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EXPLORING DEEP TECH: STUDENT PERSPECTIVES AND CROSS-UNIVERSITY ANALYSIS

Abstract: This paper focuses on exploration of deep tech potential at three universities in South East Wurope: University of Sarajevo (UNSA) from Bosnia and Herzegovina, Polytechnic University of Tirana (UPT) from Albania and University of Montenegro (UoM) from Montenegro. One-way analysis of variance (ANOVA) and Tukey procedure for multiple comparisons were performed to assess and compare perceptions of students of these three universities regarding different deep tech issues. Research hypotheses were that there were differences in the interest of students of these three universities to (i) take one or more university courses to gain knowledge on certain deep tech technologies, (ii) attend other means of learning about deep tech (workshops, trainings, online courses, etc.) outside of the University, (iii) start own company in a deep tech field, and (iv) be actively engaged in deep tech research and development projects. Results of the research showed that hypotheses were not supported except regarding start of the own company in a deep tech field where there was difference in the interest of UNSA and UPT students and UoM and UPT students. There were differences in offering courses in deep tech areas, and that students at all three universities are highly motivated to acquire deep tech competences especially in the areas of robotics, artificial intelligence and machine learning including big data, and sustainable energy and clean technologies. Higher education, as one of three knowledge triangle components, may serve as very important point in creating dynamic knowledge triangle deep tech ecosystem and be the driving force as the source of educated relevant experts needed for deep tech development.

Keywords: deep tech, statistical hypothesis test, ANOVA, Tukey procedure for multiple comparisons, cross-university analysis

1. Introduction

Deep technology or deep tech refers to advanced and cutting-edge technology solutions based on substantial scientific discoveries and/or engineering innovations.

Development of such advanced and cutting-edge technology solutions involves significant level of complexity, high level of expertise and may bring breakthroughs in various fields. Deep tech continues to evolve rapidly and has the potential to reshape

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industries, improve human life, and address many global challenges and as deep tech researchers push the boundaries of science and technology it is expected to see more advancements in the coming years. The development of deep tech is highly competitive on a global level and thus represents a frontier of exploration and discovery.

Deep tech is often associated with substantial and extensive research and development to create new products or services with transformative potential that may make impact on society and lasting changes. Thus, protecting intellectual property rights is crucial in deep tech sector. Deep tech is interdisciplinary in its nature and requires collaboration across multiple disciplines since integrating knowledge from various fields is crucial for solving complex problems and pushing the boundaries of science and technology. Because of high complexity deep tech projects typically have longer development cycles compared to conventional technologies. Deep tech projects are usually associated with high financial investment to support research, development, and prototyping. That is why startups and companies working on deep tech projects usually seek funding from different sources. Bringing deep tech innovations to market and achieving widespread adoption and successful commercialization could potentially be a significant challenge.

Close collaboration and partnership between three components of the knowledge triangle, education, research, and businesses (startups and established companies) are essential for boost and acceleration of deep tech. Development of deep tech solutions require high quality education especially STEM (Science, Technology, Engineering, and Mathematics) education which is vital for fostering of advanced deep tech ecosystem. The aim of this research is to explore deep tech potential in education at three universities in Western Balkan: University of Sarajevo (UNSA), Polytechnic University of

Tirana (UPT) and University of Montenegro (UoM) and perform cross-university analysis using statistical hypothesis testings.

1.1. Literature review

The New European Innovation Agenda, unveiled by the European Commission in July 2022, launched five flagship actions out of which certain flagship actions explicitly refer to deep tech (European Commission, 2022).

- Flagship 1: Funding for deep tech scale-ups
- Flagship 2: Enabling deep tech innovation through experimentation spaces and public procurement
- Flagship 3: Accelerating and strengthening innovation in European Innovation Ecosystems across the EU and addressing the innovation divide.
- Flagship 4: Fostering, attracting and retaining deep tech talents.
- Flagship 5: Improving policy making tools.

European Institute of Innovation & Technology (EIT), a body of European Union (EU), established Deep Tech Talents for Europe Initiative (DTTI) as flagship under the New European Innovation Agenda with aim to skill one million people within deep tech fields by the end of 2025. The Deep Tech Talent Initiative was officially launched by the European Commissioner for Innovation, Research, Culture, Education and Youth in June 2022 (European Institute of Innovation and Technology, 2022).

European Commission in June 2023 launched the European Innovation Council initiative to support Europe's future deep tech to identify, promote, and support the growth of 100 promising Europe's deep tech companies including a network of minimum 400 quality ecosystem players. This action supports the call for attraction and retention of deep tech talents and improved policy tool, and objective to increase access to

funding for deep tech scale-ups of the New European Innovation Agenda (European Innovation Council, 2023).

European Institute of Innovation and Technology (EIT) in order make simpler and more coherent classification defines fifteen deep tech technologies:

- Advanced Computing / Quantum Computing
- Advanced Manufacturing
- Advanced Materials
- Aerospace, Automotive and Remote Sensing
- Artificial Intelligence and Machine Learning, including Big Data
- Biotechnology and Life Sciences
- Communications and Networks, including 5G
- Cybersecurity and Data Protection
- Electronics and Photonics
- Internet of Things, W3C, Semantic Web
- Robotics
- Semiconductors (microchips)
- Sustainable Energy and Clean Technologies
- Virtual Reality, Augmented Reality, Metaverse
- Web 3.0, including Blockchain, Distributed Ledgers, NFTs

Detailed deep tech definitions by technology with examples are provided as well. In addition to above defined deep tech technologies, the EIT has identified three transversal dimensions for Deep Tech: innovation and entrepreneurship, gender and inclusion, and the Global Challenges/Sustainable Development Goals (European Institute of Innovation and Technology, 2023).

The European Research Area (ERA) was established with aim at creating EU unified research area open to the world that would improve European R&I through coordination, cooperation and competition, and to enable free circulation of researchers, scientific knowledge and technology. The

idea of ERA was based on the internal market to inspire the best talents to enter research careers, to incite industry to invest more in the European research and to strongly contribute to the creation of sustainable growth and jobs (European Commission, 2020).

Hence, research played an important role in setting the stage for future innovations by providing fundamental discoveries and breakthroughs that can enable future products and services, while invention usually occurred after research and involved the development of patentable products or processes. Equally important was that research and innovation should be accompanied by policy frameworks that would effectively encourage, stimulate and promote innovation (World Intellectual Property Organisation, 2015), which would boost the work of research and technology organisation (RTOs). As one of the main goals of RTOs was to transfer research and technology to the market through their open-innovation business model, resulting in a significant positive social impact. RTOs could accomplish their mission in different ways, among which was through incubator, spin-off companies, and/or deep-tech startups. According to the European Association of Research and Technology Organisations report (2015) RTO-created deep-tech startups had strong industry focus, are based on deep technology that led to breakthrough innovation and/or innovation through use of solving profit or loss problems, which made them distinct and frequently protected by powerful IP (European Association of Research and Technology Organisation, 2017).

Deep tech technologies were considered to be “game-changers” across many industries and sectors, such as telecommunication, transportation, healthcare, manufacturing, advertising, and education (Reddy et al., 2020; Lee et al., 2018; Langer, 2020). Research done by Agbaraji et al. (2019) was focused on the study of deep learning technology as a vital tool for national

development. Actually, there were many problems hindering the growth of most developing nations and this research showed that deep learning could solve most of the challenges facing the developing nations.

Deep tech projects required large initial investments and long development times to find their market and policy makers and academia had lagged in assimilating this concept. Although deep tech was characterized as complex, distant, beneath, and profound, it was also challenging to leverage and implement and represents exciting area to build competitive advantage and to fuel future economic growth (Romasanta et al., 2022).

Dionisio et al. (2023) used a novel approach known as necessary condition analysis (NCA) to data on entrepreneurial ecosystems and deep-tech startups from 132 countries, collected in a global innovation index and Crunchbase data sets in order to analyse necessary conditions to deep-tech entrepreneurship. Regarding the dimension entitled “Human capital and research,” they found that “Education” showed large and “Research and development”, medium effect size and being both statistically significant. However, tertiary education showed a small effect size to deep-tech entrepreneurship. On the other side, Delera et al., (2022) showed that STEM education facilitates the adoption of deep technologies. The adoption of new technologies was a key driver of economic development although the process of transferring and adopting new technologies was not seamless.

Engineering study programmes and non-entrepreneurship courses that engineering students attended helped them to develop certain entrepreneurship competences during their university studies, which was unintentional process, since the syllabuses of courses and learning outcomes were not created for the purpose of development of entrepreneurship competences (Pasic et al., 2023).

Michelacci & Schivardi (2020) calculated the average yearly income obtained by entrepreneurs during their venture. The authors' findings indicated that entrepreneurs holding postgraduate degrees earn more than those with college degrees. This divergence in earnings was especially pronounced at the upper percentiles of the income distribution, surpassing a twofold increase. The increase in the premium for postgraduate education has been notably higher among entrepreneurs when compared to employees. Entrepreneurs who have received tertiary education, are more likely to create innovative ventures.

Deep tech in Europe has grown strongly and many European deep tech successes had their roots in academia and spinout processes (Dealroom.co. et al., 2023). Universities played a multifaceted role and were crucial for innovation providing resources such as technical and scientific training, sophisticated facilities, talent, etc. but although high quality in theoretical training, lacks a practical focus on solving real-world problems and showed many limitations in terms of innovation and entrepreneurship training (Basilio Ruiz de Apodaca et al., 2022). Based on research about deep-tech entrepreneurship in Spain the Authors recommended creating training programs in innovation and deep-tech entrepreneurship that tackled the challenges that the current education model faces. One of five recommendations by the Authors was that a deep-tech entrepreneurship and innovation school should be created at a higher education level in order to solve the main weakness affecting the lack of human capital “fit” for deep tech.

With the world faced by numerous development and climate change challenges that undermined sustainable development locally, nationally, and globally, research reinforced by innovation and inventions needed to lead green economy transformation (Söderholm, 2020).

In early stages of sustainable development movement, radical technologies and thus inventions have been confounded due to the notion that they frequently take a long time to develop and require a variety of organizational and legislation changes, as well as new values (Kemp, 1994). Over the decades, learning and research outcomes, and technological dynamics have contributed to industrial renaissance and period of innovation. Industrialization and industrial clusters led structural transformation, not only in advanced but emerging and advanced economies as well. Economic benefits of industrial clusters have been weighted beyond production, employment and revenue generation, as supporting technology and innovation and incubators of industrialization, thus expediting sustainable growth (Oqubay & Lin, 2020).

As development leads to new ones, industrialisation has directed digital transformation, which is leading to “fourth industrial revolution” and the emergence of “4.0 technologies” and has a fundamental alteration and impact on social, organizations and economies structure and development (Laffi & Lenz, 2021). Nevertheless, and despite digital transformation attractiveness (Artificial Intelligence (AI), Robotics and the Internet of Things (IoT)) and its wide application, sustainable development challenges substantial innovation and inventions backed by new technology, which a great number of companies are investing in basic technologies and innovation (Mugge et al., 2020).

With new processes and products, the market and economies have been introduced with “high-tech” industries based on the level of their impact and effect on the economies. The “high-technology companies were described as those engaged in the design, development, and introduction of new products and/or innovative manufacturing processes through the systematic application of scientific and technical knowledge” (Heckler, 2005). Due to the paradigm shift in

business models because of innovations and new technologies introduced in manufacturing sector, service sector emerged as potential for employing more labor, development of wide range of new services as well as potential for the economic growth (Pasic et al., 2022). In this research identification, analysis and description of education programmes and practices related to service orientation in South East Europe was examined.

Since deep tech needed long time to be developed and large investments, when developing novel and uncertain innovation, companies should not only analyse whether acquiring a new innovation would improve their competitive advantage, but to compare how that new distinct capability was optimally different from other developed capabilities within the company (Romasanta et al., 2019). Commercialization of deep tech required talents with understanding of both science and business. Universities should focus on developing students with necessary competencies to get on board with entrepreneurship and rapidly evolving deep tech. In this sense universities should prepare students of different backgrounds to work together and be prepared to build the future of deep tech. Students should acquire competences in their own scientific field, but be open minded to collaborate with other fields (Romasanta, 2021).

Social entrepreneurship was a way of solving social problems, but it has not received much attention. Only people who wanted to help others could decide to become a social entrepreneur. The authors emphasized the role of intrinsic motivation, which was the internal drive to do something meaningful and more powerful (Asante et al., 1970). Digital technologies could enhance education by making it more accessible and affordable as well as showed strong impact on education system. Benefits and challenges of using online platforms, interactive tools, and adaptive learning systems to deliver quality education to diverse learners across different contexts

were examined (Haleem et al., 2022). Universities were a key source of knowledge and ideas for public sector innovation and helped public organizations to enhance public service quality and employee satisfaction (Demircioglu & Audretsch, 2017).

Day (2023) argued that universities played a crucial role in fostering deep tech entrepreneurship, which required novel solutions to complex problems. It is emphasized that more collaboration between academic staff and external stakeholders, such as industry, government and civil society, was needed to support the development and diffusion of deep tech innovations. The need for interdisciplinary collaborations, especially involving the social sciences, to address the ethical, social and political implications of deep tech was highlighted as well.

Utilized primarily for information delivery impact of technology on learning is neutral in terms of its benefits and drawbacks. Nevertheless, its potential for positive impact becomes evident when it integrates unique features that harness the power of effective learning principles (Yeung et al., 2021).

The aim of this research was to explore deep tech potential at three universities in South East Europe: University of Sarajevo (UNSA) from Bosnia and Herzegovina, Polytechnic University of Tirana (UPT) from Albania and University of Montenegro (UoM) from Montenegro and to perform cross-university analysis of the interest of students of these three universities to (i) take one or more university courses to gain knowledge on certain deep tech technologies, (ii) attend other means of learning about deep tech (workshops, trainings, online courses, etc.) outside of the University, (iii) start own company in a deep tech field, and (iv) be actively engaged in deep tech research and development projects, as well as to analyse (i) which deep tech technologies students have had a chance

so far to learn at the Faculty/University, (ii) which deep tech technologies students have had a chance so far to learn outside of the Faculty/University (non-formal education), e.g., workshops, trainings, online courses, etc., (iii) technological area(s) in which students are interested to create deep tech start-up (company), and (iv) which deep tech technologies would students like to learn more about at their Faculty/University.

2. Research methodology

Research methodology was discussed in terms of questionnaire development, proposed hypotheses of the research, sampling and data collection, and data analysis.

2.1. Development of questionnaire

The team from the University of Sarajevo developed the online questionnaire. All deep tech technologies included in the questionnaire were same as fifteen above mentioned deep tech technologies classified by EIT with extracted two more deep tech technologies such as Mechatronics and Digital Twins. So, total seventeen deep tech technologies were included in this research as follows:

- Advanced Computing / Quantum Computing
- Advanced Manufacturing
- Advanced Materials
- Aerospace, Automotive and Remote Sensing
- Artificial Intelligence and Machine Learning, including Big Data
- Biotechnology and Life Sciences
- Communications and Networks, including 5G
- Cybersecurity and Data Protection
- Electronics and Photonics
- Internet of Things, W3C, Semantic Web
- Robotics
- Mechatronics

- Digital Twin
- Semiconductors (microchips)
- Sustainable Energy and Clean Technologies
- Virtual Reality, Augmented Reality, Metaverse
- Web 3.0, including Blockchain, Distributed Ledgers, NFTs

Questions related to deep tech analyzed in this research are as follows:

- Q1: Please select which of the following deep tech technologies you have had a chance so far to learn at your Faculty/University? Multiple answers are possible
- Q2: Please select which of the following deep tech technologies you have had a chance so far to learn outside of your Faculty/University (non-formal education), e.g., workshops, trainings, online courses, etc.? Multiple answers are possible.
- Q3: Please select technological area(s) in which you are interested to create deep tech start-up (company). Multiple answers are possible.
- Q4: Please select which of the following deep tech technologies would you like to learn more about at your Faculty/University? Multiple answers are possible.
- Q5: I am interested to take one or more university courses to gain knowledge on certain deep tech technologies.
- Q6: I am interested to attend other means of learning about deep tech technologies (workshops, trainings, online courses, etc.) outside of my Faculty/University
- Q7: I would like to start my own company in a deep tech field.
- Q8: Would you like to be actively engaged in deep tech research and development projects

For the selection of deep tech technologies for the questions 1-4 students were offered the list of seventeen above defined deep tech technologies.

To measure different interests of the students as written in questions 5-8 measurement instrument was designed and students were offered to choose one number in numerical scale from 1 to 5. In measurement instrument designed for this research anchors or labels were provided only at the extremes and such instruments are called numerical rating scale. Individual rating items with numerical response formats at least five categories in length may generally be treated as continuous data (Harpe, 2015). Also, when analyzing the data, particularly when only a numerical scale is used without descriptive labels many users of survey data treat data as interval (Evans, 2012).

2.2. Hypotheses of the research

Proposed research hypotheses are:

- H1: There is difference in the interest of UNSA, UPT and UoM students to take one or more university courses to gain knowledge on certain deep tech technologies.
- H2: There is difference in the interest of UNSA, UPT and UoM students to attend other means of learning about deep tech technologies (workshops, trainings, online courses, etc.) outside of their Faculty/University.
- H3: There is difference in the interest of UNSA, UPT and UoM students to start own company in a deep tech field.
- H4: There is difference in the interest of UNSA, UPT and UoM students to be actively engaged in deep tech research and development projects.

Data were analyzed using descriptive statistics and one-way or single factor analysis of variance (ANOVA) and Tukey procedure for multiple comparisons at the level of significance $\alpha=0.05$. Also, for all differences in the two means for all measured values 95% confidence intervals

were constructed.

2.3. Sampling and data collection

Survey was conducted in June 2023. Students included in the survey were all students of all three study cycles who were studying at three universities: University of Sarajevo (UNSA), Bosnia and Herzegovina, Polytechnic University of Tirana (UPT), Albania, and University of Montenegro (UoM), Montenegro except those students studying the first and the second year of the bachelor study programme. Students were able to access the questionnaire and answer the questions using QR code or the web link. Number of respondents from UNSA was 121, from UPT 105 and from UoM 87.

2.4. Results and discussion

One-way or single factor analysis of variance (ANOVA) was applied to obtain within groups and between groups variations and conclude whether there were differences in the population means of measured values of different interests of students in deep tech defined in questions 5, 6, 7, and 8. There were three factor levels and each level was represented by particular university: UNSA, UPT, and UoM.

The null hypothesis stated the claim that means of measured values of different interests of students in deep tech defined in questions 5, 6, 7, and 8 at the three universities are equal. The research hypothesis stated that at least one of the means (μ_1 , μ_2 , and μ_3) differs from at least one of the others. Subscripts 1, 2, and 3 in the null hypothesis given by equation (1) refer to UNSA, UPT and UoM respectively, while subscript k in the research hypothesis given by equation (2) refers to the number of factor levels.

$$H_0: \mu_1 = \mu_2 = \mu_3 \quad (1)$$

$$H_1: \text{Not all } \mu_k \text{ are equal} \quad (2)$$

(where $k = 1, 2, 3$)

If calculated statistical F value, F_{stat} , was greater than critical F value, F_{crit} , for specified level of significance $\alpha = 0.05$, $F_{stat} \geq F_{crit}$, or if p -value $\leq \alpha = 0.05$, then the decision was to reject the null hypothesis with the conclusion that there is enough evidence to conclude that not all μ_k were equal (where $k = 1, 2, 3$), or in other words one or more means were significantly different. Otherwise, decision was not to reject the null hypothesis with the conclusion that there was not enough evidence to conclude that there were differences of the means. If $F_{stat} < 1$ the decision was not to reject the null hypothesis without comparing F_{stat} and F_{crit} . After ANOVA, Tukey procedure for multiple comparisons was performed at the level of significance $\alpha = 0.05$ to test which means were different from one another, which involved the use of probability distribution called the studentized range distribution, as well as to obtain Tukey simultaneous 95% confidence intervals for the differences in means. This test maintained the Type I error at the specified level while calculating all possible pairwise comparisons between the sample means. Although the sample size for each University (level) was not same, the experiment had a balanced design since the ratio of the largest sample size to the smallest sample size had not exceed 1.5.

As explained above a numerical rating scale with five categories in length from 1 to 5 was used, with labels provided only at the extremes with number 1 meaning “not at all” and with number 5 meaning “very much”, and as such individual rating items with numerical response formats at least five categories in length may generally be treated as continuous data.

Table 1 depicts proportions of students with respect to their interest to take one or more university courses to gain knowledge on certain deep tech technologies, as well as the means, standard deviations (StDev) and 95% confidence intervals (CI) for the means. It can be seen that more than 30% of students

at each university chose 5 as the highest offered numerical value, meaning that they would very much like to take one or more university courses to gain knowledge on certain deep tech technologies. Means depicted in Table 1 are 3.60 for UNSA, 3.49 for UPT and 3.55 for UoM.

Table 2. depicts results of one-way analysis of variance for interest of students to take one or more university courses to gain knowledge on certain deep tech technologies. Since $F_{stat} < 1$ the decision is not to reject $H_0: \mu_1 = \mu_2 = \mu_3$.

Table 1. Interest of students to take one or more university courses to gain knowledge on certain deep tech technologies.

University	n	1 (%)	2 (%)	3 (%)	4 (%)	5 (%)	Mean	StDev	95% CI for mean
UNSA	121	11.57	8.26	20.66	28.10	31.40	3.60	1.32	(3.34; 3.85)
UPT	105	17.14	10.48	20.95	9.52	41.90	3.49	1.53	(3.21; 3.76)
UoM	87	12.64	10.34	24.14	14.94	37.93	3.55	1.41	(3.25; 3.85)

The conclusion is that there is not enough evidence to conclude that means of interest of students of UNSA, UPT, and UoM to take one or more university courses to gain knowledge on certain deep tech technologies are different at $\alpha=0.05$ level of significance.

interest of students of UNSA, UPT and UoM to take one or more university courses to gain knowledge on certain deep tech technologies, along with 95% confidence intervals (CI), t -value and adjusted p -value are depicted.

In Table 3 differences of means in the

Table 2. ANOVA - interest of students to take one or more university courses to gain knowledge on certain deep tech technologies.

Source of variation	SS	df	MS	F_{stat}	p -value	F_{crit}
Between Groups	0.68	2	0.34	0.17	0.85	3.02
Within Groups	624.90	310	2.02			
Total	625.57	312				

Table 3. Tukey simultaneous tests for differences of means in the interest of students to take one or more university courses to gain knowledge on certain deep tech technologies.

Difference of levels	Difference of means	95% CI	t -value	Adjusted p -value
UNSA - UPT	0.11	(-0.33; 0.55)	0.58	0.83
UNSA - UoM	0.04	(-0.42; 0.51)	0.22	0.97
UoM - UPT	0.07	(-0.42; 0.55)	0.32	0.94

Individual confidence level = 98.01%

Based on data presented in Table 3 it can be concluded that that there is no evidence that corresponding means are significantly different. Figure 1 presents Tukey simultaneous 95% confidence intervals (CI) for the differences of the means in the interest of students to take one or more university courses to gain knowledge on certain deep tech technologies. Since all

intervals contains zero it can be concluded that there is no evidence that corresponding means are significantly different. It can be concluded that H_1 : There is difference in the interest of UNSA, UPT and UoM students to take one or more university courses to gain knowledge on certain deep tech technologies is not supported.

Table 4 depicts proportions of students with respect to their interest to attend other means of learning about deep tech technologies (workshops, trainings, online courses, etc.) outside of their Faculty/University, as well as the means, standard deviations (StDev) and 95% confidence intervals (CI) for the means. It can be seen that more than 30% of students at UNSA and more than 40% of

students at UPT and UoM chose 5 as the highest offered numerical value, meaning that they would very much like to attend other means of learning about deep tech technologies (workshops, trainings, online courses, etc.) outside of their Faculty/University. Means depicted in Table 4 are 3.72 for UNSA, 3.85 for UPT and 3.72 for UoM.

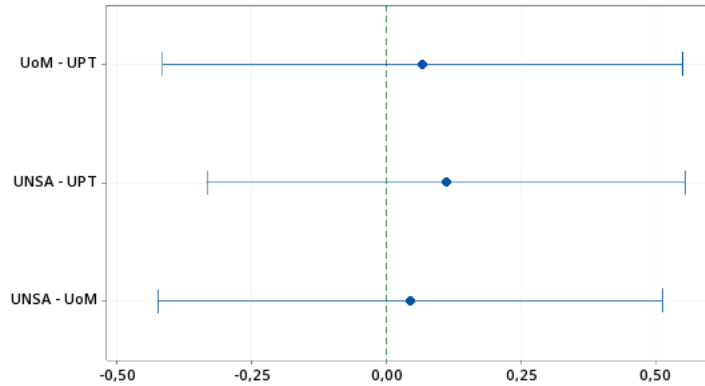


Figure 1. Tukey simultaneous 95% confidence intervals for the differences of the means in the interest of students to take one or more university courses to gain knowledge on certain deep tech technologies

Table 4. Interest of students to attend other means of learning about deep tech technologies (workshops, trainings, online courses, etc.) outside of the Faculty/University.

University	n	1 (%)	2 (%)	3 (%)	4 (%)	5 (%)	Mean	StDev	95% CI for mean
UNSA	121	8.26	4.96	28.10	23.97	34.71	3.72	1.23	(3.49; 3.95)
UPT	105	9.52	5.71	20.95	18.10	45.71	3.85	1.32	(3.60; 4.10)
UoM	87	9.20	11.49	19.54	17.24	42.53	3.72	1.36	(3.45; 4.00)

Table 5. depicts results of one-way analysis of variance for interest of students to attend other means of learning about deep tech technologies (workshops, trainings, online courses, etc.) outside of the Faculty/University. Since $F_{stat} < 1$ the decision is not to reject $H_0: \mu_1 = \mu_2 = \mu_3$. The conclusion is that there is not enough

evidence to conclude that means of interest of students of UNSA, UPT, and UoM to attend other means of learning about deep tech technologies (workshops, trainings, online courses, etc.) outside of the Faculty/University are different at $\alpha=0.05$ level of significance.

Table 5. ANOVA - Interest of students to attend other means of learning about deep tech technologies (workshops, trainings, online courses, etc.) outside of the Faculty/University.

Source of variation	SS	df	MS	F_{stat}	p-value	F_{crit}
Between Groups	1.12	2	0.56	0.33	0.72	3.02
Within Groups	521.39	310	1.68			
Total	522.50	312				

In Table 6 differences of means in the interest of students of UNSA, UPT and UoM to attend other means of learning about deep tech technologies (workshops, trainings, online courses, etc.) outside of the Faculty/University, along with 95%

confidence intervals (CI), t -value and adjusted p -value are depicted. Based on data presented in Table 6 it can be concluded that there is no evidence that corresponding means are significantly different.

Table 6. Tukey simultaneous tests for differences of the means in the interest of students to attend other means of learning about deep tech technologies (workshops, trainings, online courses, etc.) outside of the Faculty/University.

Difference of levels	Difference of means	95% CI	t -value	Adjusted p -value
UNSA - UPT	-0.13	(-0.53; 0.28)	-0.74	0.74
UNSA - UoM	-0.01	(-0.43; 0.42)	-0.03	1.00
UoM - UPT	-0.12	(-0.56; 0.32)	-0.66	0.79

Individual confidence level = 98.01%

Figure 2 presents Tukey simultaneous 95% confidence intervals (CI) for the differences of the means in the interest of students to attend other means of learning about deep tech technologies (workshops, trainings,

online courses, etc.) outside of the Faculty/University. Since all intervals contains zero it can be concluded that there is no evidence that corresponding means are significantly different.

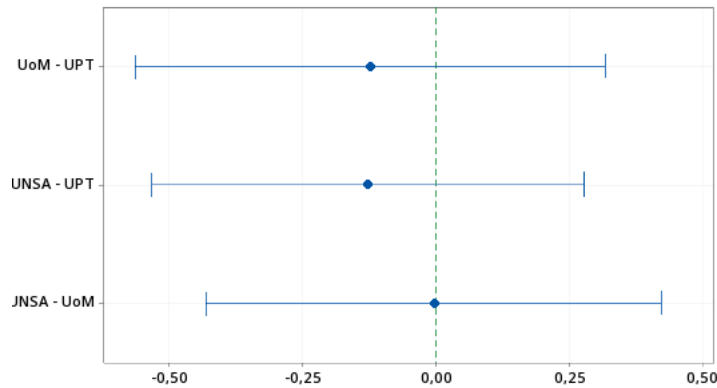


Figure 2. Tukey simultaneous 95% confidence intervals for the differences of the means in the interest of students to attend other means of learning about deep tech technologies (workshops, trainings, online courses, etc.) outside of the Faculty/University

It can be concluded that H2: There is difference in the interest of UNSA, UPT and UoM students to attend other means of learning about deep tech technologies (workshops, trainings, online courses, etc.) outside of their Faculty/University is not supported. Table 7 depicts proportions of students with respect to their interest to start own company in a deep tech field as well as

the means, standard deviations (StDev) and 95% confidence intervals (CI) for the means. It can be seen that more than 40% of UPT students chose 5 as the highest offered numerical value, meaning that they would very much like to start own company in a deep tech field. Replies from UNSA students show that almost 30% of students are neutral regarding starting own company in a deep

tech field while UoM students show similar pattern as UNSA students with exception that 10.34% of students chose numerical value 4 comparing to UNSA students where 17.36% of students chose numerical value 4.

This reflected the values of the means as depicted in Table 7 with the highest mean 3.82 for UPT and lower values 3.03 for UNSA, and 2.89 for UoM.

Table 7. Interest of students to start own company in a deep tech field.

University	n	1 (%)	2 (%)	3 (%)	4 (%)	5 (%)	Mean	StDev	95% CI for mean
UNSA	121	17.36	16.53	28.93	19.83	17.36	3.03	1.33	(2.80; 3.28)
UPT	105	8.57	7.62	20.95	19.05	43.81	3.82	1.31	(3.56; 4.08)
UoM	87	25.29	19.54	20.69	10.34	24.14	2.89	1.51	(2.60; 3.18)

Table 8. depicts results of one-way analysis of variance for interest of students to start own company in a deep tech field. Since $F_{stat} > F_{crit}$ the decision is to reject $H_0: \mu_1 = \mu_2 = \mu_3$.

The conclusion is that there is enough evidence to conclude that the means of interest of students of UNSA, UPT, and UoM to start own company in a deep tech field are different at $\alpha=0.05$ level of significance.

Table 8. ANOVA - Interest of students to start own company in a deep tech field.

Source of variation	SS	df	MS	F_{stat}	p-value	F_{crit}
Between Groups	51.27	2	25.64	13.56	0.00	3.02
Within Groups	586.28	310	1.89			
Total	637.55	312				

In Table 9 differences of means in the interest of students of UNSA, UPT and UoM to start own company in a deep tech field, along with 95% confidence intervals (CI), t – value and adjusted p – value are depicted.

Based on data presented in Table 9 it can be concluded that there is evidence that UNSA and UPT means are significantly different as well as UoM and UPT means, while UNSA and UoM means are not significantly different.

Table 9. Tukey simultaneous tests for differences of the means in the interest of students to start own company in a deep tech field.

Difference of levels	Difference of means	95% CI	t-value	Adjusted p-value
UNSA - UPT	-0.79	(-1.22; -0.36)	-4.29	0.00
UNSA - UoM	0.15	(-0.30; 0.60)	0.77	0.72
UoM - UPT	-0.93	(-1.40; -0.47)	-4.68	0.00

Individual confidence level = 98.01%

Figure 3 presents Tukey simultaneous 95% confidence intervals (CI) for the differences of the means in the interest of students to start own company in a deep tech field. Since intervals UoM – UPT and UNSA – UPT do not contain zero, it can be concluded that corresponding means are significantly

different. Interval UNSA – UoM contains zero, so it can be concluded that there is no evidence that corresponding means are significantly different.

It can be concluded that H3: There is difference in the interest of UNSA, UPT and UoM students to start own company in a

deep tech field is partially supported only that there is difference in the interest of UNSA and UPT students as well as UoM and UPT students.

Table 10 presents proportions of students with respect to their interest to be actively engaged in deep tech research and development projects, as well as the means, standard deviations (StDev) and 95% confidence intervals for the means. It can be

seen that more than 45% of students at UPT chose the highest offered numerical value meaning that they would very much like to be actively engaged in deep tech research and development projects, while 20.66% UNSA students and 26.44% of UoM students chose the highest offered numerical value and showed less interest than UPT students.

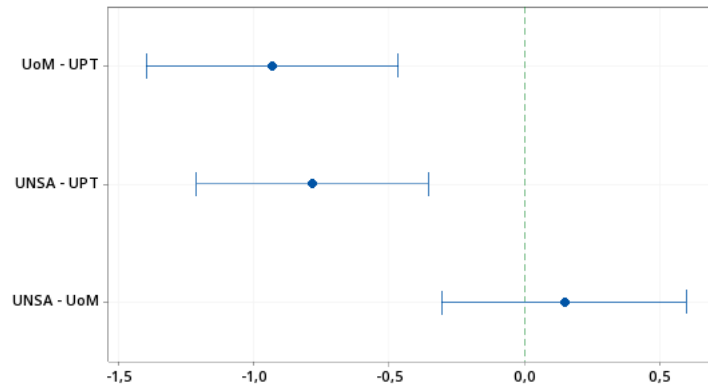


Figure 3. Tukey simultaneous 95% confidence intervals for the differences of the means in the interest of students to start own company in a deep tech field.

The highest proportion of UNSA students, 33.06%, chose numerical value of 3, while the highest proportion of UoM students,

25.29%, chose numerical value 4. Means depicted in Table 10 are 3.45 for UNSA, 3.77 for UPT and 3.33 for UoM.

Table 10. Interest of students to be actively engaged in deep tech research and development projects.

University	n	1 (%)	2 (%)	3 (%)	4 (%)	5 (%)	Mean	StDev	95% CI for mean
UNSA	121	7.44	9.92	33.06	28.93	20.66	3.45	1.15	(3.22; 3.69)
UPT	105	11.43	7.62	19.05	16.19	45.71	3.77	1.40	(3.52; 4.02)
UoM	87	13.79	17.24	17.24	25.29	26.44	3.33	1.39	(3.06; 3.61)

Table 11 shows results of one-way analysis of variance for interest of students to be actively engaged in deep tech research and development projects. Since $F_{stat} < F_{crit}$ the decision is not to reject $H_0: \mu_1 = \mu_2 = \mu_3$.

The conclusion is that there is not enough evidence to conclude that means of interest

of students of UNSA, UPT, and UoM to be actively engaged in deep tech research and development projects are different at $\alpha=0.05$ level of significance. However, it should be noted that the value of $F_{stat} = 2.99$ is very close to the value of $F_{crit} = 3.02$.

Table 11. ANOVA - Interest of students to be actively engaged in deep tech research and development projects.

Source of variation	SS	df	MS	F_{stat}	p -value	F_{crit}
Between Groups	10.17	2	5.09	2.99	0.05	3.02
Within Groups	527.85	310	1.70			
Total	538.02	312				

In Table 12 differences of the means in the interest of students of UNSA, UPT and UoM to be actively engaged in deep tech research and development projects, along with 95% confidence intervals (CI), t -value and

adjusted p -value are depicted. Based on data presented in Table 12 it can be concluded that there is no evidence that corresponding means are significantly different.

Table 12. Tukey simultaneous tests for differences of the means in the interest of students to be actively engaged in deep tech research and development projects.

Difference of levels	Difference of means	95% CI	t -value	Adjusted p -value
UNSA - UPT	-0.32	(-0.72; 0.09)	-1.82	0.16
UNSA - UoM	0.12	(-0.31; 0.55)	0.66	0.79
UoM - UPT	-0.44	(-0.88; 0.00)	-2.32	0.05

Individual confidence level = 98.01%

Figure 4 presents Tukey simultaneous 95% confidence intervals (CI) for the differences of the means the interest of students to be actively engaged in deep tech research and

development projects. Since all intervals contains zero it can be concluded that there is no evidence that corresponding means are significantly different.

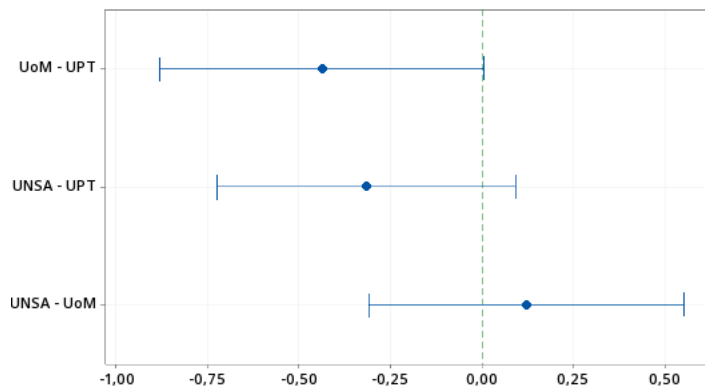


Figure 4. Tukey simultaneous 95% confidence intervals for the differences of the means the interest of students to be actively engaged in deep tech research and development projects.

It can be concluded that H4: There is difference in the interest of UNSA, UPT and UoM students to be actively engaged in deep tech research and development projects is not supported.

Figure 5 depicts deep tech technologies students have had a chance so far to learn at their Faculty/University. From Figure 5 it can be seen that UNSA students had a chance to learn much more about deep tech technologies comparing to UPT and UoM

students. Most of UNSA students selected Robotics (30.57%), Artificial Intelligence and Machine Learning including Big Data (26.45%), Mechatronics (24.79%), Sustainable Energy and Clean Technologies (23.97%), Advanced Materials (23.14%) and Advanced Manufacturing (19.83%) as deep tech technologies they have had a chance so far to learn at the UNSA. UNSA students indicated all deep tech technologies they had a chance to learn so far at UNSA. Most of UPT students had a chance to learn Sustainable Energy and Clean Technologies (31.43%), while most of UoM students

selected Artificial Intelligence and Machine Learning, including Big Data (18.39%). Also, at both UPT and UoM, it can be seen that all deep tech technologies were selected as a chance for students to learn about at their Faculty/University. At UNSA 15.70%, at UPT 26.67% and at UoM 40.23% students indicated that they haven't had a chance so far to learn any deep tech technologies. Only one student per each university indicated they have had a chance so far to learn about Digital Twin at their Faculty/University.

	UNSA	UoM	UPT
Advanced Computing / Quantum Computing	11.57%	11.49%	13.33%
Advanced Manufacturing	19.83%	11.49%	12.38%
Advanced Materials	23.14%	14.94%	13.33%
Aerospace, Automotive and Remote Sensing	5.79%	4.60%	1.90%
Artificial Intelligence and Machine Learning, including Big Data	26.45%	18.39%	6.67%
Biotechnology and Life Sciences	2.48%	5.75%	2.86%
Communications and Networks, including 5G	4.96%	9.20%	8.57%
Cybersecurity and Data Protection	3.31%	4.60%	2.86%
Electronics and Photonics	4.96%	12.64%	11.43%
Internet of Things, W3C, Semantic Web	4.13%	6.90%	6.67%
Robotics	30.58%	10.34%	8.57%
Mechatronics	24.79%	9.20%	12.38%
Digital Twin	0.83%	1.15%	0.95%
Semiconductors (microchips)	1.65%	3.45%	5.71%
Sustainable Energy and Clean Technologies	23.97%	12.64%	31.43%
Virtual Reality, Augmented Reality, Metaverse	7.44%	4.60%	2.86%
Web 3.0, including Blockchain, Distributed Ledgers, NFTs	4.13%	1.15%	0.95%
None	15.70%	40.23%	26.67%

Figure 5. Deep tech technologies students have had a chance so far to learn at their Faculty/University

Figure 6 presents deep tech technologies students have had a chance so far to learn outside of their Faculty/University (non-formal education), e.g., workshops, trainings, online courses, etc. Most of UNSA students (23.14%) selected Artificial Intelligence and Machine Learning, including Big Data, followed by Communications and Networks, including 5G (17.36%) and Sustainable Energy and Clean Technologies (17.36%) and Robotics (14.88%). Most of UPT students selected Sustainable Energy and Clean Technologies

(33.33%), while Sustainable Energy and Clean Technologies was prime selection by UoM students (20.68%). At UNSA 30.58%, at UPT 23.81% and at UoM 28.57% indicated that they haven't had a chance so far to learn about any deep tech technology outside of their Faculty/University (non-formal education). The minimum frequency of selected deep tech technologies was Biotechnology and Life Sciences at UNSA (1.65%), Digital Twin at UPT (2.86%), and Web 3.0, including Blockchain, Distributed Ledgers, NFTs at UoM (1.15%).

	UNSA	UoM	UPT
Advanced Computing / Quantum Computing	8.26%	11.49%	19.05%
Advanced Manufacturing	12.40%	5.75%	9.52%
Advanced Materials	11.57%	9.20%	9.52%
Aerospace, Automotive and Remote Sensing	6.61%	9.20%	5.71%
Artificial Intelligence and Machine Learning, including Big Data	23.14%	16.09%	14.29%
Biotechnology and Life Sciences	1.65%	6.90%	7.62%
Communications and Networks, including 5G	17.36%	10.34%	6.67%
Cybersecurity and Data Protection	10.74%	6.90%	3.81%
Electronics and Photonics	4.13%	5.75%	4.76%
Internet of Things, W3C, Semantic Web	10.74%	11.49%	11.43%
Robotics	14.88%	8.05%	9.52%
Mechatronics	11.57%	4.60%	8.57%
Digital Twin	3.31%	2.30%	2.86%
Semiconductors (microchips)	3.31%	2.30%	3.81%
Sustainable Energy and Clean Technologies	17.36%	20.69%	33.33%
Virtual Reality, Augmented Reality, Metaverse	9.92%	13.79%	3.81%
Web 3.0, including Blockchain, Distributed Ledgers, NFTs	13.22%	1.15%	6.67%
None	30.58%	34.48%	23.81%

Figure 6. Deep tech technologies students have had a chance so far to learn outside of their Faculty/University (non-formal education), e.g., workshops, trainings, online courses, etc.

Figure 7 shows deep tech technologies in which students are interested to create deep tech start-up (company). Most of UNSA students (24.79%) selected Internet of Things W3C, Semantic Web, followed by Artificial Intelligence and Machine Learning, including Big Data (23.14%) and Sustainable Energy and Clean Technologies (19.83%). UPT students preferred Artificial Intelligence and Machine Learning, including Big Data (23.81%), and Advanced Computing/Quantum Computing (20.00%),

while most of UoM students selected Artificial Intelligence and Machine Learning, including Big Data (22.99%). At UNSA 13.22%, at UPT 7.62% , and at UoM 25.29% students indicated no deep tech technologies in which they are interested to create deep tech start-up (company). Semiconductors (microchips) at UNSA (0.83%), students indicated no deep tech technologies in which they are interested to create deep tech start-up (company).

	UNSA	UoM	UPT
Advanced Computing / Quantum Computing	9.92%	10.34%	20.00%
Advanced Manufacturing	15.70%	11.49%	15.24%
Advanced Materials	9.09%	12.64%	11.43%
Aerospace, Automotive and Remote Sensing	13.22%	6.90%	14.29%
Artificial Intelligence and Machine Learning, including Big Data	23.14%	22.99%	23.81%
Biotechnology and Life Sciences	2.48%	12.64%	9.52%
Communications and Networks, including 5G	7.44%	13.79%	14.29%
Cybersecurity and Data Protection	10.74%	9.20%	20.00%
Electronics and Photonics	8.26%	6.90%	14.29%
Internet of Things, W3C, Semantic Web	4.13%	10.34%	7.62%
Robotics	24.79%	16.09%	27.62%
Mechatronics	15.70%	8.05%	16.19%
Digital Twin	4.96%	3.45%	2.86%
Semiconductors (microchips)	0.83%	5.75%	4.76%
Sustainable Energy and Clean Technologies	19.83%	16.09%	31.43%
Virtual Reality, Augmented Reality, Metaverse	11.57%	10.34%	9.52%
Web 3.0, including Blockchain, Distributed Ledgers, NFTs	9.09%	5.75%	6.67%
None	13.22%	25.29%	7.62%

Figure 7. Deep tech technologies in which students are interested to create deep tech start-up (company)

Semiconductors (microchips) at UNSA (0.83%), Internet of Things, W3C, Semantic Web at UPT (7.62%) and Digital Twin at UoM (3.45%) were with the minimal frequency of selection at three universities.

Figure 8 illustrates deep tech technologies which students would like to learn more about at their Faculty/University, Most of UNSA students indicated Robotics (34.71%), Artificial Intelligence and Machine Learning, including Big Data (33.06%), Mechatronics (27.27%), Advanced Manufacturing (23.97%), Sustainable Energy and Clean Technologies (21.49%), Advanced Materials (19.01%), and Virtual Reality, Augmented Reality, Metaverse (18.18%). At UPT most of the students selected Sustainable Energy and

Clean Technologies (36.19%), Artificial Intelligence and Machine Learning, including Big Data (29.52%), Robotics (20.00%), Advanced Manufacturing (19.05%) and Advanced Computing/Quantum Computing (18.10%). Most of UoM students selected Artificial Intelligence and Machine Learning, including Big Data (28.74%), Sustainable Energy and Clean Technologies (25.29%), Robotics (21.84%), Virtual Reality, Augmented Reality, Metaverse (20.69%), and Biotechnology and Life Sciences (19.54%). Semiconductors (microchips) at UNSA (4.13%) and at UPT (0.95%), and at UoM Digital Twin (4.60%) were selection of students with minimal frequency.

	UNSA	UoM	UPT
Advanced Computing / Quantum Computing	13.22%	14.94%	18.10%
Advanced Manufacturing	23.97%	12.64%	19.05%
Advanced Materials	19.01%	9.20%	17.14%
Aerospace. Automotive and Remote Sensing	14.05%	14.94%	17.14%
Artificial Intelligence and Machine Learning, including Big Data	33.06%	28.74%	29.52%
Biotechnology and Life Sciences	6.61%	19.54%	9.52%
Communications and Networks, including 5G	14.88%	18.39%	15.24%
Cybersecurity and Data Protection	13.22%	18.39%	13.33%
Electronics and Photonics	10.74%	10.34%	14.29%
Internet of Things, W3C, Semantic Web	8.26%	13.79%	8.57%
Robotics	34.71%	21.84%	20.00%
Mechatronics	27.27%	11.49%	12.38%
Digital Twin	8.26%	10.34%	0.95%
Semiconductors (microchips)	4.13%	4.60%	8.57%
Sustainable Energy and Clean Technologies	21.49%	25.29%	36.19%
Virtual Reality, Augmented Reality, Metaverse	18.18%	20.69%	11.43%
Web 3.0, including Blockchain, Distributed Ledgers, NFTs	11.57%	8.05%	10.48%
None	3.31%	11.49%	6.67%

Figure 8. Deep tech technologies which students would like to learn more about at their Faculty/University

3. Conclusion

In this research student perspectives and cross-university analysis of deep tech potential at three universities in South East Europe: University of Sarajevo (UNSA) from Bosnia and Herzegovina, Polytechnic University of Tirana (UPT) from Albania and University of Montenegro (UoM) from Montenegro was performed. Following hypotheses were not supported: (H1) There

is difference in the interest of UNSA, UPT and UoM students to take one or more university courses to gain knowledge on certain deep tech technologies, (H2) There is difference in the interest of UNSA, UPT and UoM students to attend other means of learning about deep tech technologies (workshops, trainings, online courses, etc.) outside of their Faculty/University, and (H4) There is difference in the interest of UNSA, UPT and UoM students to be actively

engaged in deep tech research and development projects. However, proposed hypothesis (H3) There is difference in the interest of UNSA, UPT and UoM students to start own company in a deep tech field was partially supported only that there was difference in the interest of UNSA and UPT and UoM and UPT students.

Regarding deep tech technologies students have had a chance so far to learn at their Faculty/University UNSA students selected Robotics (30.57%), Artificial Intelligence and Machine Learning including Big Data (26.45%), Mechatronics (24.79%), Sustainable Energy and Clean Technologies (23.97%) and Advanced Material (23.14%) and Advanced Manufacturing (19.83%) were selected as major deep tech technologies they have had a chance so far to learn. Most of UPT students indicated that they had a chance to learn Sustainable Energy and Clean Technologies (31.43%), Advanced Manufacturing (13.33%) and Advanced Computing/Quantum Computing (13.33%), while most of UoM students selected Artificial Intelligence and Machine Learning, including Big Data (18.39%) and Advanced Materials (14.49%). At UNSA 15.70%, at UPT 26.67% and at UoM 40.23% students indicated that they haven't had a chance so far to learn any deep tech technologies.

Deep tech technologies students have had a chance so far to learn outside of their Faculty/University (non-formal education), e.g., workshops, trainings, online courses, etc., Artificial Intelligence and Machine Learning, including Big Data (23.14%), followed by Communications and Networks, including 5G (17.36%) and Sustainable Energy and Clean Technologies (17.36%) and Robotics (14.88%) were selected by the most of UNSA students. Most of UPT students selected Sustainable Energy and Clean Technologies (33.33%), followed by Advanced Computing/Quantum Computing (19.04%) and Artificial Intelligence and Machine Learning, including Big Data (14.28%), while Sustainable Energy and

Clean Technologies was most frequent selection by UoM students (20.69%) followed by Artificial Intelligence and Machine Learning, including Big Data (16.09%) and Virtual Reality, Augmented Reality, Metaverse (13.79%). At UNSA 30.58%, at UPT 23.81% and at UoM 28.57% indicated that they haven't had a chance so far to learn any deep tech technology outside of their Faculty/University (non-formal education).

Deep tech technologies in which students are interested to create deep tech start-up (company) selected by most of UNSA students selected Internet of Things, W3C, Semantic Web (24.79%), followed by Artificial Intelligence and Machine Learning, including Big Data (23.14%) and Sustainable Energy and Clean Technologies (19.83%). UPT students would prefer Artificial Intelligence and Machine Learning, including Big Data (23.81%), and Advanced Computing/Quantum Computing (20.00%), while most of UoM students selected Artificial Intelligence and Machine Learning, including Big Data (22.99%), and Communications and Networks, including 5G (13.79%). At UNSA 13.22%, at UPT 7.62% and at UoM 25.29% students indicated no deep tech technologies in which they are interested to create deep tech start-up (company).

Regarding deep tech technologies which students would like to learn more about at their Faculty/University, most of UNSA students indicated Robotics (34.71%), Artificial Intelligence and Machine Learning, including Big Data (33.06%), Mechatronics (27.27%), Advanced Manufacturing (23.97%), Sustainable Energy and Clean Technologies (21.49%), Advanced Materials (19.01%), and Virtual Reality, Augmented Reality, Metaverse (18.18%). At UPT most of the students selected Sustainable Energy and Clean Technologies (36.19%), Artificial Intelligence and Machine Learning, including Big Data (29.52%), Robotics (20.00%), Advanced Manufacturing

(19.05%) and Advanced Computing/Quantum Computing (18.10%), while most of UoM students selected Artificial Intelligence and Machine Learning, including Big Data (28.74%), Sustainable Energy and Clean Technologies (25.29%), Robotics (21.84%), Virtual Reality, Augmented Reality, Metaverse (20.69%), and Biotechnology and Life Sciences (19.54%). At UNSA 3.33%, at UPT 6.67%, and at UoM 11.49% students indicated none deep tech technologies that they would like to learn more about at their Faculty/University.

Students from all three universities indicated that they had a chance to learn about all listed deep tech technologies at their universities, which can be considered as

great potential of these universities. Results of the research showed that there were differences in what students of these three universities could learn about deep tech. Students at all three universities are highly motivated to acquire deep tech competences especially in the areas of robotics, artificial intelligence and machine learning including big data, and sustainable energy and clean technologies.

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