	0	0	0	1	1	1	1	1	1	1
T_2	0	0	0	0	0	0	0	0	0	0	0	0
T_3	0	0	0	0	0	1	1	1	1	1	1	1

T_4	0	0	0	0	0	0	0	0	0	0	0	0
T_5	0	0	0	0	0	0	0	0	0	0	0	0
T_6	0	0	0	0	0	0	0	0	0	0	0	0
T_7	0	0	0	0	0	0	0	0	0	0	0	0
T_8	0	0	0	0	0	0	0	0	0	0	0	0
T_9	0	0	0	0	0	0	0	0	0	0	0	0
T_{10}	0	0	0	0	0	0	0	0	0	0	0	0
T_{11}	0	0	0	0	0	0	0	0	0	0	0	0
T_{12}	0	0	0	0	0	0	0	0	0	0	0	0

TABLE 18. Cross-matrix for the relation "topic-module" according to the competence C_6

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	M_{11}	M_{12}
T_1	0	0	0	0	0	0	0	0	0	0	0	0
T_2	0	0	0	0	0	1	1	1	1	1	1	1
T_3	0	0	0	0	0	0	0	0	0	0	0	0
T_4	0	0	0	0	0	1	1	1	1	1	1	1
T_5	0	0	0	0	0	1	1	1	1	1	1	1
T_6	0	0	0	0	0	1	1	1	1	1	1	1
T_7	0	0	0	0	0	1	1	1	1	1	1	1
T_8	0	0	0	0	0	1	1	1	1	1	1	1
T_9	0	0	0	0	0	1	1	1	1	1	1	1
T_{10}	0	0	0	0	0	1	1	1	1	1	1	1
T_{11}	0	0	0	0	0	1	1	1	1	1	1	1
T_{12}	0	0	0	0	0	1	1	1	1	1	1	1

TABLE 19. Cross-matrix for the relation "topic-module" according to the competence C_7

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	M_{11}	M_{12}
T_1	0	0	0	0	0	1	1	1	1	0	1	1
T_2	0	0	0	0	0	0	0	0	0	0	0	0
T_3	0	0	0	0	0	1	1	1	1	0	1	1
T_4	0	0	0	0	0	0	0	0	0	0	0	0
T_5	0	0	0	0	0	0	0	0	0	0	0	0
T_6	0	0	0	0	0	1	1	1	1	0	1	1
T_7	0	0	0	0	0	1	1	1	1	0	1	1
T_8	0	0	0	0	0	1	1	1	1	0	1	1
T_9	0	0	0	0	0	1	1	1	1	0	1	1
T_{10}	0	0	0	0	0	1	1	1	1	0	1	1
T_{11}	0	0	0	0	0	1	1	1	1	0	1	1
T_{12}	0	0	0	0	0	0	0	0	0	0	0	0

TABLE 20. Cross-matrix for the relation "topic-module" according to the competence C_8

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	M_{11}	M_{12}
T_1	0	0	0	0	0	1	1	1	1	1	0	0
T_2	0	0	0	0	0	0	0	0	0	0	0	0
T_3	0	0	0	0	0	1	1	1	1	0	1	1
T_4	0	0	0	0	0	1	1	1	1	1	0	0
T_5	0	0	0	0	0	0	0	0	0	0	0	0

T_6	0	0	0	0	0	1	1	1	1	1	0	0
T_7	0	0	0	0	0	1	1	1	1	1	0	0
T_8	0	0	0	0	0	1	1	1	1	1	0	0
T_9	0	0	0	0	0	1	1	1	1	1	0	0
T_{10}	0	0	0	0	0	1	1	1	1	1	0	0
T_{11}	0	0	0	0	0	1	1	1	1	1	0	0
T_{12}	0	0	0	0	0	0	0	0	0	0	0	0

TABLE 21. Cross-matrix for the relation "topic-module" according to the competence C_9

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	M_{11}	M_{12}
T_1	0	0	0	0	0	0	0	0	0	0	0	0
T_2	0	0	0	0	0	0	0	0	0	0	0	0
T_3	0	0	0	0	0	0	0	0	0	0	0	0
T_4	0	0	0	0	0	1	1	1	1	0	0	0
T_5	0	0	0	0	0	0	0	0	0	0	0	0
T_6	0	0	0	0	0	1	1	1	1	0	0	0
T_7	0	0	0	0	0	1	1	1	1	0	0	0
T_8	0	0	0	0	0	1	1	1	1	0	0	0
T_9	0	0	0	0	0	1	1	1	1	0	0	0
T_{10}	0	0	0	0	0	1	1	1	1	0	0	0
T_{11}	0	0	0	0	0	1	1	1	1	0	0	0
T_{12}	0	0	0	0	0	0	0	0	0	0	0	0

TABLE 22. Cross-matrix for the relation "topic-module" according to the competence C_{10}

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	M_{11}	M_{12}
T_1	0	0	0	0	0	0	0	0	0	0	0	0
T_2	0	0	0	0	0	1	1	1	1	1	1	1
T_3	0	0	0	0	0	0	0	0	0	0	0	0
T_4	0	0	0	0	0	1	1	1	1	1	1	1
T_5	0	0	0	0	0	1	1	1	1	1	1	1
T_6	0	0	0	0	0	1	1	1	1	1	1	1
T_7	0	0	0	0	0	1	1	1	1	1	1	1
T_8	0	0	0	0	0	1	1	1	1	1	1	1
T_9	0	0	0	0	0	1	1	1	1	1	1	1
T_{10}	0	0	0	0	0	1	1	1	1	1	1	1
T_{11}	0	0	0	0	0	1	1	1	1	1	1	1
T_{12}	0	0	0	0	0	1	1	1	1	1	1	1

TABLE 23. Cross-matrix for the relation "topic-module" according to the competence C_{11}

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	M_{11}	M_{12}
T_1	0	0	0	0	0	0	0	0	0	0	0	0
T_2	0	0	0	0	0	0	0	0	0	0	0	0
T_3	0	0	0	0	0	0	0	0	0	0	0	0
T_4	0	0	0	0	0	0	0	0	0	0	0	0
T_5	0	0	0	0	0	0	0	0	0	0	0	0
T_6	1	1	1	1	1	1	1	0	1	1	1	1
T_7	1	1	1	1	1	1	1	0	1	1	1	1
T_8	1	1	1	1	1	1	1	0	1	1	1	1
T_9	1	1	1	1	1	1	1	0	1	1	1	1
T_{10}	1	1	1	1	1	1	1	0	1	1	1	1
T_{11}	1	1	1	1	1	1	1	0	1	1	1	1
T_{12}	0	0	0	0	0	0	0	0	0	0	0	0

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TABLE 24. Cross-matrix for the relation "topic-module" according to the competence C_{12}

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	M_{11}	M_{12}
T_1	0	0	0	0	0	0	0	0	0	0	0	0
T_2	0	0	0	0	0	0	0	0	0	0	0	0
T_3	0	0	0	0	0	0	0	0	0	0	0	0
T_4	0	0	0	0	0	0	0	0	0	0	0	0
T_5	0	0	0	0	0	0	0	0	0	0	0	0
T_6	0	0	0	0	0	1	1	0	1	1	1	1
T_7	0	0	0	0	0	1	1	0	1	1	1	1
T_8	0	0	0	0	0	1	1	0	1	1	1	1
T_9	0	0	0	0	0	1	1	0	1	1	1	1
T_{10}	0	0	0	0	0	1	1	0	1	1	1	1
T_{11}	0	0	0	0	0	1	1	0	1	1	1	1
T_{12}	0	0	0	0	0	0	0	0	0	0	0	0

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