Practical Learning
of Artificial Intelligence
on the Edge for indusTry 4.0

# R1.5
# TRAINING NEEDS ASSESSMENT

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**Note**
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# INTRODUCTION

Training needs for the PLANET4 course are defined according to the feedback collected from students, academics, and companies and filtered through the lens of the market needs and experience of the partner companies.

Special focus is given to providing the answers to the “why” training is needed, “how” will training cure the problems identified, “what” is the best way to get the best results and “when” training should take place.

Training needs analysis is the cornerstone of the project and this outcome will influence all the future tasks. Therefore, special care will be given to ensure the reliability, validity, and trustworthiness of this result. This document is open for public.

The report is a pivotal reference for the outcomes’ development planned for the implementation phase (WP3 and WP4).

The report is focused on providing answers to the questions put forth by the aim of the WP1:

- What is the current situation in “AI and ML on the edge for I-IOT” both in research and training?
- What are future trends in research?
- What are the current problems from a lack of training?
- What are the main gaps in skills, if training can be replaced and, if so, how?
- How to make reliable recommendations on tailored training and other action?
- How the educational providers are reacting to the technological changes affecting the companies’ productivity?

The gaps existing in the educational offer are identified. The focus is on learning content and approaches that contribute to closing the gaps.

The company partners shared their actual needs. Moreover, research in the companies was performed to have a wider scope of the industrial problems and needs. The shortcomings of the current educational offer on Artificial Intelligence, Machine Learning, Internet of Things and Edge Computing are identified and the contribution of the companies to the process in order to close the gap between theoretical knowledge and practical use is adjusted.

# 1 ASSESSMENT OF THE TRAINING NEEDS

## 1.1 Basics for the assessment

To assess the training needs the following researches were performed:

- Research conducted among **companies** in the form of survey and additional interviews to identify the problems which can be addressed by the technologies connected with AI, ML, IoT and EC. The information comes from **70 companies** from **25 countries**. They are micro companies (13%), small companies (19%), medium companies (26%) and large companies (42%) operating in aerospace, machine, metallurgical, automotive, food, energy, software, chemical, and other **industries**. In the research **departments** as R&D, Manufacturing, Technology, IT, Data Science, Maintenance, Management, and others were involved
- Literature review was performed in the frame of the taxonomy development. In the research **46 valuable sources** of information were identified (see Appendix A). The main goal was to identify technologies that are already able to support companies in solving current and future problems related to the implementation of Industry 4.0.
- Research conducted among **academics** was performed to identify the topics and technologies connected with AI, ML, IoT and EC, which are used in educational programs. Total number of received questionnaires in the research was 144. The information presented in this report comes from **86 questionnaires** filled by academics from **23 countries** who teach the topics connected with AI, ML, IoT and EC.
- Research conducted among **students** was performed to understand what are the current students' competences connected with AI, ML, IoT and EC, which can be used to solve industrial problems. The information presented in this report comes from **563 questionnaires** received from students studied in **39 countries**.
- Statistical analysis made with the use of data from research among academics and students. The main goal of the analysis was to identify statistically justified differences between what academics taught and what students learned.

The idea behind the research is presented in Figure 1.

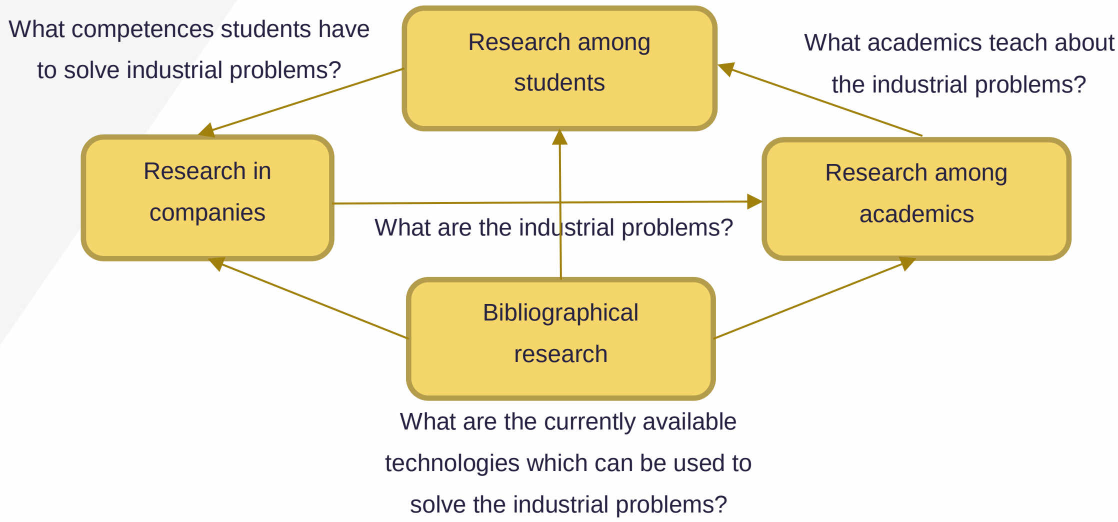

**Figure 1** The idea behind the research

The research designed this way allowed to assessed the current and future training needs in the context of the available technologies and the existing industrial problems/challenges.

## 1.2 Technologies for Industry 4.0 identified in bibliographical research

A bibliographical research performed as a part of the Planet4 project allowed to identify the current situation connected with technologies used in the production industry. The research led to the development of a taxonomy. Technologies available for the application in innovative businesses were divided into domains and grouped into areas. Conclusions from the research are presented in Table 1, Table 2, Table 3 and Table 4.

Table 1 Technologies for the Industry 4.0 – Data science

| **Area** | **Domain** | **Techniques** | **Tools** |
|---|---|---|---|
| Data science | Data Visualization and Dashboarding | | |
| | | Grafana | |
| | | Kibana | |
| | | Metabase | |
| | Data Analytics | | |
| | | Data lake and Data Warehouse design | |
| | | Data Mining | Python (Numpy, Pandas, sklearn, Scipy) |
| | | | R |
| | | | Julia |
| | | Process Mining | |
| | Advanced reporting and self-service business intelligence tools | | |
| | | | Tableau |
| | | | PowerBI |
| | | | SAP Business Intelligence |
| | | | QlikView/Qlik Sense |
| | Databases | | |
| | | SQL DB | |
| | | Non SQL DB | |
| | | Time series DB | influxDB |
| | | | Prometheus |
| | | | Graphite |
| | | Data engines | Apache Hadoop |

| | | | |
|---|---|---|---|
| | | | Apache Kafka |
| | | | Apache Spark |

Table 2 Technologies for the Industry 4.0 – Artificial Intelligence

| **Area** | **Techniques** |
|---|---|
| Artificial Intelligence | Machine learning |
| | Deep Learning |
| | Reinforcement Learning |
| | Continuous Learning |
| | Natural Language Processing |

Table 3 Technologies for the Industry 4.0 – Cloud computing

| **Area** | **Techniques** | **Tools** |
|---|---|---|
| Cloud computing | Container technologies | |
| | | Docker |
| | | Kubernates |
| | | Terraform |
| | Serverless programming | |
| | | AWS Lambda functions |
| | | Azure functions |
| | Device Management | |
| | | Zerynth Device Manager |
| | | AWS IoT Device Management |
| | | Azure IOT Hub |
| | | WinCC OA IOT OPA |
| | Cloud Data Storage | |
| | | AWS S3 |
| | | Google Cloud Storage |
| | | Microsoft Azure Storage |

Table 4 Technologies for the Industry 4.0 – IoT and IoE

| **Area** | **Domain** | **Techniques** | **Tools** |
|---|---|---|---|
| IOT and IOE | Industrial IOT | | |
| | | Industrial communication protocols | Ethernet based (EtherNet / IP, ProfiNET, Modbus, OPC, EtherCAT) |
| | | | Fieldbus based (Profibus DP, Modbus-RTU) |
| | | | Wireless (WLAN, Bluetooth) |

| | | | |
|---|---|---|---|
| | | Industrial Gateway and data acquisition device | |
| | Embedded Computing | | |
| | | Microcontroller programming and RTOS | Arduino |
| | | | STM32 |
| | | | ESP32 |
| | | | FPGA |
| | | Microprocessor programming and embedded Linux | RaspberryPi |
| | | | Other SBC |
| | Sensors (hardware) | | |
| | Signal Processing | | |
| | Blockchain | | |
| | Connectivity | | |
| | | GSM/4G/5G | |
| | | MQTT, Node-Red | |
| | | REST API and Webhook | |
| | | RFID/NFC | |
| | | Bluetooth | |
| | | LPWAN (Low power wide area network) | |
| | Internet of Everything | | |

The presented technologies are used in solving industrial problems. In the further part of the work, the results of bibliographic research are compared with the results of research carried out in industry and the list of technologies that students learn about.

## 1.3 Assessment of the current situation in “AI and ML on the edge for I-IOT” both in research and training

The current state of technologies, identified in the bibliographical research, enabled for the industry is presented in the section 1.2. Here we provide an information about the technologies implemented in industry, what comes from our industrial research. Moreover, a comparative analysis of those technologies with training courses that are conducted at universities is presented.
Based on the research performed in the companies the Industry 4.0 solutions implementation can be summarized as it is presented in Figure 2. At least 20% of the companies, what comes from 70 questionnaires, want to implement the presented solutions. This means that they need the competencies necessary to implement the solutions, they need to have the knowledge about the

technologies being behind the presented solutions. From the Figure 2 it can be also seen what is the percentage of companies which already implemented the presented solutions.

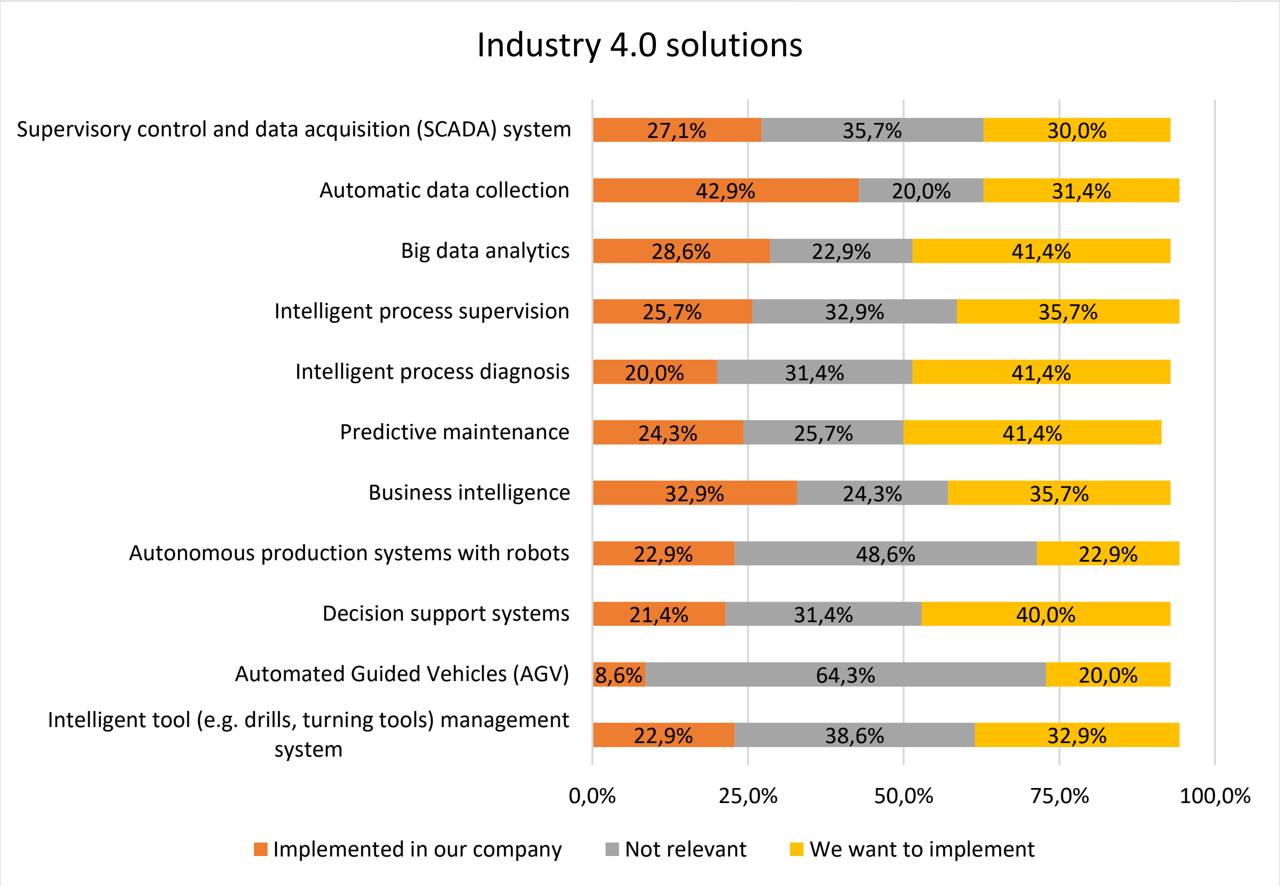


**Figure 2** Industry 4.0 solutions in the studied companies

The companies also indicated other Industry 4.0 solutions which **they want to implement**, as follow:

- Digital Paperless technology, PMI,
- Asset Condition Monitoring and Tracking,
- Automatic data analysis between machine tools / CMM / other measuring devices - data correlation and data cross,
- Further automation of production processes along with integration with the ERP system. The use of machine learning algorithms for more efficient preparation and management of technological data,
- AI transport trolleys.

The main challenges identified above can be significantly supported on the operational level by existing IT systems and Industry 4.0 technologies. However, scientific research and systems development are required for development of cognitive systems in order to fully meet the needs of businesses in the future on tactical and strategic level.

Currently, the companies have some practical skills in the technologies presented in Figure 3. However, a large percentage of companies do not possess the mentioned skills.

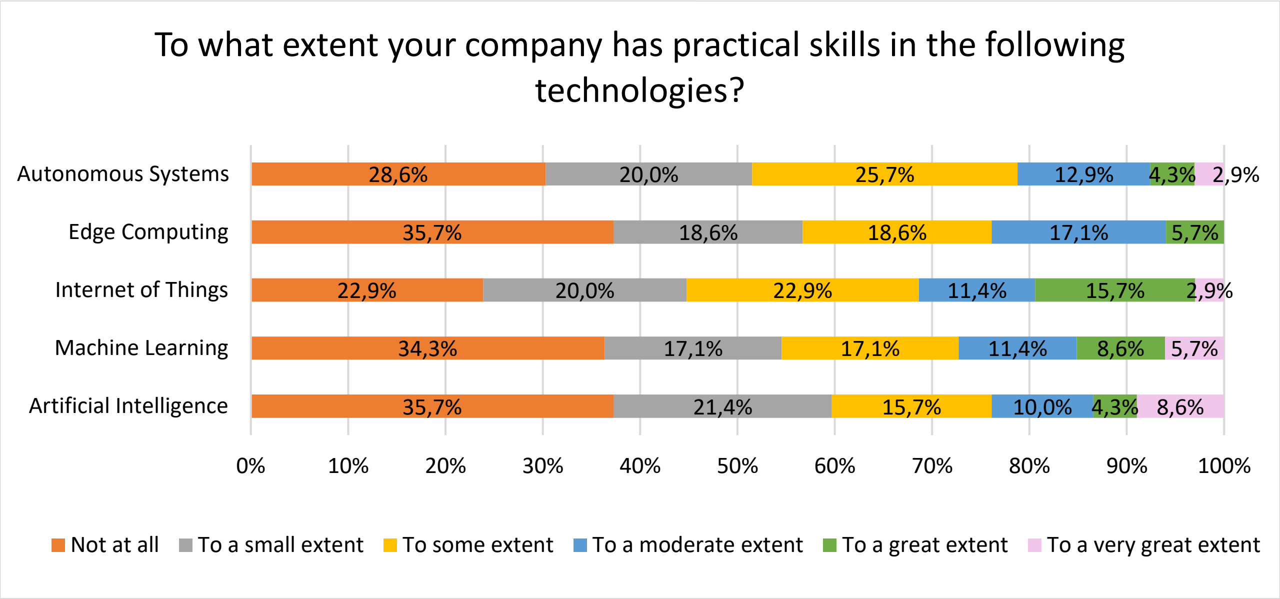


**Figure 3** Practical skills level of the presented technologies

Additionally, the companies indicated the skills which they need to deal with the current problems, and they are:

- Programming, electronic hardware and mechanical engineering, combined knowhow,
- Solving complex problems,
- Data science technology, including AI to improve predictive maintenance,
- IT Development & Programming Skills,
- Data scientists, Digital architects, Full stack developers,
- Change management,
- Strategic Digital mindset,
- Designing of solution,
- Industrial automation skills, data security, IT,
- Artificial intelligence,
- Real Industrial IT - hardware & software, IoT knowledge to prepare functional diagrams how systems should be connected (a lot of different equipment and systems),
- Greater openness on the part of top management.

Companies require support in developing with their current and future employees the competences required for the effective implementation of Industry 4.0 solutions, including both in the technical and soft areas.

Based on the survey results it can be summarized that the companies need:

- Support in the implementation of integrated IT systems, including in particular MES and MIS-class systems and their advanced functionalities.
- Support in the implementation of automatic data collection systems.

- Support in the implementation of intelligent condition monitoring systems, especially with functionality of failures prediction of processes and machines.
- Support in spreading knowledge of the possibilities and practical methods of implementing integrated platforms for automatic data exchange between IT systems, including cooperating companies, i.e. suppliers and clients.
- Support for knowledge transfer on the capabilities of today's IT systems and AI as well as other Industry 4.0 technologies, including in particular their implementation into industrial practice on the operational level.
- Support in developing for current and future employees technical and soft competences required for the effective implementation of Industry 4.0 solutions.

The AI, IoT and EC technologies teaching in the universities are connected with topics and areas presented in the Figures 4 - 15. The information comes from **69 teachers** who teach **AI**, **31 teachers** who teach **IoT** and **8 teachers** who teach **EC**. Questions contained in the survey were developed based on the review of publicly accessible teaching programs from universities. The overall conclusion may be that the subject of edge computing is very little taught. It is important to know what topics are currently being taught and how they are connected with the companies' needs.

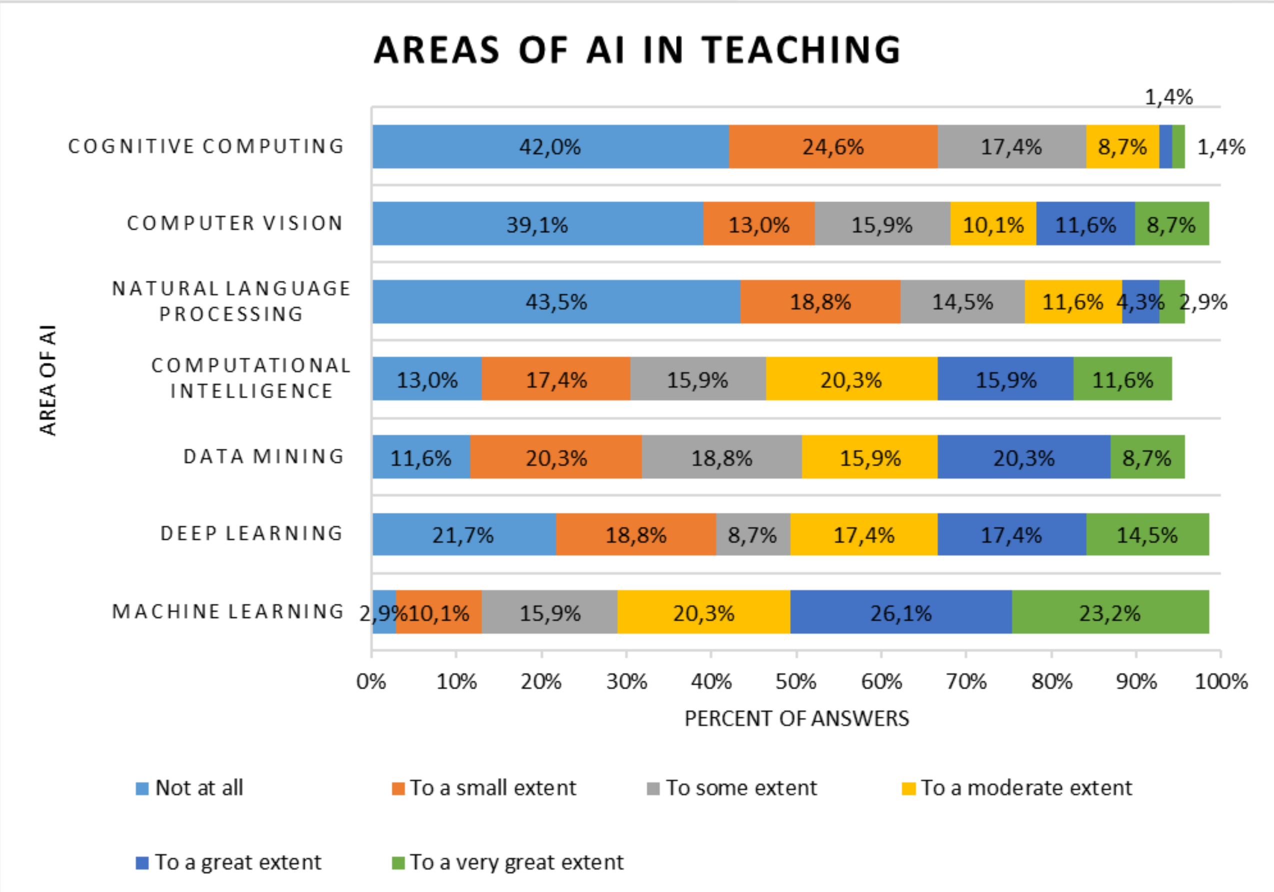


Figure 4 Areas of AI in teaching

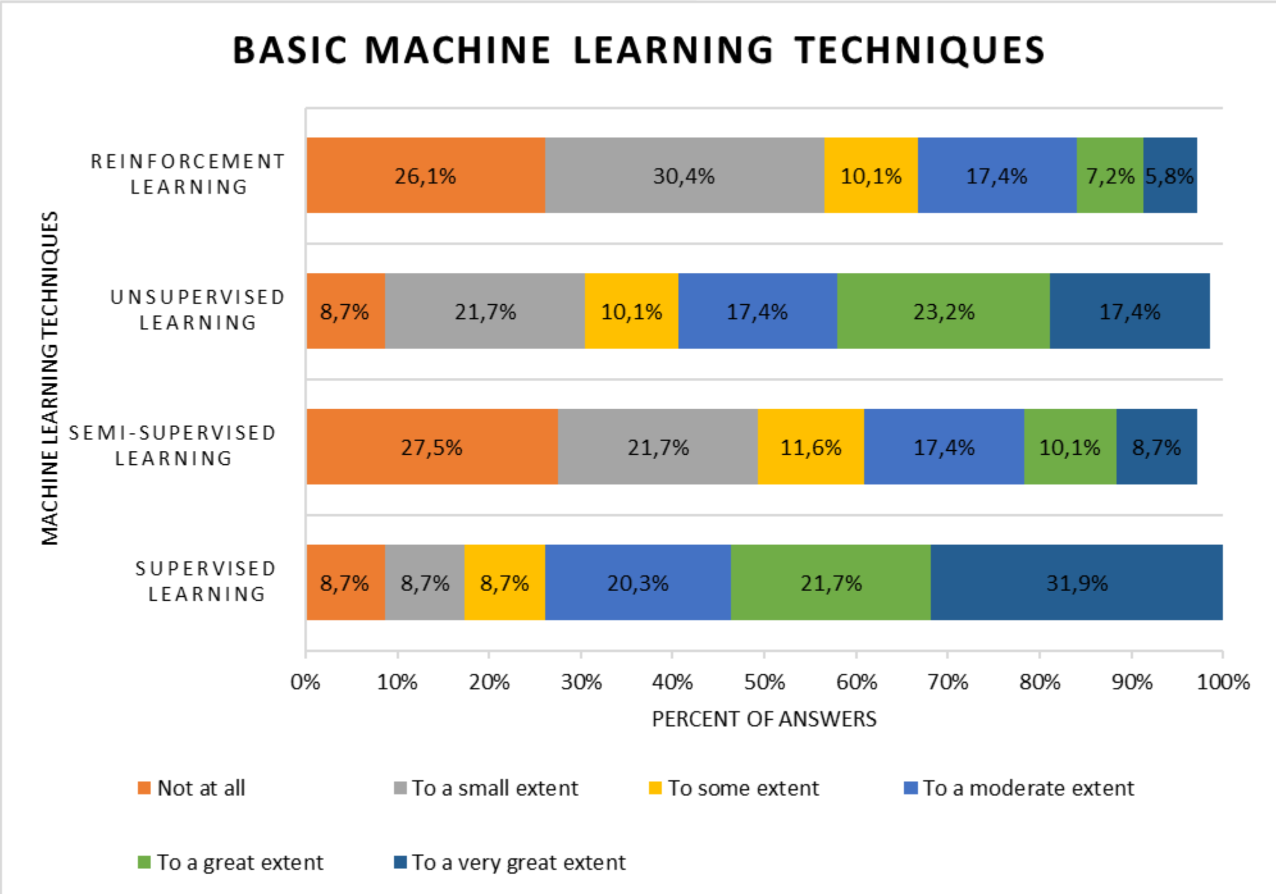


Figure 5 Basic machine learning techniques

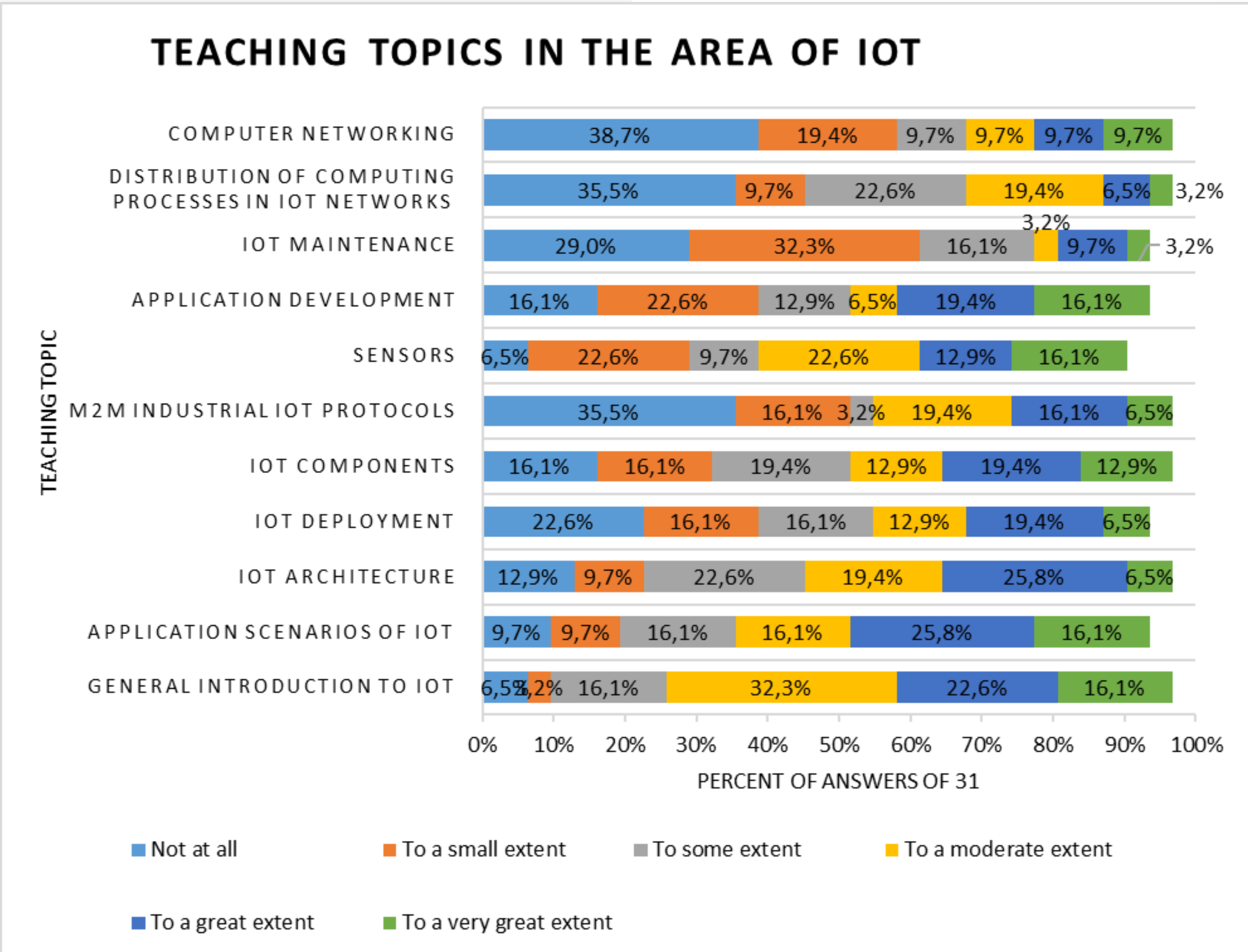

Figure 6 Teaching topics in the area of IoT

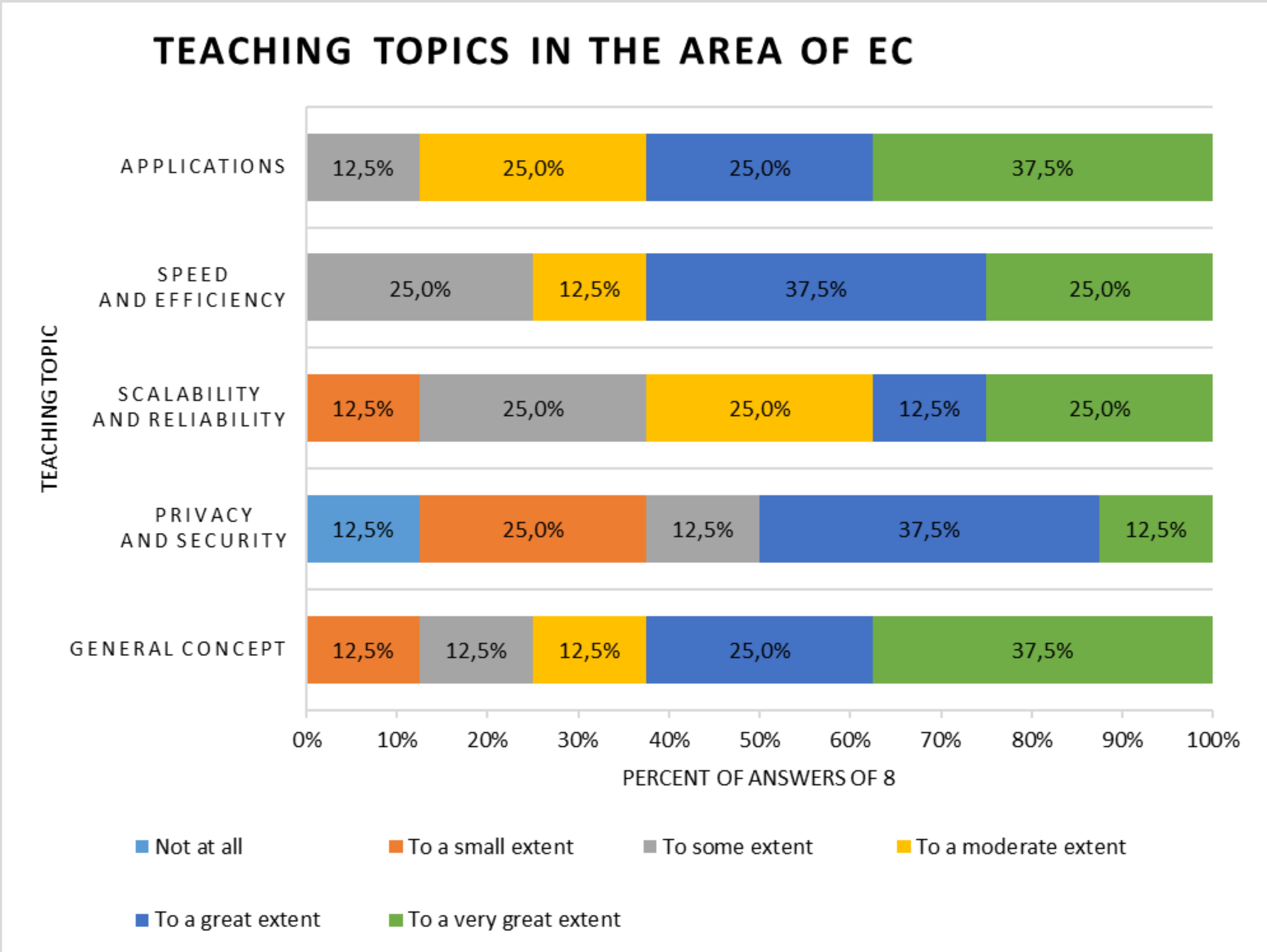


Figure 7 Teaching topics in the area of edge computing

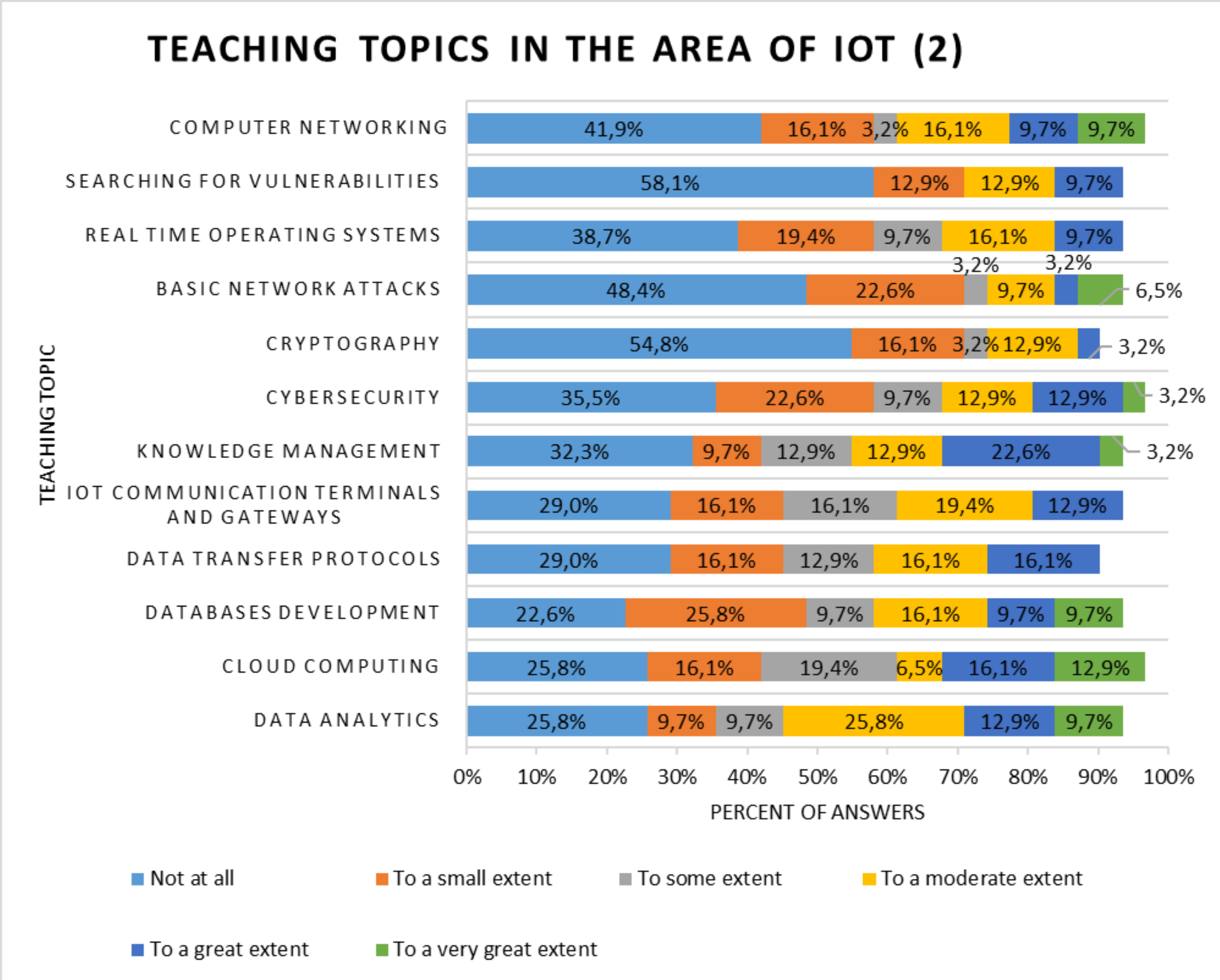


Figure 8 Teaching topics in the area of IoT (2)

The topics connected with AI, IoT and EC are taught in the applications presented in Figures 9-11.

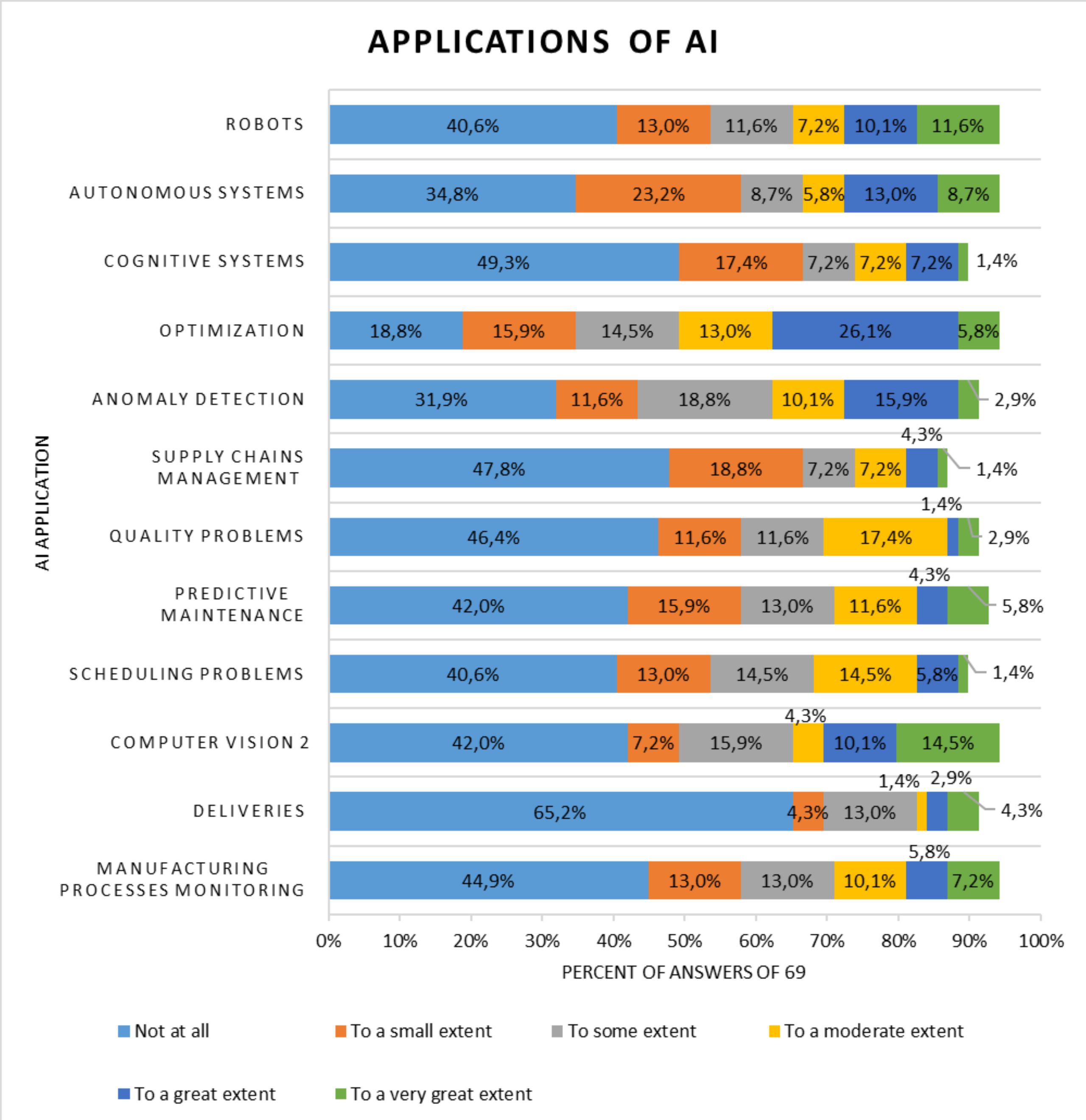


Figure 9 Teaching applications of AI

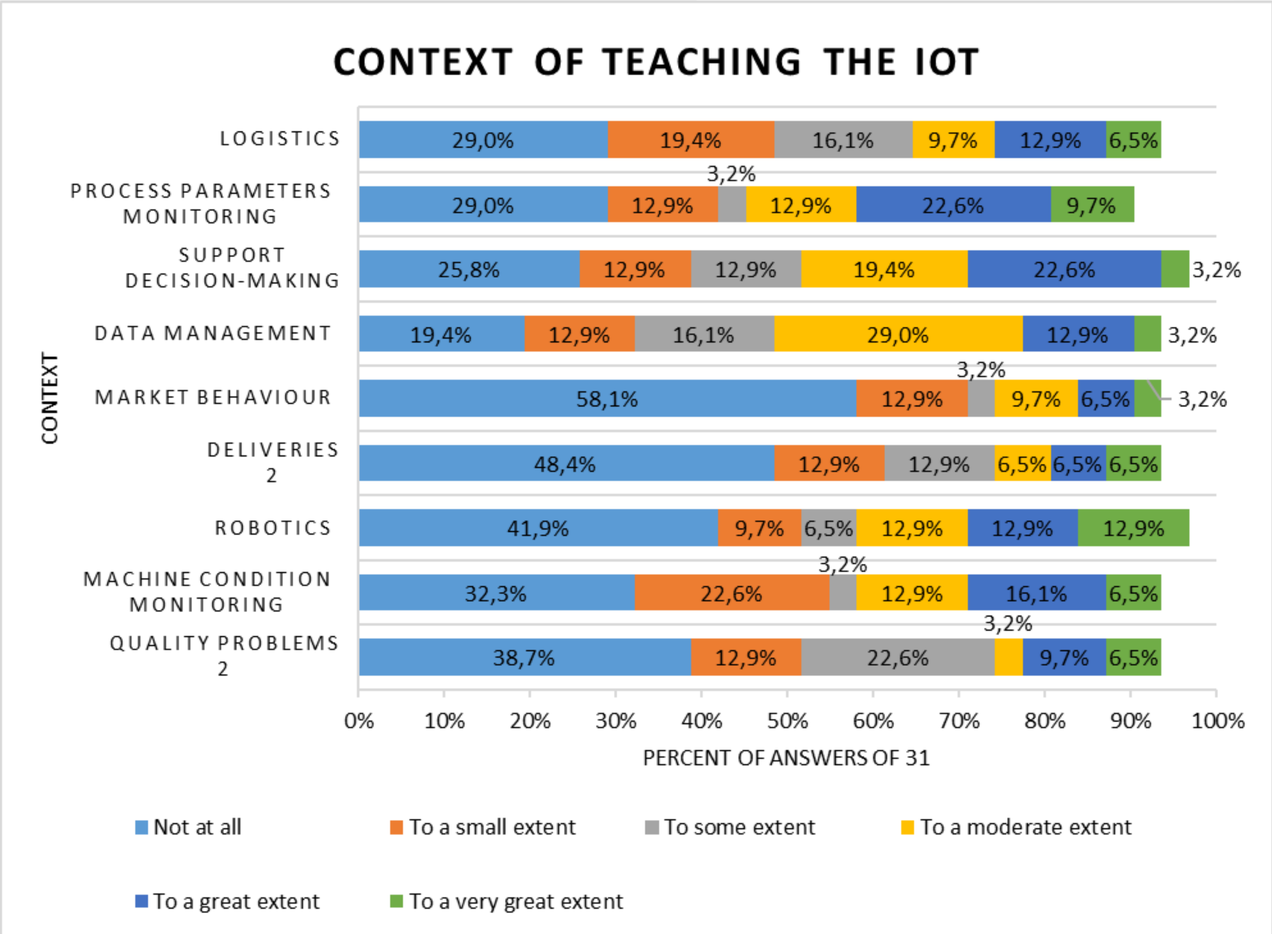


Figure 10 Context of Teaching the IoT

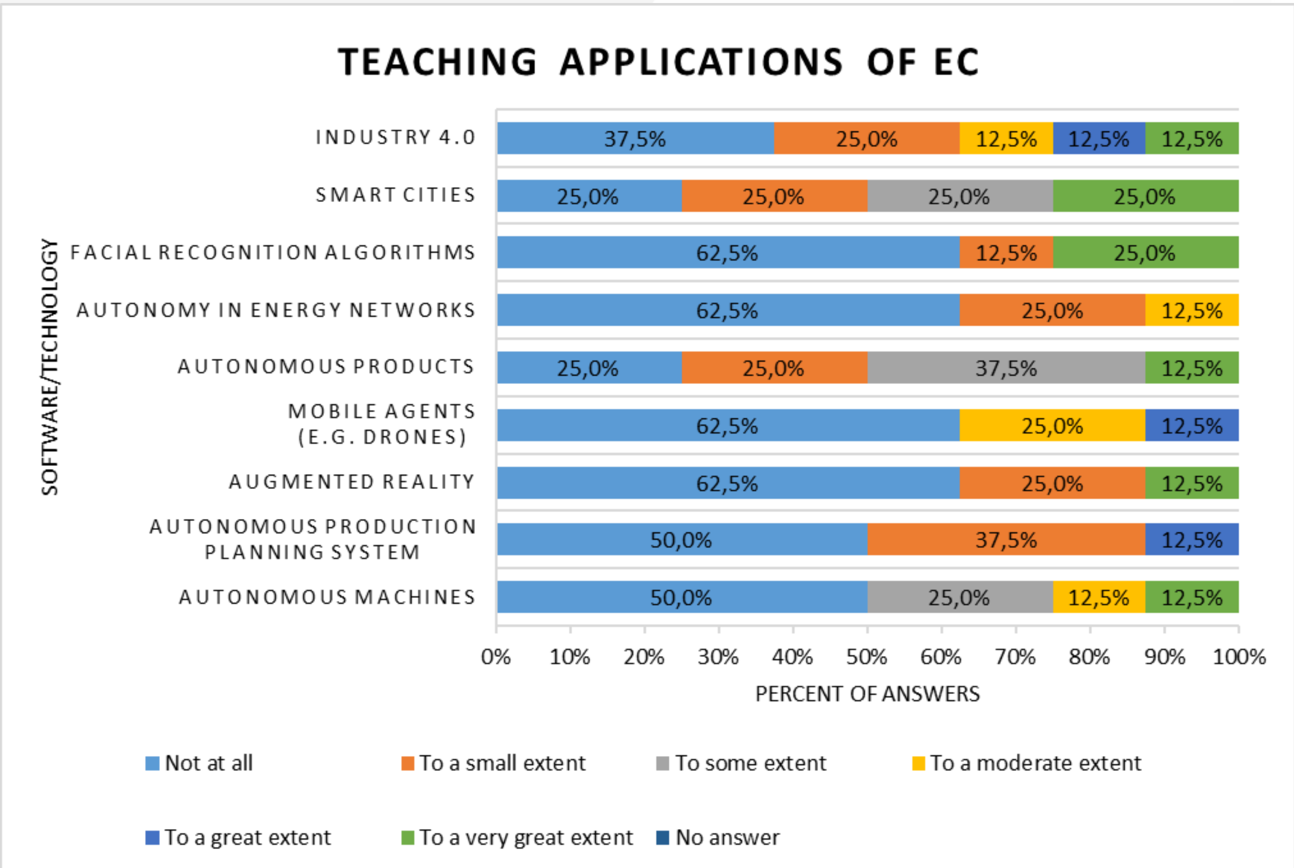


Figure 11 Teaching applications of Edge Computing

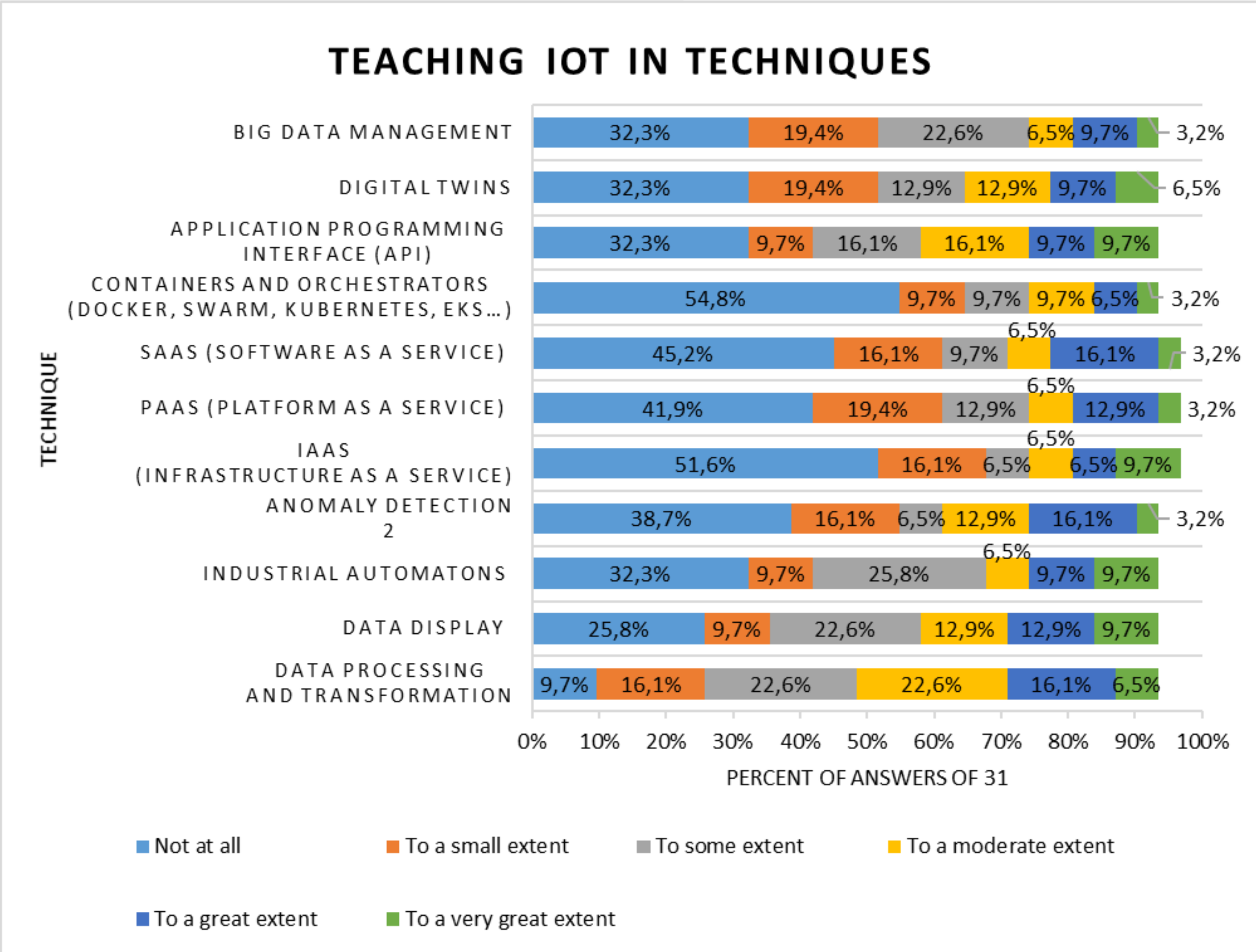


Figure 12 Teaching applications of IoT in different technologies

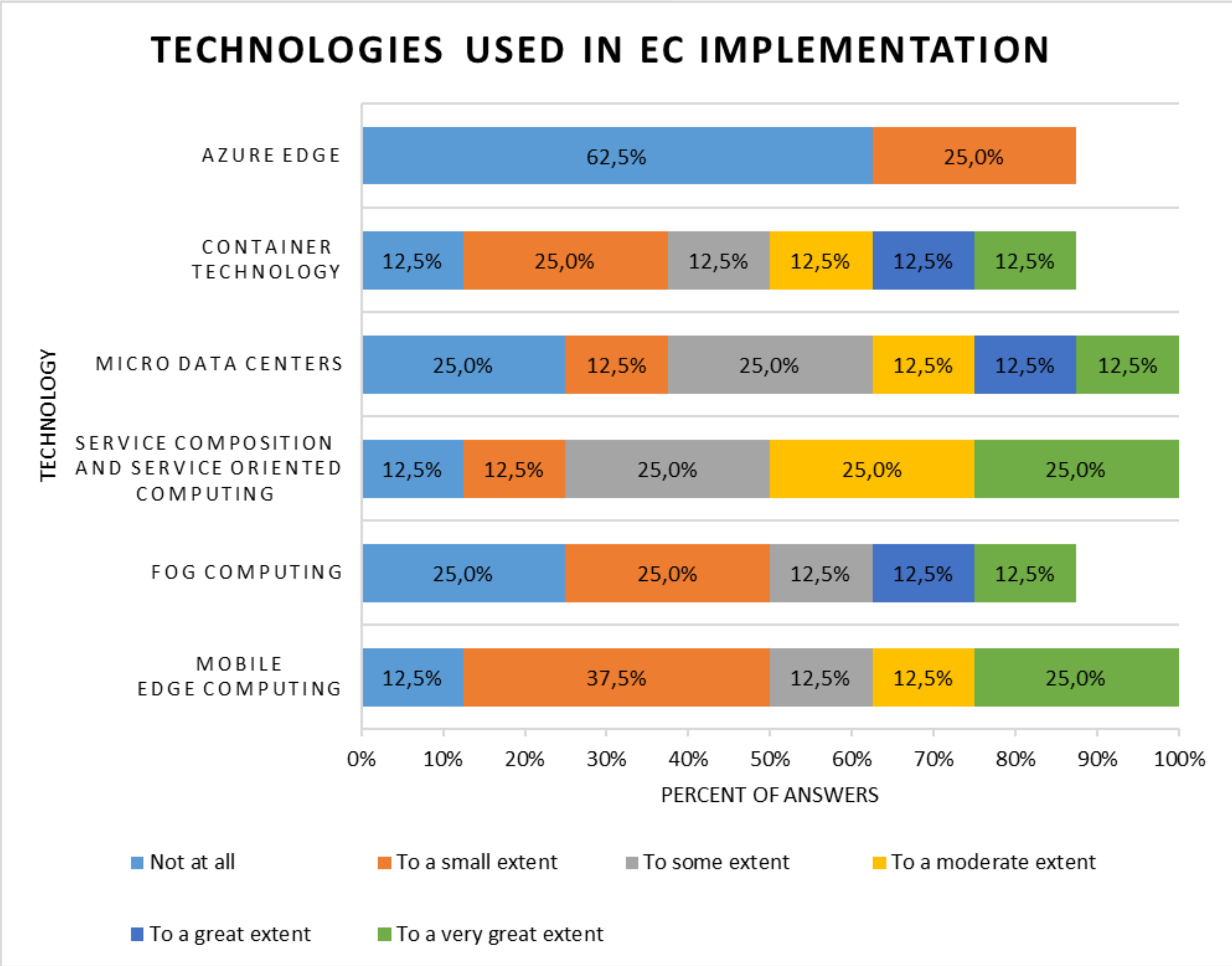


Figure 13 Technologies used in Edge Computing implementation

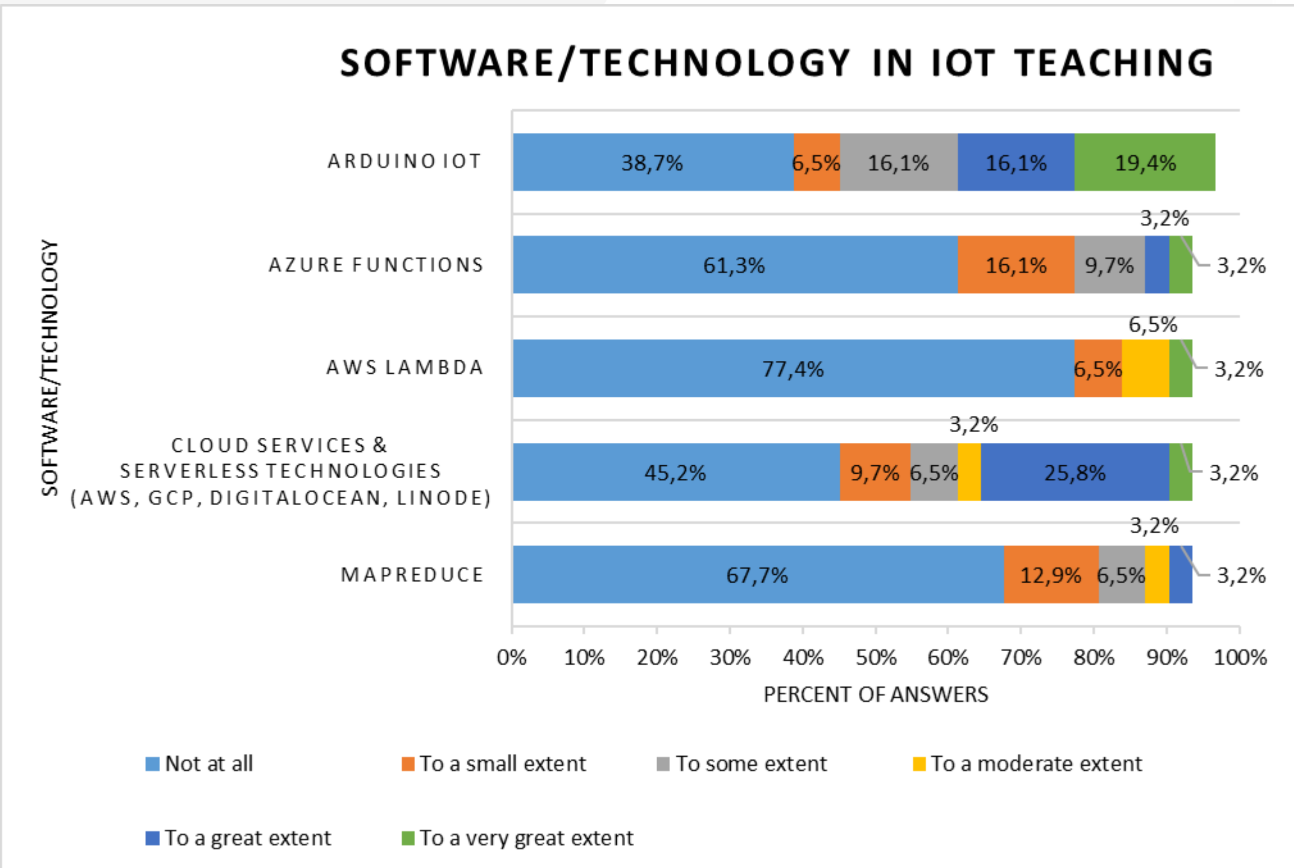


Figure 14 Software / technology in IoT teaching

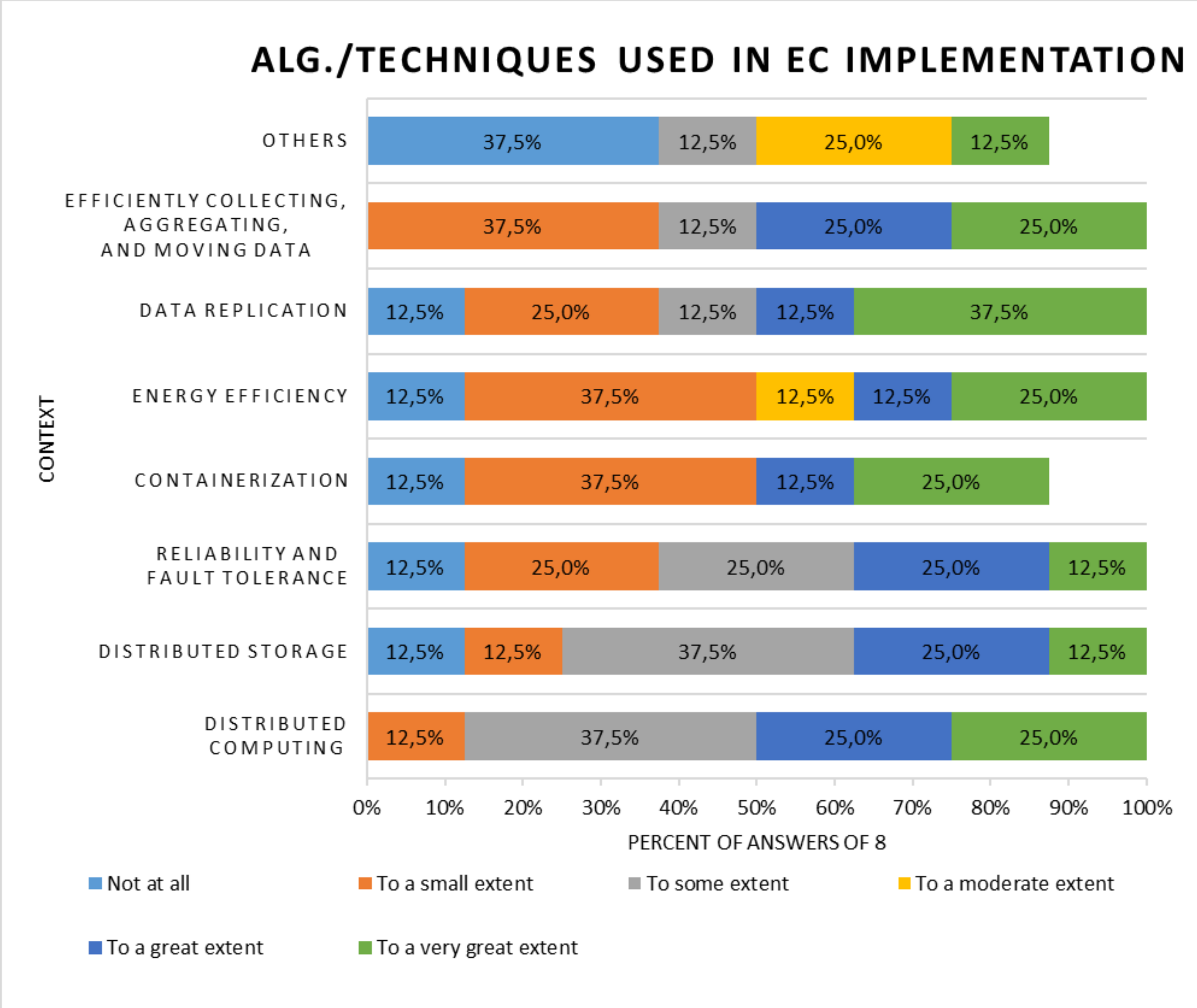


Figure 15 Algorithms/techniques used in Edge Computing implementation

Table 5 presents information which of the technologies identified in the bibliographic research are applied in the industry and exist in educational programs connected with AI, IoT and EC.

Table 5 Existence of demanded technologies in training programs

| Area | Technology identified in bibliographical research | A technology applied in industry | A technology exists in training programs |
|---|---|---|---|
| Data science | Data Visualization and Dashboarding | Yes | No |
| | Data Analytics | Yes | Yes |
| | Advanced reporting and self-service business intelligence tools | Yes | No |
| | Databases | Yes | Yes |
| Artificial Intelligence | Machine learning | Yes | Yes |
| | Deep Learning | Yes | Yes |
| | Reinforcement Learning | No | Yes |
| | Computer vision | Yes | Yes |
| | Continuous Learning | No | No |

| | | | |
|---|---|---|---|
| | Natural Language Processing | No | Yes |
| Cloud computing | Container technologies | Yes | Yes |
| | Serverless programming | Yes | Yes |
| | Device Management | Yes | No |
| | Cloud Data Storage | Yes | Yes (distributed storage) |
| | Edge computing | Yes | Yes |
| IOT and IOE | Industrial IOT | Yes | Yes |
| | Embedded Computing | Yes | Yes (SW/technology in IoT teaching) |
| | Sensors (hardware) | Yes | Yes |
| | Signal Processing | Yes | No |
| | Blockchain | Yes | No |
| | Connectivity | Yes | Yes (M2M industrial protocols, Data transfer protocols) |
| | Internet of Everything | Yes | No |

**Lack of teaching** following technologies in the field of AI, IoT and EC has been detected:

1. Data visualization and dashboarding.
2. Advanced reporting and self-service business intelligence tools.
3. Device Management in cloud computing.
4. Internet of Things domain:
    a. Signal processing.
    b. Blockchain.
5. Internet of Everything.

Table 6 presents assessment of degree of teaching based on the survey performed among academics. Based on answers from academics survey it is possible to determine to what extent teachers teach a specific technology. It was decided to adopt three values relating to the degree of teaching. They are presented in Table 6: "not identified" if the technology was not found in the curricula, "sufficient" or "insufficient" depending on the following criteria:

1. Sufficient level – when the sum of answers “not at all” and “to small extent” is less than 50%.
2. Insufficient level – when the sum of answers “not at all” and “to small extent” is greater than 50%.

Table 6 Degree of teaching demanded technologies

| Taught technology Area/Domain | Technology identified in bibliographical research | Applied in industry | Degree of teaching |
|---|---|---|---|

| | | | |
|---|---|---|---|
| Data Analytics | Data lake and Data Warehouse design | No | Not identified |
| | Data Mining | Yes | Sufficient (Figure 4) |
| | Process mining | No | Not identified |
| Databases | SQL DB | Yes | Sufficient (Figure 8) |
| | Non SQL DB | Yes | Not identified |
| | Time series DB | Yes | Not identified |
| | Data engines | Yes | Not identified |
| Machine learning | | Yes | Sufficient (Figure 4) |
| Deep Learning | | Yes | Sufficient (Figure 4) |
| Reinforcement Learning | | No | Insufficient (Figure 4) |
| Computer vision | | Yes | Insufficient (Figure 4) |
| Natural Language Processing | | No | Insufficient (Figure 4) |
| Container technologies | | Yes | Sufficient (Figure 13, Figure 15) |
| Serverless programming | | Yes | Insufficient (Figure 14) |
| Cloud Data Storage | | Yes | Sufficient (Figure 15) |
| Edge computing | | Yes | Sufficient (Figure 7) |
| Industrial IOT | Industrial communication protocols | Yes | Sufficient (Figure 8) |
| | Industrial Gateway and data acquisition device | Yes | Sufficient (Figure 8) |
| Embedded Computing | Microcontroller programming and RTOS | Yes | Insufficient (Figure 14) |
| | Microprocessor programming and embedded Linux | Yes | Not identified |
| IOT and IOE | Sensors (hardware) | Yes | Sufficient (Figure 6) |
| | M2M industrial protocols | Yes | Insufficient (Figure 6) |
| | Data transfer protocols | Yes | Sufficient (Figure 8) |

The conclusion is that academics should more focus on following issues:

1. Non SQL DB.
2. Time series DB.
3. Data engines.
4. Computer vision.
5. Serverless programming.
6. Microcontroller programming and RTOS.

7. Microprocessor programming and embedded Linux.
8. Connectivity (M2M industrial protocols).

## 1.4 Current industrial problems and needs, and future trends in research

The bibliographical review showed that in the production industry exist some problems. They are divided into two classes: process optimization and product innovation and collected in the Table 7 Process optimization problems in the industry found in the bibliographical research and Table 8 Product innovation problems in the industry found in the bibliographical research.

Table 7 Process optimization problems in the industry found in the bibliographical research

| **Category** | **Issue identified in bibliographical research** |
|---|---|
| Equipment efficiency improvement | Real-time Production monitoring analysis and supervision |
| | Predictive maintenance |
| | Vertical interconnection and integration (between departments in a factory) |
| Worker security improvement and accident prevention | Smart PPE (personal protection equipment) |
| | Worker attention and mental state monitoring |
| | People counting, analysis and crowd detection |
| Worker routine and operation optimization | Time and Method smart measurement |
| Supply Chain | Horizontal interconnection and integration (between different actors of the supply chain) |
| | Production on demand enabling technology |
| | Smart warehouse |
| | Intralogistics 4.0 - material flow control |
| | Supply chain transparency and reliability improvement |
| Quality Assurance | Technological Processes intelligent supervision |
| | Intelligent FMEA |

Table 8 Product innovation problems in the industry found in the bibliographical research

| **Category** | **Issue identified in bibliographical research** |
|---|---|
| Product servitization | |
| Usability improvement | |
| Smart products - Intelligent self-diagnosing products | |
| Cost and number of parts/component reduction | |
| After-Sales support | Automatic consumables reorder |
| | Inventory Management |

In this section of the report we analyze if training programs focus on problems identified in the industry. In bibliographical research for the following issues the AI, IoT and EC technologies, which can be used to solve the problems, were not identified:

1. Worker attention and mental state monitoring.
2. Intralogistics 4.0 - material flow control.
3. Technological Processes intelligent supervision.
4. Intelligent FMEA.
5. Smart products - Intelligent self-diagnosing products.

Few questions from the academics survey were addressed directly to problems. These are:

1. Real-time Production monitoring analysis and supervision.
2. Predictive maintenance.
3. Supply chain transparency and reliability improvement.

Remaining problems do not occur directly in the academics survey. The summary of the above discussion is shown in the Table 9 Problems in the industry found in the bibliographical research in the context of training programs.

Table 9 Problems in the industry found in the bibliographical research in the context of training programs

| **Issue from bibliographic research** | **A technology to solve the problem is indicated in the searched bibliography** | **Issue is analyzed in the frame of training programs** |
|---|---|---|
| Real-time Production monitoring analysis and supervision | Yes | Yes (Figure 10) |
| Predictive maintenance | Yes | Yes (Figure 9) |
| Vertical interconnection and integration (between departments in a factory) | Yes | No |
| Smart PPE (personal protection equipment) | Yes | No |
| Worker attention and mental state monitoring | No | No |
| People counting, analysis and crowd detection | Yes | No |
| Time and Method smart measurement | Yes | No |
| Horizontal interconnection and integration (between different actors of the supply chain) | Yes | No |
| Production on demand enabling technology | Yes | No |
| Smart warehouse | Yes | No |
| Intralogistics 4.0 - material flow control | No | No |
| Supply chain transparency and reliability improvement | Yes | Yes (Figure 9) |
| Technological Processes intelligent supervision | No | No |
| Intelligent FMEA | No | No |
| Product servitization | Yes | No |

| Issue from bibliographic research | A technology to solve the problem is indicated in the searched bibliography | Issue is analyzed in the frame of training programs |
|---|---|---|
| Usability improvement | Yes | No |
| Smart products - Intelligent self-diagnosing products | No | No |
| Cost and number of parts/component reduction | Yes | No |
| Automatic consumables reorder | Yes | No |
| Inventory Management | Yes | No |

The report from the literature review of the problems found in the industry contains reference to technologies used to solve a problem. It is possible to answer the question if training programs contain topics dedicated to mentioned technologies so that a solution of a problem exists indirectly in the training program.

The analysis presented below is based on results shown in the Table 5 and Table 6. Every solvable problem from the industry has a reference to technologies. If a technology does not exist in a teaching program the sentence “No” is placed as the conclusion. Otherwise we place “sufficient” on “insufficient” as it was done in the Table 6. In case of compound technologies, such as “databases” or “Data Analytics” following process has been conducted:

1. Data analytics contains Data lake and Data Warehouse design (not applied in the production industry) and process mining (not used to solve any problem). So, the only applicable technology is data mining, which is taught in a sufficient degree.
2. Databases were assumed to be taught in an insufficient degree, because training programs contain courses of relational databases, which are universal storage engines.
3. In the connectivity category the technology M2M industrial protocols is taught insufficiently so we assume the whole connectivity as “insufficient”.

Table 10 and Table 11 contain summary of the above discussion. The conclusion is that only in case of two problems students have knowledge about indicated technologies required to solve them although the problems themselves are not included into the training programs:

1. Smart PPE (personal protection equipment).
2. Product servitization.

Table 10 Solvable process optimization problems and solving technologies in the context of training programs

| Issue from bibliographic research | Solving technology from bibliographic research | Technology exists in training program |
|---|---|---|
| | Data Visualization and Dashboarding | No |

| **Issue from bibliographic research** | **Solving technology from bibliographic research** | **Technology exists in training program** |
|---|---|---|
| Vertical interconnection and integration (between departments in a factory)<br><br>Time and Method smart measurement<br><br>Horizontal interconnection and integration (between different actors of the supply chain) | Data Analytics | Sufficient |
| | Data Mining | Sufficient |
| | Databases | Insufficient |
| | Time series DB | No |
| | Serverless programming | Insufficient |
| | device management | No |
| | Connectivity | Insufficient |
| Smart PPE (personal protection equipment) | Microcontroller programming and RTOS | Insufficient |
| | Sensors (hardware) | Sufficient |
| | Connectivity | Insufficient |
| People counting, analysis and crowd detection | Time series DB | No |
| | Artificial Intelligence | Sufficient |
| | Microcontroller programming and RTOS | Insufficient |
| Production on demand enabling technology | Data Visualization and Dashboarding | No |
| | Data Analytics | Sufficient |
| | Non SQL DB | No |
| | Time series DB | No |
| | Data engines | No |
| | Machine learning | Sufficient |
| | Cloud Data Storage | Sufficient |
| | Industrial communication protocols | Sufficient |
| | Microcontroller programming and RTOS | Insufficient |
| | Microprocessor programming and embedded Linux | No |
| | Sensors (hardware) | Sufficient |
| | Signal Processing | No |

| Issue from bibliographic research | Solving technology from bibliographic research | Technology exists in training program |
|---|---|---|
| | Connectivity | Insufficient |
| Smart warehouse | Data Visualization and Dashboarding | No |
| | databases | Insufficient |
| | Serverless programming | Insufficient |
| | Zerynth Device Manager | No |
| | Cloud Data Storage | Sufficient |
| | Industrial communication protocols | Sufficient |
| | Microcontroller programming and RTOS | Insufficient |
| | Microprocessor programming and embedded Linux | No |
| | Sensors (hardware) | Sufficient |
| | Signal Processing | No |
| | Connectivity | Insufficient |
| | blockchain | No |
| | Data Analytics | Sufficient |
| | Container technology | Sufficient |
| | Device management | No |
| | Edge computing | Sufficient |
| | Advanced reporting and self-service business intelligence tools | No |
| | Machine learning | Sufficient |
| | Time series DB | No |
| | Data mining | Sufficient |

Table 11 Solvable product innovation problems and solving technologies in the context of training programs

| Issue from bibliographic research | Solving technology from bibliographic research | Technology exists in training program |
|---|---|---|
| Product servitization | Databases | Insufficient |
| | Connectivity | Insufficient |
| Usability improvement | Data Visualization and Dashboarding | No |
| | Machine learning | Sufficient |
| | Sensors (hardware) | Sufficient |

| Issue from bibliographic research | Solving technology from bibliographic research | Technology exists in training program |
|---|---|---|
| Automatic consumables reorder | Data Visualization and Dashboarding | No |
| | Data Analytics | Sufficient |
| | device management | No |
| | Industrial communication protocols | Sufficient |
| | Connectivity | Insufficient |
| Cost and number of parts/component reduction | Data Visualization and Dashboarding | No |
| | Data Analytics | Sufficient |
| | Data engines | No |
| | Deep learning | Sufficient |
| | Computer vision | Insufficient |
| | Cloud Data Storage | Sufficient |
| | Microcontroller programming and RTOS | Insufficient |
| | Microprocessor programming and embedded Linux | No |
| | Sensors (hardware) | Sufficient |
| | Connectivity | Insufficient |
| | Time series DB | No |
| | Machine learning | Sufficient |
| | Data mining | Sufficient |
| | databases | Insufficient |
| | Serverless programming | Insufficient |
| | device management | No |
| | Edge computing | Sufficient |
| | Industrial communication protocols | Sufficient |
| | Signal Processing | No |
| Inventory Management | Data Visualization and Dashboarding | No |
| | Data Analytics | Sufficient |
| | device management | No |
| | Industrial communication protocols | Sufficient |
| | Connectivity | Insufficient |
| | Advanced reporting and self-service business intelligence tools | No |
| | Microcontroller programming and RTOS | Insufficient |
| | Sensors (hardware) | Sufficient |
| | Signal Processing | No |
| | Cloud Data Storage | Sufficient |

| Issue from bibliographic research | Solving technology from bibliographic research | Technology exists in training program |
|---|---|---|
| | Machine learning | Sufficient |
| | Time series DB | No |
| | Data mining | Sufficient |

In order to evaluate level of deficiency in training programs let us introduce two percentage indices. For each problem we calculate:

1. How many technologies required to solve a problem are taught.
   taught technologies = (*e* / no. of required technologies)*100%
   where *e* is the number of technologies existing in training programs.
2. How many technologies are taught in a sufficient degree.
   Sufficiently taught technologies = (*s* / no. of required technologies)*100%
   where *s* is the number of technologies that exist in training programs and are taught in sufficient degree.

Proposed indices are show in the Table 12.

Table 12 Solvable problems and teaching of solving technologies

| Issue from bibliographic research | No. of required technologies | Taught technologies | Sufficiently taught technologies |
|---|---|---|---|
| Vertical interconnection and integration (between departments in a factory)<br><br>Time and Method smart measurement<br><br>Horizontal interconnection and integration (between different actors of the supply chain) | 8 | 62,5% | 25% |
| Smart PPE (personal protection equipment) | 3 | 100% | 33% |
| People counting, analysis and crowd detection | 3 | 67% | 33% |
| Production on demand enabling technology | 13 | 54% | 38% |
| Smart warehouse | 19 | 63% | 42% |
| Product servitization | 2 | 100% | 0% |
| Usability improvement | 3 | 66% | 66% |
| Automatic consumables reorder | 5 | 60% | 40% |
| Cost and number of parts/component reduction | 19 | 68% | 42% |
| Inventory Management | 13 | 62% | 46% |

Future trends in research should be connected with the challenges existing in industry. In the performed industrial research, among others, the challenges connected with the following areas are identified:

- customer acquisition and contract planning,
- manufacturing process preparation,
- manufacturing process realization,
- manufacturing process monitoring and improvement.

Figures 16-19 summarize the percentage of companies which indicated the presented challenges as important.

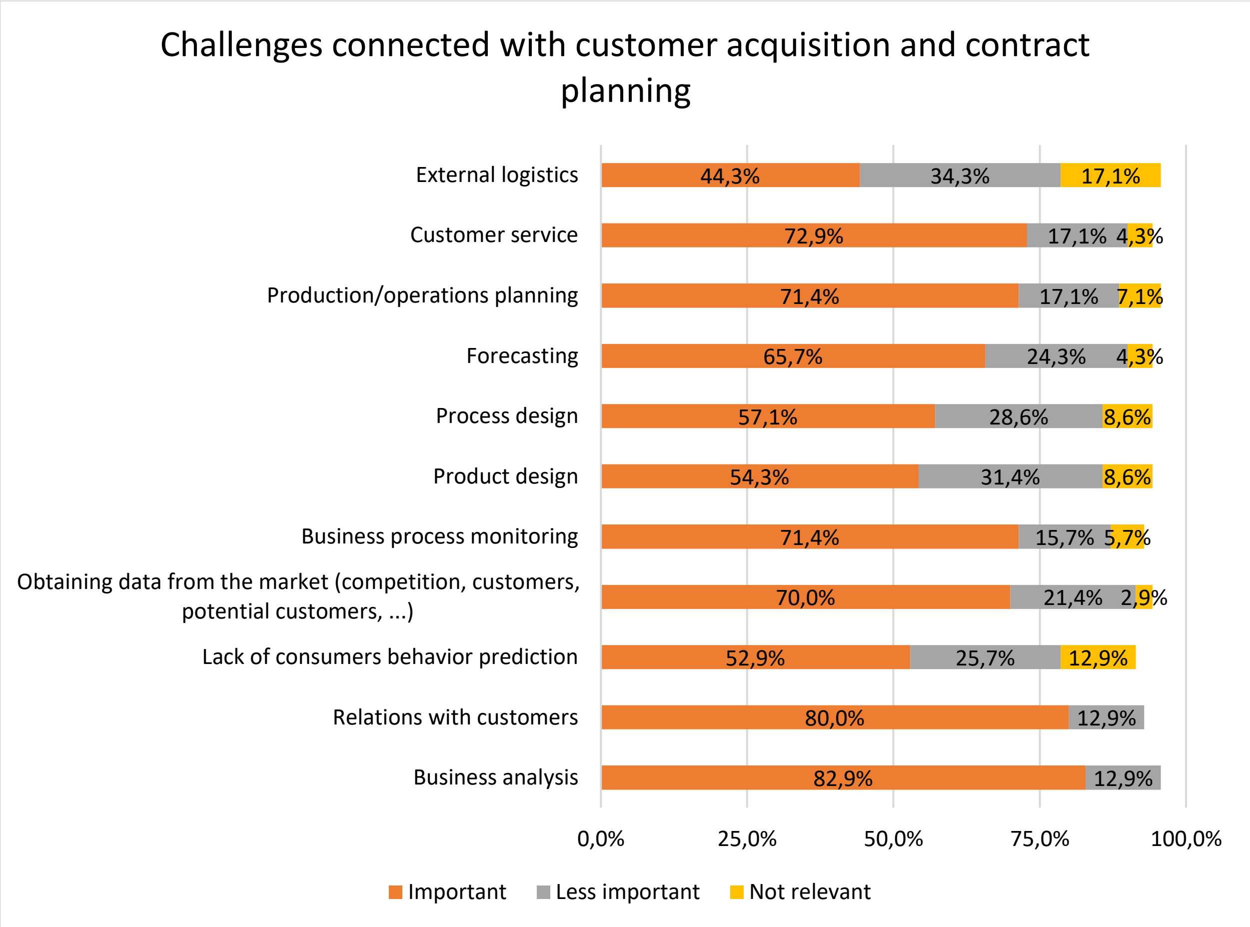


**Figure 16** Challenges connected with customer acquisition and contract planning

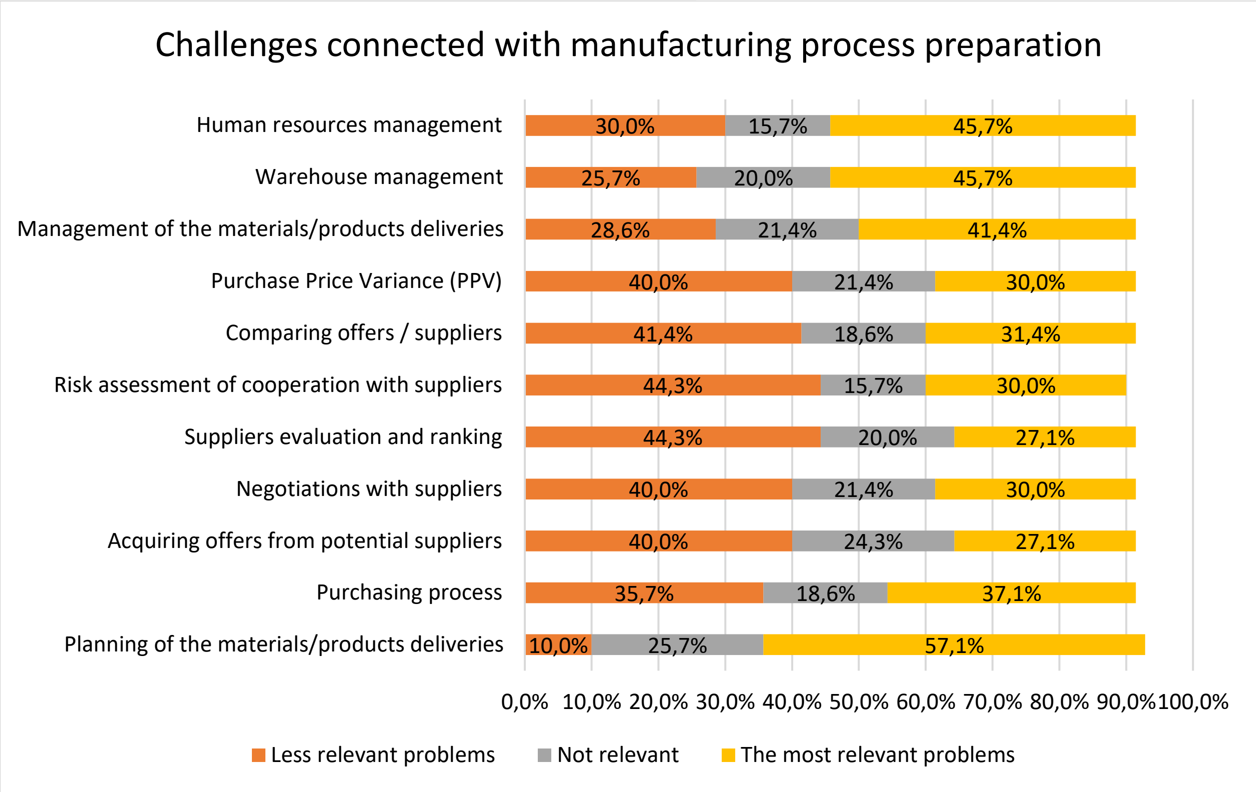


**Figure 17** Challenges connected with manufacturing process preparation

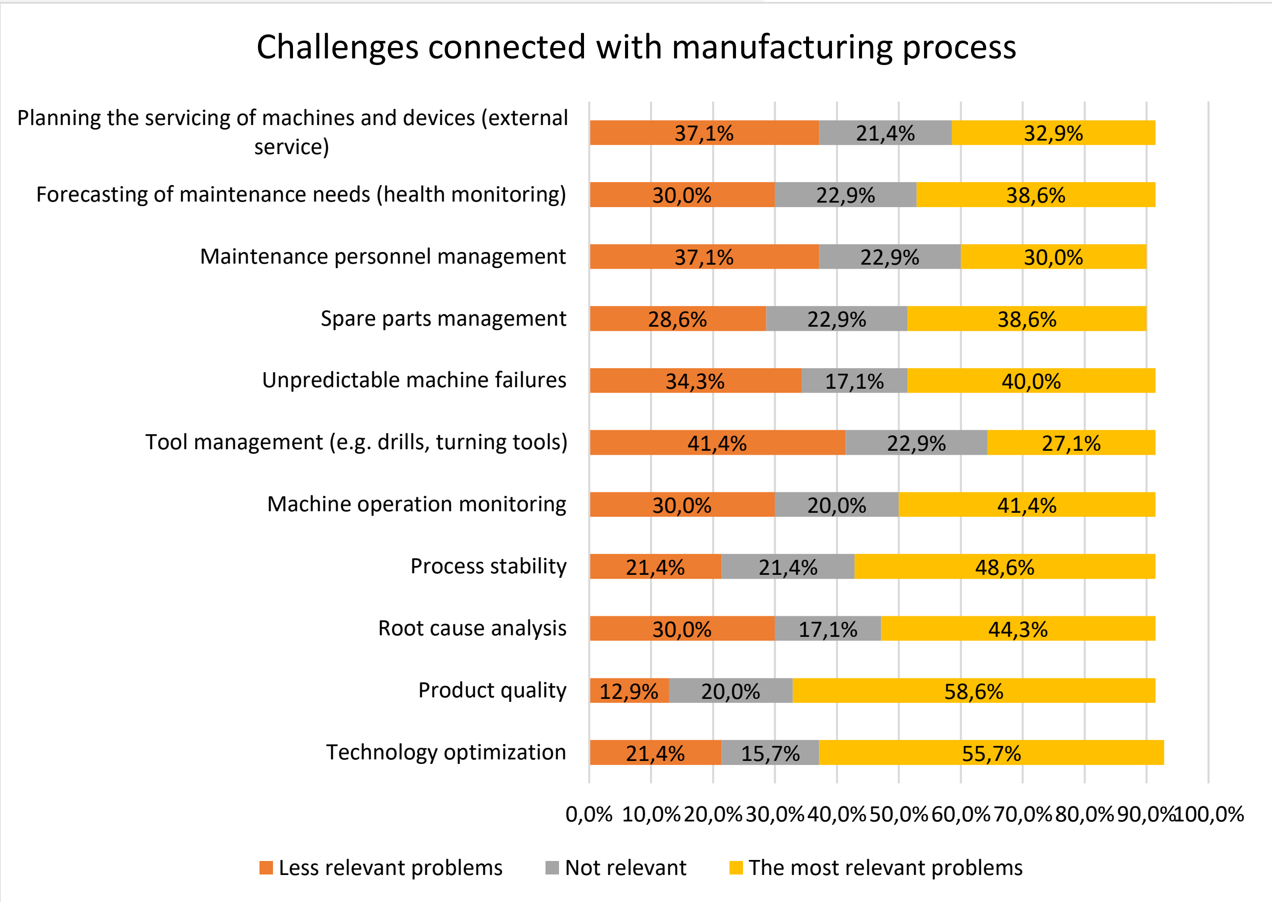


**Figure 18** Challenges connected with manufacturing process

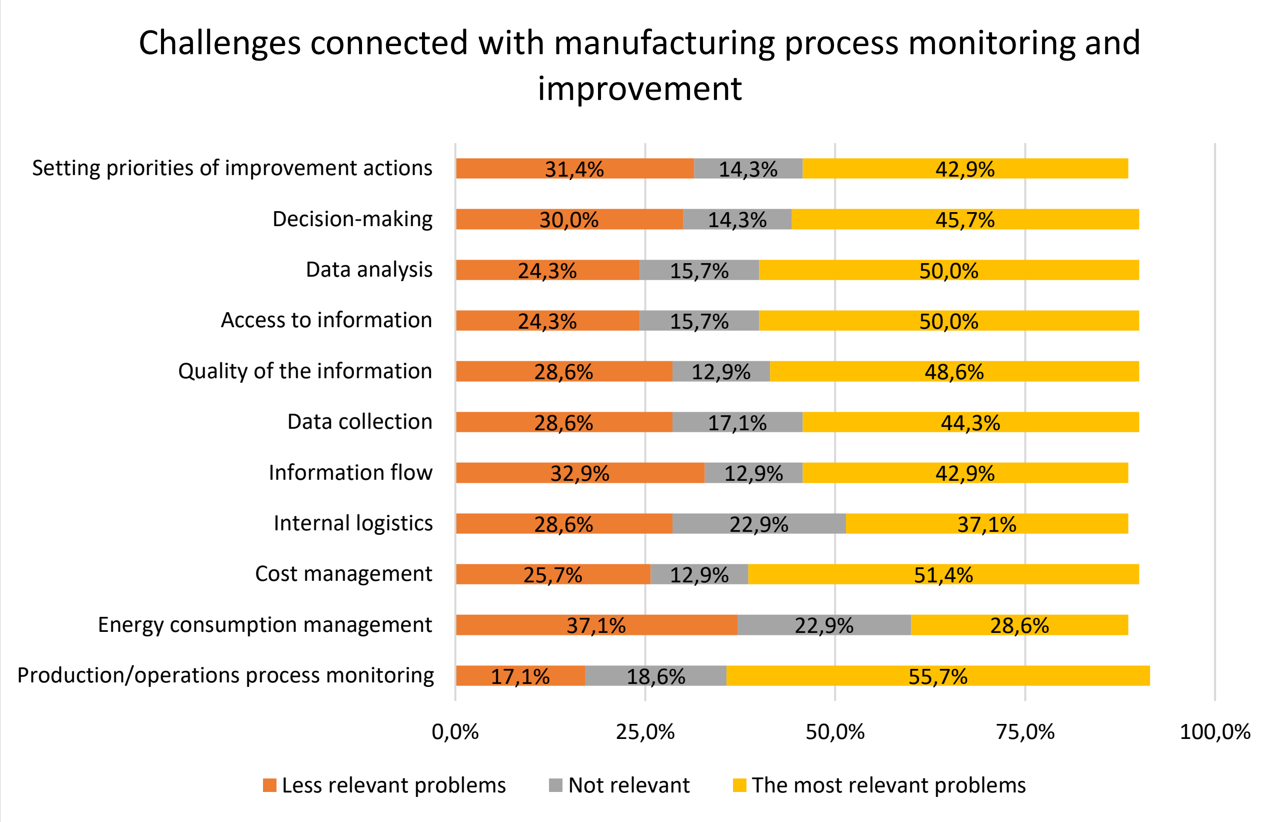


**Figure 19** Challenges connected with manufacturing process monitoring and improvement

The problems were assessed to indicate the priorities. 20% of the problems which were indicated in the most answers as important were given the higher priority (1). Next, the problems up to 30% of the problems which were indicated in the most answers as important were given the higher priority (2). Rest of the problems were given the priority (3).

Table 13 The prioritization of the industrial problems

| **How important are the following challenges?** | **Percentage of answers where the problem was assessed as important** | **Priority** |
|---|---|---|
| Business analysis | 82,90% | 1 |
| Relations with customers | 80,00% | 1 |
| Customer service | 72,90% | 1 |
| Business process monitoring | 71,40% | 1 |
| Production/operations planning | 71,40% | 1 |
| Obtaining data from the market (competition, customers, potential customers, ...) | 70,00% | 1 |
| Forecasting | 65,70% | 1 |
| Product quality | 58,60% | 2 |
| Planning of the materials/products deliveries | 57,10% | 2 |

| | | |
|---|---|---|
| Process design | 57,10% | 2 |
| Production/operations process monitoring | 55,70% | 2 |
| Technology optimization | 55,70% | 2 |
| Product design | 54,30% | 3 |
| Lack of consumers behavior prediction | 52,90% | 3 |
| Cost management | 51,40% | 3 |
| Access to information | 50,00% | 3 |
| Data analysis | 50,00% | 3 |
| Process stability | 48,60% | 3 |
| Quality of the information | 48,60% | 3 |
| Decision-making | 45,70% | 3 |
| Human resources management | 45,70% | 3 |
| Warehouse management | 45,70% | 3 |
| Data collection | 44,30% | 3 |
| External logistics | 44,30% | 3 |
| Root cause analysis | 44,30% | 3 |
| Information flow | 42,90% | 3 |
| Setting priorities of improvement actions | 42,90% | 3 |
| Machine operation monitoring | 41,40% | 3 |
| Management of the materials/products deliveries | 41,40% | 3 |
| Unpredictable machine failures | 40,00% | 3 |
| Forecasting of maintenance needs (health monitoring) | 38,60% | 3 |
| Spare parts management | 38,60% | 3 |
| Internal logistics | 37,10% | 3 |
| Purchasing process | 37,10% | 3 |
| Planning the servicing of machines and devices (external service) | 32,90% | 3 |
| Comparing offers / suppliers | 31,40% | 3 |
| Maintenance personnel management | 30,00% | 3 |
| Negotiations with suppliers | 30,00% | 3 |
| Purchase Price Variance (PPV) | 30,00% | 3 |
| Risk assessment of cooperation with suppliers | 30,00% | 3 |
| Energy consumption management | 28,60% | 3 |
| Acquiring offers from potential suppliers | 27,10% | 3 |
| Suppliers’ evaluation and ranking | 27,10% | 3 |
| Tool management (e.g. drills, turning tools) | 27,10% | 3 |

The companies indicated also other challenges, such as:

- Maintain maintenance line, associated logistics and spare parts control

- Industry 4.0
- prediction on needs of customers, btoc and btob
- Pricing
- Connected with corporates
- Internal communication
- Becoming an approved service center for a certain aircraft type
- greater demand than production
- Industry 4.0 Solutions

The problems are compared to these discussed in the literature for which certain technologies are already proposed.

Table 14 presents the comparison of the problems identified in bibliographical research with the problems identified in industrial research and the topics included in educational programs.

Table 14 Comparison of the problems identified in bibliographical research with the problems identified in industrial research and the problems included in educational programs; in red – priority (1), in blue – priority (2), in green – priority (3), in purple – additional problems indicated by industry in interviews

| **Problems identified in the bibliographical research** | **Challenges pointed by industry** | **Topics included in educational program** |
|---|---|---|
| Real-time Production monitoring analysis and supervision | Machine operation monitoring<br>Production/operations process monitoring<br>Process stability<br>Identifying problems on an ongoing basis<br>Automatic and immediate notification of problems to the right people | Manufacturing processes monitoring<br>Quality problems<br>Process parameters monitoring<br>Scheduling problems<br>Autonomous production planning system |
| Predictive maintenance | Unpredictable machine failures<br>Spare parts management<br>Forecasting of maintenance needs (health monitoring)<br>Planning the servicing of machines and devices (external service) | Predictive maintenance<br>Anomaly detection |

| Problems identified in the bibliographical research | Challenges pointed by industry | Topics included in educational program |
|---|---|---|
| | Maintenance personnel management | |
| Vertical interconnection and integration (between departments in a factory) | Business process monitoring<br>Information flow<br>Problem with transferring data between systems<br>Systems integration | |
| Smart PPE (personal protection equipment) | | |
| Worker attention and mental state monitoring | Human resources management<br>Employee fluctuation | |
| People counting, analysis and crowd detection | | Smart cities<br>Facial recognition algorithms |
| Time and Method smart measurement | Data collection<br>Quality of the information<br>Logical interpretation of data and the results of the analysis<br>Automatic data collection and data flow<br>Problems with data registration due to high diversity of machinery<br>Lack of systematic approach for data collection.<br>Collecting data not used later for analysis.<br>Lack of knowledge how to analyze data.<br>Centralized data analysis.<br>Privacy issue in data collocating. | Data management |
| Horizontal interconnection and integration (between different actors of the supply chain) | Production/operations planning<br>Forecasting<br>Prediction of customer needs<br>Pricing<br>Relations with customers | Deliveries<br>Supply chains management |

| Problems identified in the bibliographical research | Challenges pointed by industry | Topics included in educational program |
|---|---|---|
| | Management of materials/ product deliveries<br>Purchase Price Variance (PPV)<br>Business analysis<br>Acquiring offers from potential suppliers<br>Comparing offers/suppliers<br>External logistic<br>Purchasing process<br>Planning of materials / products deliveries | |
| Production on demand enabling technology | Customer service<br>Obtaining data from the market (competitors, customers, potential customers, etc.) | |
| Smart warehouse | Warehouse management | Autonomous systems |
| Intralogistics 4.0 - material flow control | Production/operations planning<br>Internal logistics | Logistics |
| Supply chain transparency and reliability improvement | Process design<br>Risk assessment of cooperation with suppliers<br>Suppliers' evaluation and ranking<br>Negotiations with suppliers | |
| Technological Processes intelligent supervision | Technology optimization<br>Production/operations process monitoring | Optimization |
| Intelligent FMEA | Product design<br>Process design<br>Product quality<br>Root cause analysis<br>Setting priorities of improvement actions<br>Service | |
| Product servitization | Customer service | |

| Problems identified in the bibliographical research | Challenges pointed by industry | Topics included in educational program |
|---|---|---|
| | Business analysis | |
| Usability improvement | Product design | |
| Smart products - Intelligent self-diagnosing products | Product design | Autonomous products |
| Cost and number of parts/component reduction | Product design<br>Cost management | |
| Automatic consumables reorder | Production/operations planning | |
| Inventory Management | Warehouse management<br>Tool management (e.g. drills, turning tools) | |
| | Customers behavior prediction | Market behavior |
| | Energy consumption management | Autonomy in energy networks |
| | Access to information | Data management |
| | Data analysis | Data management |
| | Decision-making | Support decision-making |
| | | Computer vision |
| | | Cognitive systems |
| | Implementation of robots for production | Robots, Robotics |
| | | Autonomous machines |
| | | Augmented reality |
| | | Mobile agents (e.g. drones) |
| | Understanding of Industry 4.0 concept | Understanding of Industry 4.0 concept |
| | Insufficient knowledge of software integrators on production specificity | |
| | Cybersecurity | |

From the conducted analysis it can be seen that more problems were identified in the industrial research than in the bibliographical research. However, some of the problems identified in the bibliographical research did not appear in industrial research. Moreover, the topics existing in teaching programs do not cover the mentioned problems. Therefore, the problems cannot be currently easy solved because of lack of necessary trainings.

It is also important to summarize what topics the teachers should focus in education process to pass to the students right knowledge and competences to solve industrial problems. The teachers should focus on the following topics:

1. Present examples of applications computer vision, natural language processing and cognitive computing in the industry.
2. Present applications of generative adversarial networks and transformer to solve practical problems from industry.
3. Bound data mining to examples from industry in order to show importance of business understanding and deployment phases.
4. Show applications of fuzzy systems and genetic algorithms in computational intelligence.
5. Apply natural language processing in teaching.
6. Show applications of computer vision and cognitive computing in Industry 4.0.
7. Show applications of cognitive systems, supply chains management, delivery in Industry 4.0.
8. Give practical examples of AI applications in Industry 4.0 (for workshops and problem based learning).
9. Introduce security issues in teaching Internet of Things.
10. Present issues concerning market behavior and deliveries in the IoT context.
11. Present deployment of IoT products and technologies in the production environment.
12. Give practical examples of IoT applications in Industry 4.0 (for workshops and problem based learning).
13. Discuss processing data gathered by intelligent sensors in IoT area.
14. Develop new study programs in the field of edge computing with cooperation with industry partners.

In the industrial research the following needs were also identified:

**Company 1:**

- Developing the competence of low-level-staff to operate and use ICT systems
    - training and courses
    - ability to use ICT systems
- Understanding the purpose and idea of Industry 4.0 by mid-level-staff
    - training and courses
    - familiarize and understand the opportunities that Industry 4.0 technologies offer for specific areas of business operation and increase work places efficiency
- Acquisition of practical skills in the use of AI tools and methods by senior-level-staff
    - knowledge raising – seminars, discussions, experts panels
    - training and practical courses – tools and software
- Soft competences
    - raising awareness of the need for Industrial 4.0 implementation in the company

  - building a culture of active participation in the implementation of ICT and Industry 4.0 technologies in the company
- Development of employees competences in data engineering and data science
- Support for human personnel by AI systems in data analysis and decision-making
- Improving in ICT and Industry 4.0 systems implementation process – quality and efficiency
  - standards and unified platforms
- Advanced predictive maintenance systems and systems for diagnosis and supervision of technological processes
- Automated intralogistics systems
- Automated systems for machines retooling with intelligent decision support

**Company 2:**

- Development of knowledge and practical skills among employees in the application of AI methods and Industry 4.0 technology
  - knowledge raising – seminars, discussions, experts panels
  - training and practical courses – tools and software
- Development of employees soft competences
  - involvement
  - ability to think logically
  - ability to work as a team
- Development of employees competences in data engineering and data science
- Improving in ICT and Industry 4.0 systems implementation process – quality and efficiency
  - standards and unified platforms
- Use of AI systems in data analysis and support for human employees in decision-making in products quality area – quality assurance
- Advanced predictive maintenance systems and systems for diagnosis and supervision of technological processes

**Company 3:**

- Development of knowledge and practical skills among employees in the application of AI methods and Industry 4.0 technology
  - knowledge raising – seminars, discussions, experts panels
  - training and practical courses – tools and software
- Development of employees competences in data engineering and data science
  - automated dashboards
  - automated reports
- Improving in ICT and Industry 4.0 systems implementation process – quality and efficiency
  - standards
  - unified platforms for data collection and integration
- Application of AI methods to prediction of
  - faculty results at the end of the month
  - engine behavior during testing

- Use of AI systems in data analysis and support for human employees in decision-making in current production management

**Company 4:**

- Development of knowledge and practical skills among employees in the application of AI methods and Industry 4.0 technology
  - knowledge raising – seminars, discussions, experts panels
  - training and practical courses – tools and software
- Development of employees competences in data engineering and data science
  - automated dashboards
  - automated reports
- Development of employees competences in
  - lean manufacturing
  - production understanding – OEE, etc.
  - running projects using project management methods
- Improving in ICT and Industry 4.0 systems implementation process – quality and efficiency
  - standards
  - unified platforms for data collection and integration
- Use of AI systems in data analysis and support for human employees in decision-making in the field of technological processes
- Development of employees soft competences
  - involvement
  - ability to think logically
  - ability to work as a team
  - interpersonal communication
  - self-motivation and self-organization
  - ability to establish relationships
  - ability for decision making
  - perseverance

**Company 5:**

- Implementation of self-management for two manufacturing lines operating on a supplier-customer basis.
- Implementation of automatic quality control in different areas.
- Implementation of AI in scheduling optimization.
- Implementation of automatic data acquisition.
- Implementation of data analytics.

The lacking competencies are as follow:

- Ability to identify areas where I4.0 solutions can be implemented.
- Knowledge about solutions that can be implemented.
- Knowledge about possible benefits of implementing I4.0 technologies, in particular economical savings. All expenses have to be justified.

**Company 6:**

- The need of identification important manufacturing process parameters to be monitored and then analyzed to support decision making process.
- The need of systems integration.
- The need of implementation a system which support the planning process.
- The need of machines condition monitoring.
- The need of cause-effect analysis based on data.

**Company 7:**

- Knowledge of AI capabilities and possible usage.
- Implementation of edge data processing to overcome customers' skepticism about data streams.
- Implementation of local data analysis, eliminating the need to transmit data to a central office.
- Need of workers with more managerial skills, even at the cost of less specific expertise.

**Company 8:**

- Standardization of data extraction
- Standardization of data analysis
- Knowledge and possible applications of EC
- Need of workers with a wider point of view about data, ranging from data collection to its applications

**Company 9:**

Employees need more training to understand Industry 4.0, Robotics, Artificial Intelligence and how these technologies impact companies. How to implement Industry 4.0 solutions on supply chain or how to make predictive maintenance.

**Company 10:**

- Students are not formed to implement AI solutions for Industry 4.0
- Enable students to get more experience on Quality Control System
- Projects where to implement IoT system on a Supply Chain

**Company 11:**

- ability to revamp older machines, allowing them to collect data;
- ability to analyze the data captured from machines, monitoring different parameters necessary for compliance with current regulations;
- knowledge of AI systems for taking decisions or helping human figures in detecting anomalies that need an intervention;
- improvement of current professional figures, teaching them new technologies and their potential.

**Company 12:**

- Implementation of automated ways of getting data
  - Data from customers
  - Data from Maintenance at the shop floor level

- Implementation of AI for Maintenance
  - Condition monitoring
  - Predictive Maintenance
- More knowledge on EC to bring intelligence to the shop floor level
  - Data security, powering of EC entities, Administration of EC entities and retrofit
- Condition monitoring
- Development of employees competences in data engineering and data science
- Development of employees competences in the application of AI in embedded systems.
- New employees with interdisciplinary engineering knowledge (networks, electronics, data analytics, programming, etc.) and incorporating knowledge in the latest technologies such as EC and AI.
- Improving low-level staff motivation and commitment in the gathering (collection and production) of data

**Company 13:**

- Development of I4.0 for product selling
- Implementation of Business Intelligence for the Customers Journey
- Implementation of a more integrable antenna (plug&play) for IoT products
  - Employees with competences in hardware and software
  - Employees (engineers) with competences in “market adoption”
- Employees with
  - strong competences in electronics, antennas and Radio Frequency
  - some knowledge on the wireless industry, and radio protocols and their applications
  - English
  - Soft-skills (Good listeners, Creative, etc.)

**Company 14:**

- Implementation of I4.0 for producing polyester for swimming pools
  - Connecting machines, connecting the plants
  - Having automated (interrelated) data
  - Personalized robots (machines are not standardized)
- Implementation of IoT for machines maintenance (vibrations, etc.), emissions, humidity..
- Implementation of automated processes using robots
- Implementation of a centralized application/database for all the data (production data (production studies, quality data..) of the MES; consumes, waste management, optimization, acetone distribution acetone, KPIs from PowerBI, etc.
- Digitalization of the complete data gathering process (still some parts are done with a pen and paper)
- Need of a standardized ERP
- Effective implementation of MES
  - Current solutions lack of adaptability to internal processes. They are focused in automation companies, mono-product, mono-phase, in case of different products and

different phases, important changes have to be done (in terms of codings and for workers). The workers feel under surveillance, they do not like.

- Keep staff updated in the latest technologies
  - Robot courses (by robot selling companies)
  - Participating in fairs
- Employees with programming and network skills, and strong knowledge in automation for implementing Industry 4.0.

**Company 15:**

- Implementation of warning systems for sensing water level
- Implementation of predictive maintenance
- Implementation of a useful tool for development planning.
  - There are many development planning tools but they are mainly for software, but there are not for hardware design planning. In software one can extend with adds, but with hardware you need to control every part of this hardware. We use TFS from Azure but now we look how to show progress in time. We have many projects and we need to see if something changes how it will impact to all the projects. Project software is not very good for small tasks. Too much robust.
- Employees with knowledge on I4.0
- Employees with knowledge on data analysis and data management

**Company 16:**

- Implementation of I4.0 for car manufacturing
  - Connection of all the production components of al the production sites in the cloud
  - Using cross-data analytics for optimizing production and logistics
  - Producing information for management. Decision taking
- Implementation of AI to improve Production machines
- Implementation of Machine Learning for robots and cars maintenance
- Implementation of aggregated statistics (up to now, they are segregated by markets with different CRMs)
- Employees with knowledge in data analytics, AI and machine learning combined with business.
  - Technologic solutions should be proposed based on the needs/strategy of the Company
  - Studies should unify business world with software world and industry (agile), or fill the gap between them.
  - Engineers should have more knowledge on business.

**Company 17:**

- The need for securing the company’s network with modern technologies, as the company is vulnerable to cyber-attacks: The hard recovery after undergoing relevant experiences in the past has proven the need for adopting and integrating advanced security systems in the company’s networks.

- The exploitation of Virtual Reality technology in the direction of conducting simulations useful for the company's engineers to test their designs and drawings.
- The synchronization of production lines by using robotic arms that bear intelligence and be capable of functioning on their own.

Based on research in it can be said that the future trends in research should be connected with supporting the following challenges with AI, ML, IoT and EC:

- Business process monitoring and information flow
- Human resources management
- Prediction of customer behavior
- Data management
- Decision-making process

## 1.5 The main gaps in skills

The conducted student surveys allow to identify gaps in knowledge and skills regarding AI, IoT and EC. The general information about how much the bachelor and master students learn about AI, IoT and EC is presented in Figure 20 and Figure 21.

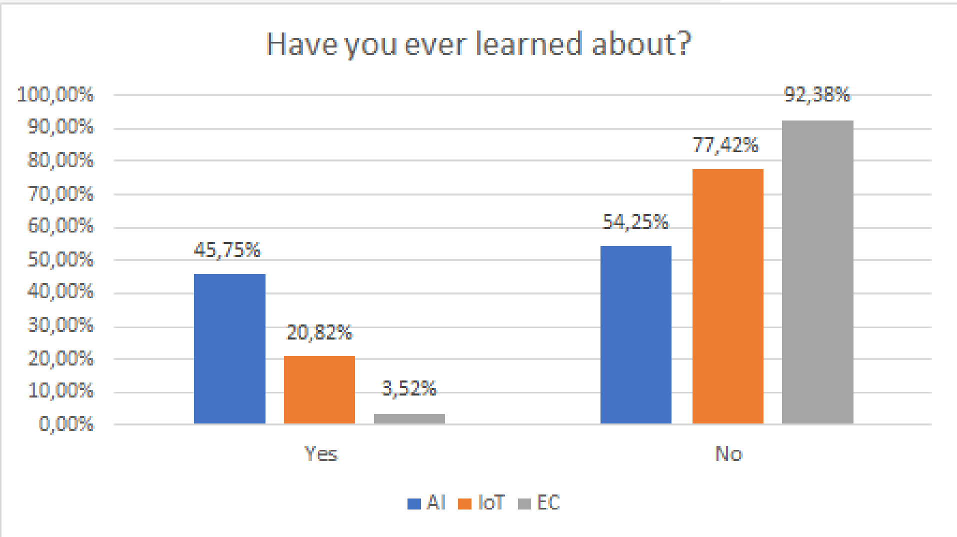


Figure 20 Responses – bachelor

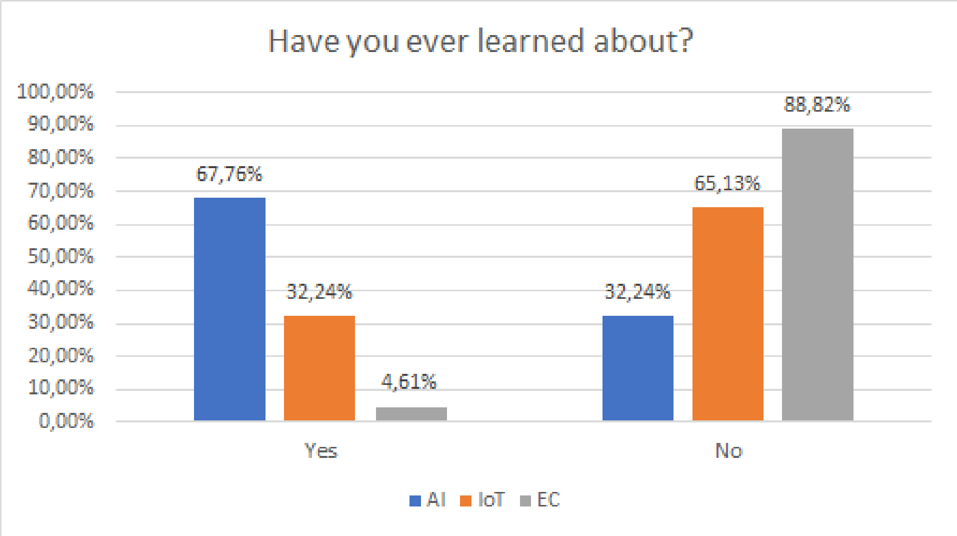


Figure 21 Responses – master

The survey conducted among students concerned, inter alia, seven AI areas. It can be concluded that that students declare the greatest knowledge in the field of machine learning which is shown in Figure 22. Moreover, the surveys went deep into each of the AI domains, as described in the seven points below.

- In terms of **machine learning techniques**, the level of knowledge of supervised learning techniques is the highest. The reason for this may be that the supervised learning methods are relatively simplest compared to the others (semi-supervised learning, unsupervised learning, reinforcement learning). These more advanced techniques are less popular among students. Especially reinforcement learning turned out to be the greatest need in the field of machine learning. Almost 30% of students have only a little knowledge about it, and almost 28% have no knowledge at all in this topic.
- Students' knowledge of **deep learning** was slightly lower compared to machine learning. The results of the surveys show a particularly low level of knowledge regarding Generative Adversarial Networks and transformers. Almost 50% of students do not know these deep learning models at all, and only about 10% know them at least to a moderate extent. Looking at the other deep learning models (convolutional neural networks and recurrent neural networks), the most well-known is the convolutional neural network, however over 22% do not know this model at all.

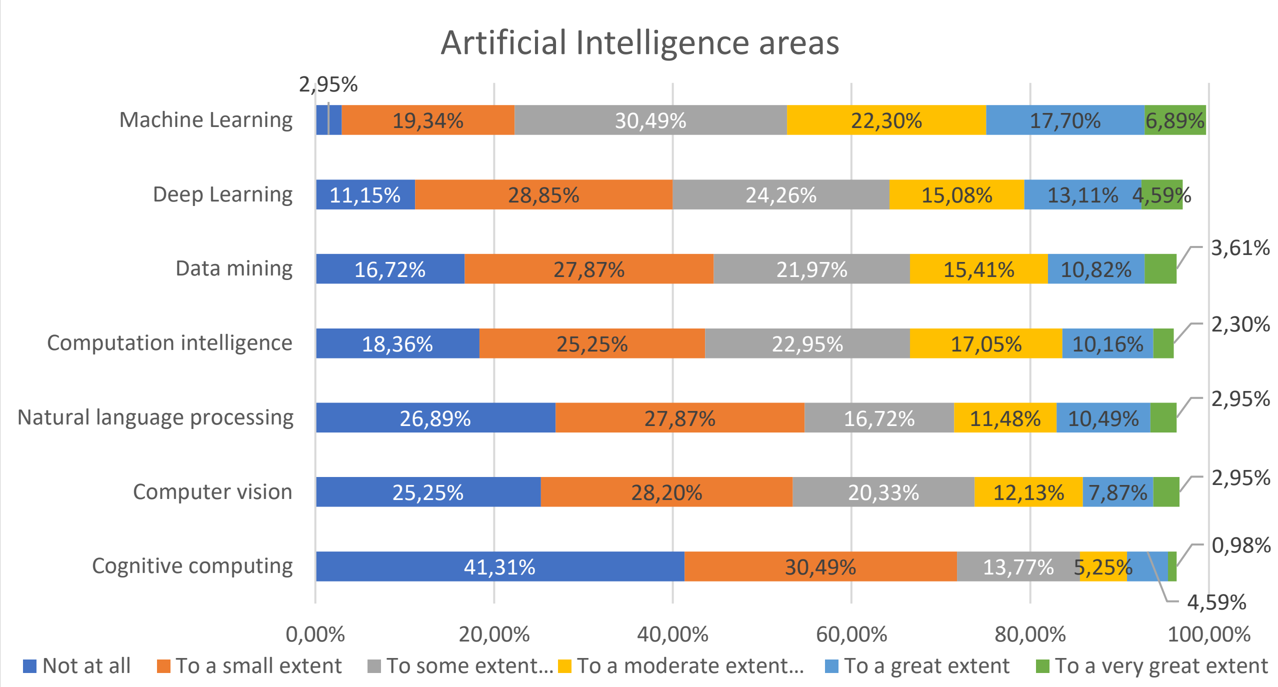


Figure 22 The level of students' knowledge in the Artificial Intelligence areas

- In the question about AI areas, students were asked, among other, about their knowledge of **data mining**. 79.67% of the respondents answered that they had any knowledge on this subject, and 29.84% of the students rated this knowledge at least at a moderate extent. One of the survey questions concerned six phases of the Cross Industry Standard Process for Data Mining (CRISP-DM). It is characteristic that students rate their knowledge the worst in the first and last phases of CRISP-DM. These are business understanding and deployment. The four internal phases of the CRISP-DM that are related to data understanding and processing, modeling and evaluation, are rated better. These results indicate the need to familiarize students with the business context of the analyzed data. This also draws attention to the implementation issues of the developed models in the business field. Data processing and modeling are not enough to master the entire data mining process and make it an added value in business applications. Without business understanding and deployment phases, even the best work of data analysts can be wasted.
- 77.70% of the students indicated that they had any knowledge about **computation intelligence**. Among computation intelligence aspects, most students are familiar with neural networks. About 20% of respondents considered their level of knowledge of neural networks to be high or very high. The situation is worse in the other aspects: fuzzy systems and genetic algorithms. In particular, fuzzy systems seems to be a field that requires more attention in the educational process, because more than a third of students declared no knowledge of fuzzy systems at all.
- The next AI area considered in the survey is **natural language processing** (NLP). The results show that this is one of the worst known areas of AI. Each of three NLP aspects (speech recognition, natural language generation, natural language translation) seems to be very poorly known among students. Even 40% of students do not know the issues related to natural language generation and natural language translation. The level of knowledge in the third aspect, speech recognition, is only slightly better.
- Another practical area of AI is **computer vision**. As in the previous area, the results show that the level of general knowledge is rather low. Among five aspects of computer vision (image classification, object localization and detection, image segmentation, domain adaptation, neural style transfer) the best known is image classification. On the other hand, the worst is the level of knowledge about domain adaptation and neural style transfer, which are unknown to over 45% of respondents. These two aspects are the most important needs in the context of increasing computer vision competences.

- The last analyzed area of AI is **cognitive computing**. This area was the worst in terms of students' knowledge. 41.31% of the respondents confirmed the lack of any knowledge about cognitive computing. Cognitive computing is divided into three aspects: interactive task learning, game playing agents, meta-algorithms in cognitive computing. Especially, meta-algorithms have by far the lowest level of students' knowledge. Most of the respondents (58.03%) have no knowledge of this topic. But results show that the entire area of cognitive computing may be a need in the context of broadening the students' knowledge in the field of widely understood artificial intelligence.

The questionnaires also asked about the **practical applications of AI**. The results show that optimization issues are known to 64.26% of students (see Figure 23).

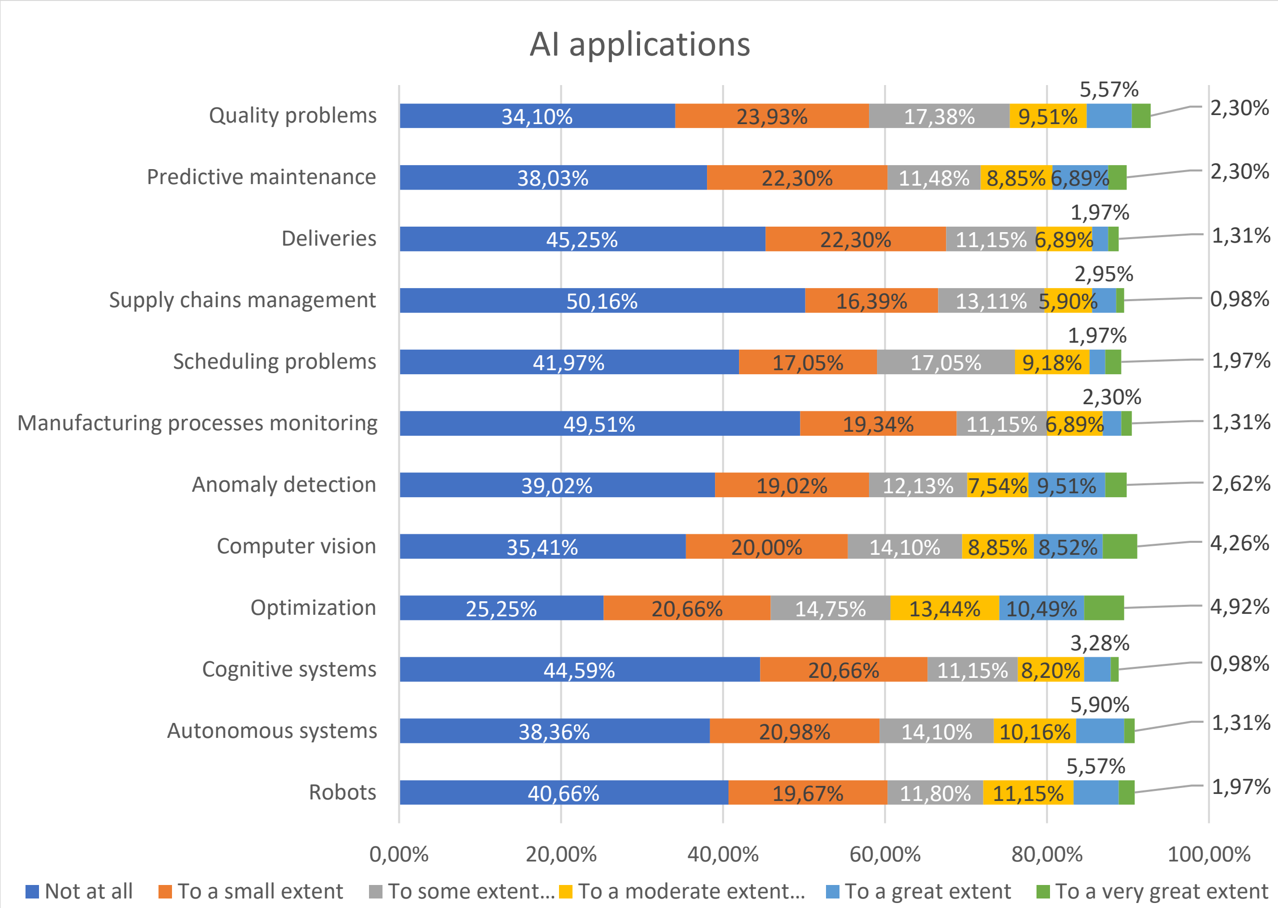


Figure 23 The level of students' knowledge about how to use AI in the following applications

In the case of the remaining eleven applications, the level of students' knowledge is lower—the percentage of students declaring knowledge of other applications does not exceed 60%. The fewest respondents can use AI in supply chains management—approximately 50% have never used AI in this area. In addition, 40 to 50% of students have no knowledge of how to use AI for manufacturing processes monitoring, deliveries, scheduling problems, cognitive systems and robots. These data may indicate the existence of a need to educate students primarily in the practical aspects of AI, in particular in the above-mentioned areas. Comparing the data on the applications of AI with the level of general students' knowledge about areas of AI, it can be concluded that students evaluate their general knowledge of methods, techniques and tools of artificial intelligence better than the knowledge about the applications of AI. This also indicates the need to pay attention to the practical aspect of using the acquired knowledge in the field of AI.

In the opened questions, students could express their views, inter alia, on **AI learning difficulties**. By far the largest number of students assessed that mastering math is the most difficult thing in learning AI. The difficulty in understanding the mathematics behind the AI algorithms was particularly emphasized. The second most frequently mentioned problem was understanding the theoretical issues related to AI. The students mentioned the following problems that made it difficult to understand the concept and intuition accompanying AI methods: the complex structure of AI issues, the “black-box nature” of many AI applications, many different approaches to solving problems, and large variety of AI areas. To sum up, the students most often mentioned difficulties with:

- understanding the concept of AI issues and how AI works (the complexity of issues causes a barrier that is difficult to overcome for people who want to start learning AI),
- mathematical issues behind AI,
- high complexity of algorithms,
- programming languages and coding,
- finding the right resources of tutorials and other materials to study.

From the IoT section of the survey, we can conclude that almost all students who have ever studied IoT know the background **information about IoT** (see Figure 24). About 95% of students also have at least a basic knowledge of IoT application scenarios. Looking at examples of practical issues related to IoT, students’ knowledge is more diverse. The best-known topics are computer networking, IoT architecture, and sensors. On the opposite side are topics such as: M2M industrial IoT protocols, searching for vulnerabilities, distribution of computing processes in IoT networks, IoT maintenance, cryptography. In each of these topics, at least 30% of students do not have any knowledge at all. Focusing on these weak-known topics may be one of the most important needs in IoT education.

One of the questions checks whether students know **how to apply IoT in different contexts**: quality problems, machine condition monitoring, robotics, deliveries, market behaviour, data management, support decision-making, process parameters monitoring, logistics. The results show that students’ knowledge in all the contexts considered is lower compared to the general IoT knowledge from the previous question (see Figure 25). High or very high level of knowledge in all contexts is declared by less than 12% of students. In all contexts, at least 23% of students declare the lack of any knowledge of using IoT. It can be concluded that all considered contexts of IoT require more attention in education process, particularly market behaviour, logistics, and deliveries, which are characterized by the lowest level of students’ knowledge.

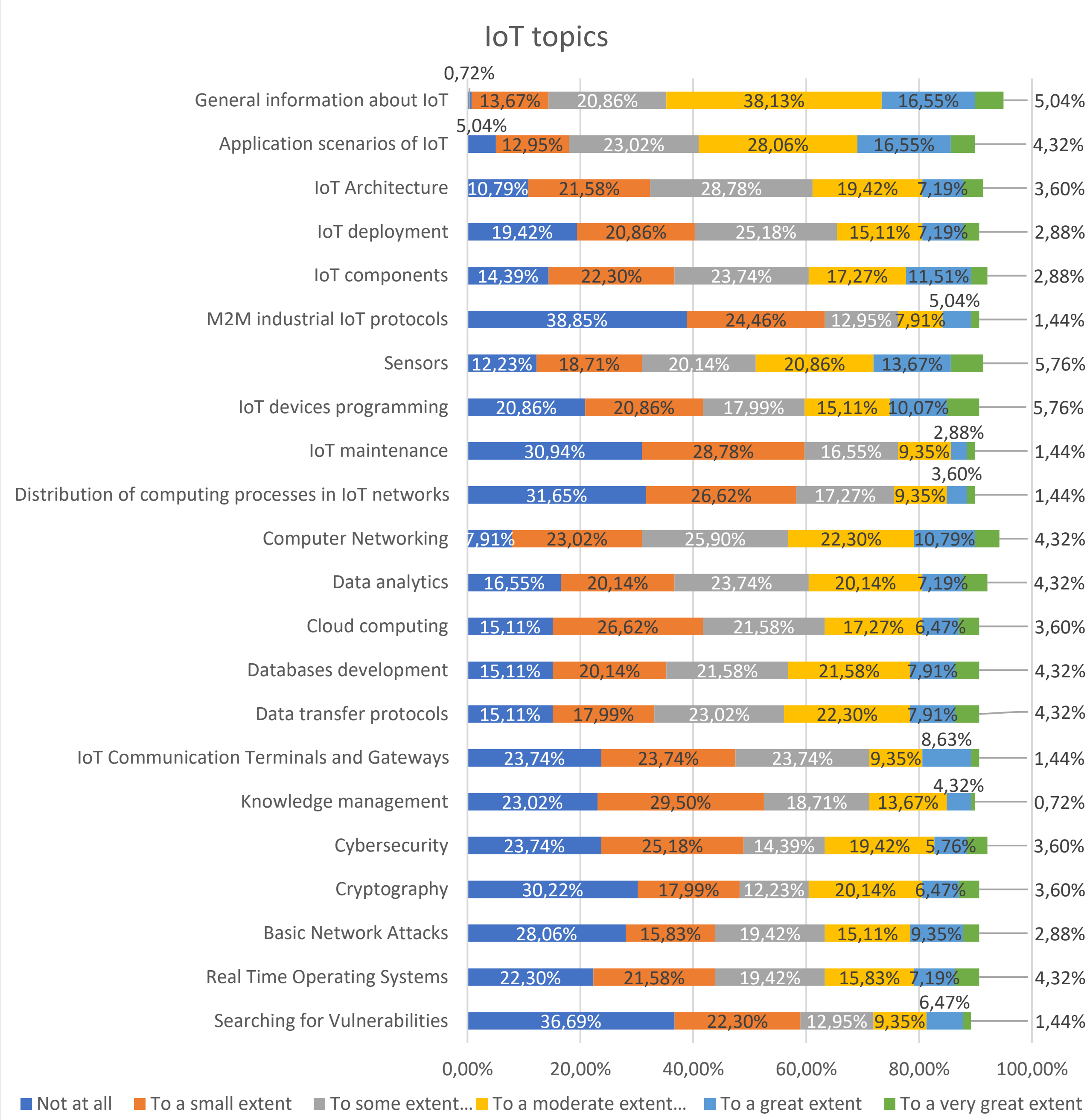


Figure 24 The level of students' knowledge connected with the presented IoT topics

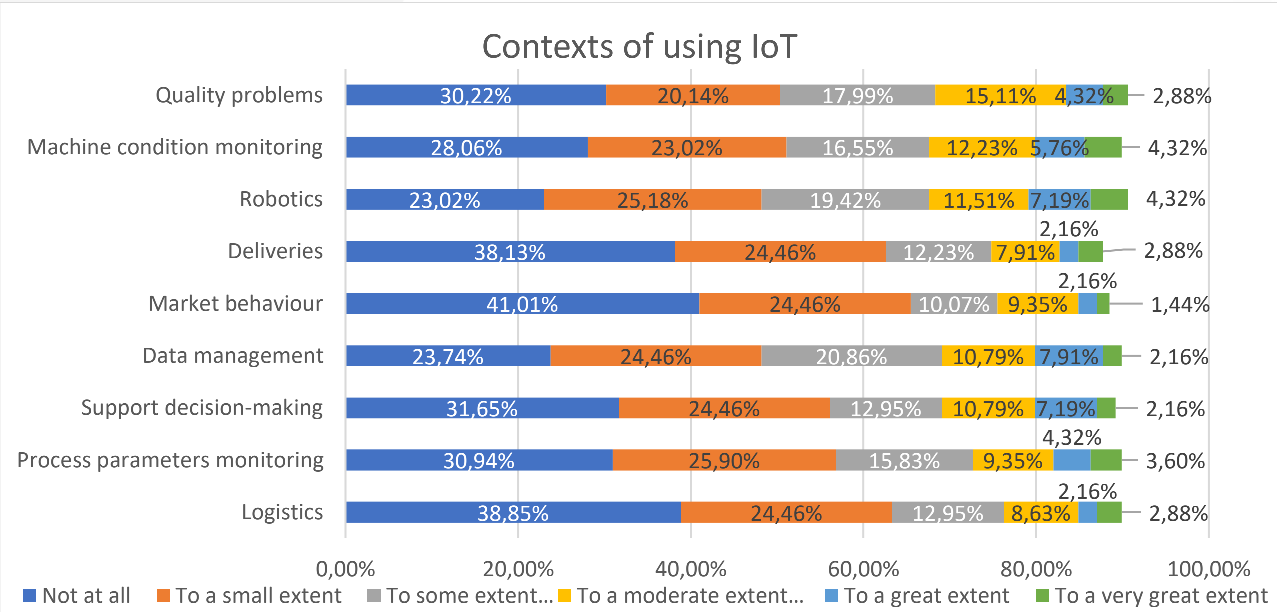


Figure 25 The level of students' knowledge about how to use IoT in different context

Students most often emphasized the **difficulties in understanding the concepts related to IoT**. This problem is mainly caused by the high complexity of IoT. The high complexity requires acquiring lots of information and knowledge to get started with IoT. It's also problematic to understand when something in IoT should be used and how to choose between different solutions. The multitude of IoT applications became a problem for students. IoT is a very broad term and many things can be classified under it. Therefore, nailing down the concept is more difficult when there are so many examples and possibilities in IoT. Many of the responses concerned the infrastructure for IoT. Infrastructure issues were mentioned as often in the responses as issues related to the general concept. In the context of infrastructure, students indicated difficulties related to:

- electronics (especially microcontrollers),
- protocols,
- sensors (especially connect sensors to the internet),
- the need to purchase an appropriate hardware,
- maintenance of IoT,
- combination of hardware and software interoperation,
- integration of multiple technologies and platforms,
- finding an appropriate environment.

**By far the least known issue to students is EC.** Only 23 respondents replied that they had learned about this. All students who have ever studied EC know the general concept about it (see Figure 26). A similar situation can be seen in the case of EC applications—all respondents who answered this question have at least a basic knowledge of EC applications. Looking at the other three EC topics (privacy and security, scalability and reliability, speed and efficiency), it can be seen that students' knowledge of them is slightly less. None of the respondents assessed their knowledge at a very high level. In addition, about 30% of students do not know these topics at all or know them little. Thus, these topics may indicate the potential needs in the field of EC education.

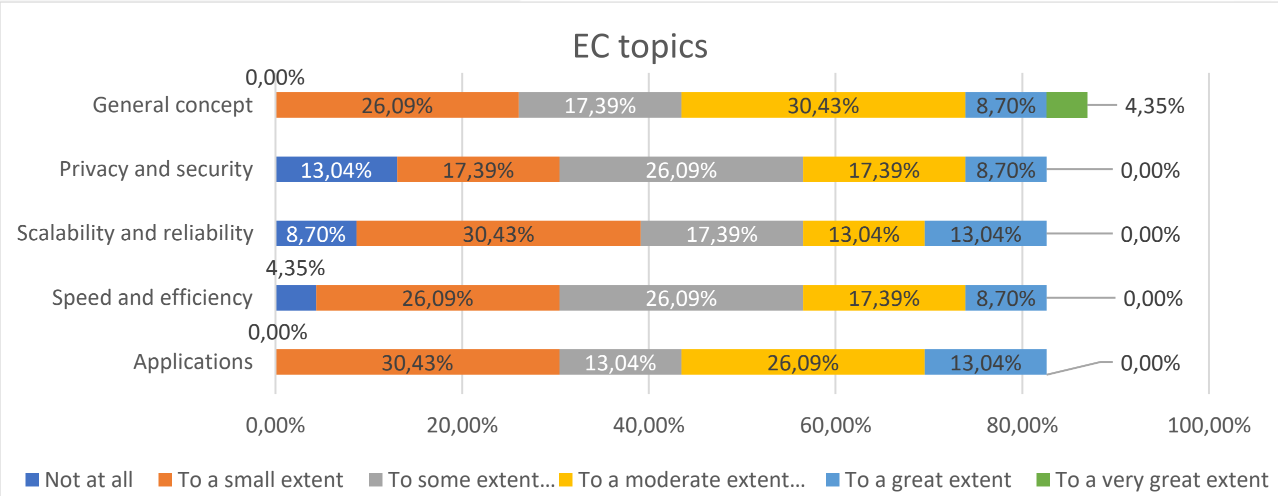


Figure 26 The level of students' knowledge on the presented topics in the area of Edge Computing

One of the questions concerned **selected technologies that are used in EC implementations**. These are:

- Mobile Edge Computing,
- Fog computing,
- Service composition and service-oriented computing,
- Micro data centers,

- Container technology,
- Azure edge.

The data shows that the smallest percentage of students knows Azure edge (47.83%). Moreover, in the case of three technologies (mobile EC, fog computing, service composition and service-oriented computing), none of the students declared a high or very high level of knowledge. Thus, education in these topics may be particularly needed to supplement students' knowledge.

Students were also asked about their knowledge of **algorithms and techniques related to EC implementation**:

- Distributed computing,
- Distributed storage,
- Reliability and fault tolerance,
- Containerization,
- Energy efficiency,
- Data replication,
- Efficiently collecting, aggregating, and moving data.

Due to the fact that about 20% of respondents did not indicate any level of knowledge, and at least a dozen or so percent of respondents do not know the issues at all, it can be concluded that each of these issues may be a potential need in the EC education process.

Additionally, the students assessed the extent to which they carry out **activities related to the EC**. The three least frequently mentioned activities in this question may indicate deficiencies in the educational process. These are:

- designing an edge computing architecture,
- implementing software solutions using EC middlewares,
- doing data analytics in EC environments.

These activities can be identified as one of the most essential needs that should be emphasized in the EC education process.

In another question the students the extent to which they use **hardware / software that enables them to use EC**. Results show that none of the five following tools are particularly widespread among students:

- FPGAs,
- Edge accelerators,
- Azure IoT Edge,
- AWS IoT Greengrass,
- RTOS.

The largest number of respondents indicated that they use Azure IoT Edge to a small extent (30.43%). However, as many as 47.83% of students have never used this tool. In the case of other tools, the percentage of students who have never used them is even greater. Therefore, education in all of the hardware and software mentioned in this question is a potential need to broaden the skills of using this tools that enabling EC platforms.

The last closed question in the survey concerned the extent to which students know the **possibilities of using EC**. The fewest students indicate that they have any knowledge of EC applications such as: autonomous products, autonomous production planning system, augmented reality, autonomy in energy networks (see Figure 27). Increasing the level of knowledge in these EC applications may be the most desirable due to, among other, the importance of these applications in today's enterprises that implement the Industry 4.0 concept.

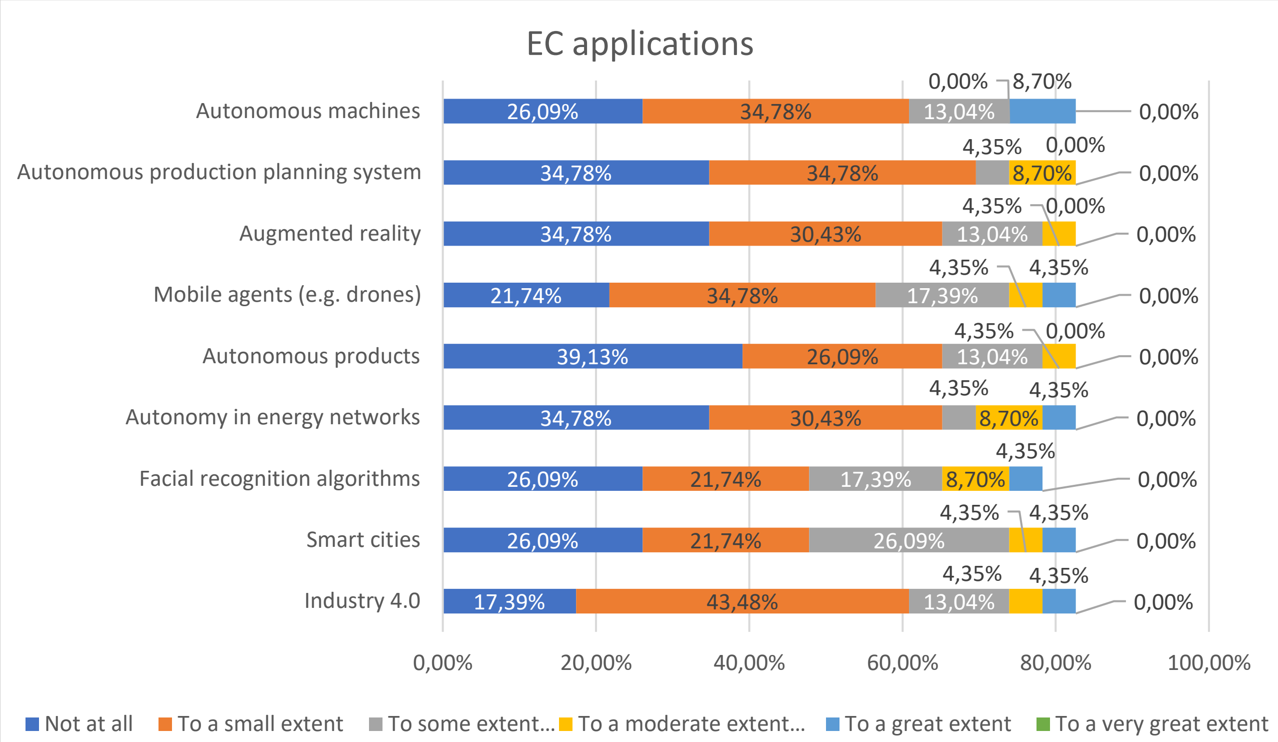


Figure 27 The level of students' knowledge on Edge Computing in the following applications

## 1.6 Recommendations for training and teaching activities

In order to propose recommendations for courses and trainings on AI and ML on the edge for I-IOT, it is worth considering the answers to the survey questions in which the students indicate some difficulties and lacks in the education process. In the survey, students also indicated what could support them in learning AI, IoT and EC. All this information may prove useful in defining new learning content.

Several questions in the survey was about learning techniques such as lectures and labs. Figure 28 shows the level of students' assessment of the usefulness of the learning techniques to teach AI. According to the students, laboratory classes are the most useful. More than half of the respondents indicated a high or very high usefulness of this form of classes. Following are Project Based Learning (individual work), Project Based Learning (team work) and workshops. The least useful are lectures, e-learning and general review of an issue. Generally speaking, each of the analyzed learning techniques has its supporters—at least 20% of the students indicated a high or very high usefulness of each technique.

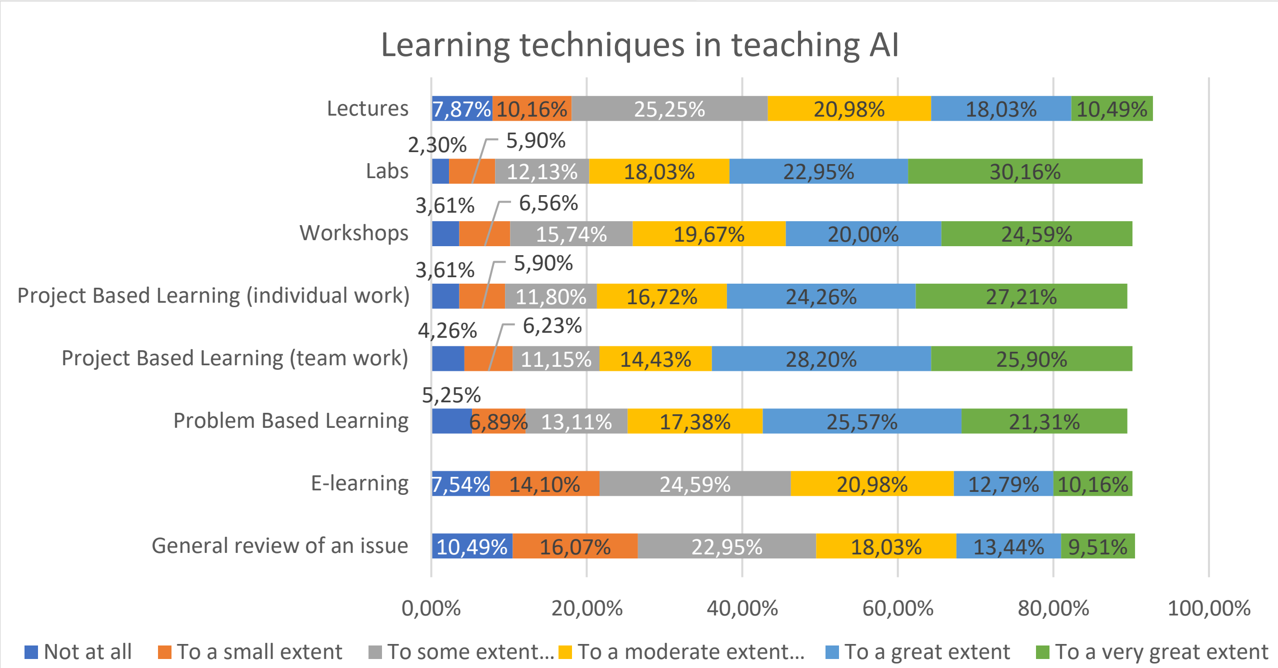


Figure 28 The level of students' assessment of the usefulness of the learning techniques to teach AI

Moreover, the survey results show that the knowledge of students involved in AI-projects is greater than that of other students. In order to check this relationship, the AI knowledge index was used, calculated as follows for each student:

1. We take into account 65 responses to closed questions covering only AI-related issues,
2. We assign the following values to answer variants: 0 "Not at all" and empty answer, 1 "To a small extent", 2 "To some extent", 3 "To a moderate extent", 4 "To a great extent", 5 "To a very great extent",
3. We sum up the values from all 65 responses for a given student.

Figure 29 shows the box-whisker plots concerning the AI knowledge index computed for students not-involved in any AI-project as well as for students involved in at least one AI project. It can be concluded that students participating in AI-projects are characterized by a greater level of knowledge in the field of AI compared to other students. Additionally, the Mann-Whitney U test was used to show that the difference between the two groups is statistically significant (the significance level $\alpha$ =0.05). These results highlight the need for education in a project-based approach. Practical skills resulting from the involving of projects can translate into general knowledge in a given area.

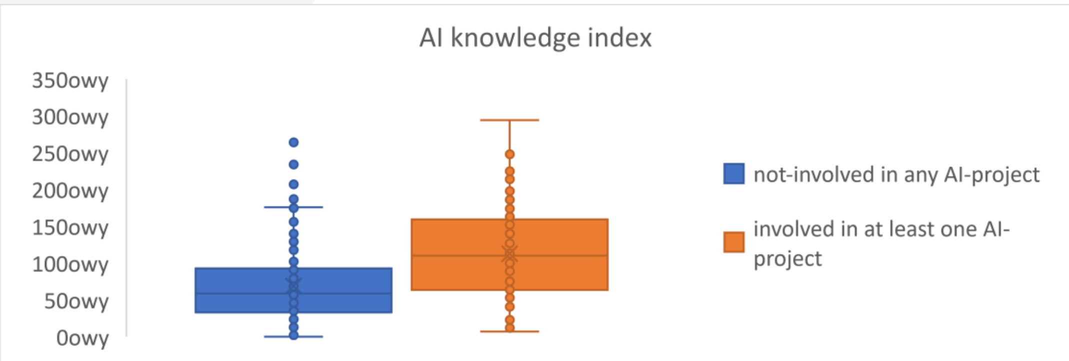


Figure 29 Box-whisker plots concerning the AI knowledge index for the two compared groups of students

To sum it up, there is a clear preference towards teaching practical skills in laboratory classes, projects and workshops. Practical realization of some tasks (e.g. in a project) gives students the most knowledge and skills in the field of AI. Analogous results were obtained from the IoT section of the survey.

**In order to propose better tailored AI education, it is also worth considering what is currently missing in AI education.** This issue was related to one of the opened questions in the survey.

- The most common answer was the lack of practical elements in the AI education process, and thus **a right balance between theory and practice is missing**.
- Students suggested that there should be more practical applications of AI (teaching AI techniques by applying them on a project that you can choice), as well as more: **real-life examples, real-world datasets, activities, workshops, and solving simple tasks**. According to the respondents, showing the practical context of AI would facilitate the implementation of AI solutions.
- There is also no information on how to: integrate different AI platforms, train AI models on cloud platforms, deploy models and perform online learning.
- It is also desirable to create: a centralized place to receive proven tested techniques, an environment to experiment the projects students are working on, a well-organized online site with projects to work on for self-study and in groups, with a forum where people can help each other.

According to the students, **the number of laboratory and project classes at universities should be increased**. This remark was also one of the most frequent. Classes should be rich in a variety of case studies, and education could be carried out in partnership with some companies, what is currently missing. There is also no easy access to sophisticated AI software, modern tools, easy to understand articles, books and other materials to deepen knowledge (especially in native languages).

In addition to the emphasis on practical education, some students also postulate to **pay attention to theoretical issues that will enable understanding of the necessary basics** (e.g. how an AI works, how AI is coded, what can AI do with a data, why a specific approach works).

The answers also include **proposals for some modifications to the course of AI education**:

- showing the basic things of AI in earlier years of education (high school),
- starting AI teaching from bachelor level,
- introducing performance-based learning,
- more programming classes,
- more lessons about neural networks,
- using open source tools like Tensorflow,
- using online open classrooms,
- teaching AI related to society,
- teaching how to overcome the difficulties of developing AI nowadays, due to ethical reasons.

Apart from that, **students suggest increasing the emphasis on**:

- importance of data,
- understanding algorithms,
- mathematical background (a better explanation of the fundamental mathematics and how they relate to the algorithm implementations).

Other important postulates are: education process should be more specialized in specific fields of AI, exercises should be based on real problems which students has to face in everyday life, the content of education should be updated to keep up with any novelties related to AI (e.g. modern AI applications).

Some respondents pointed to the **general shortcomings of the education process**, such as:

- too few hours for learning AI,
- too few competent teachers,
- poor access to simple explanations of AI and good classes.

**Summing up, the students mainly point out the following shortcomings:**

- too few practical issues and applications of AI in education,
- lack of real-life case studies primarily drawn from business and companies,
- too few laboratories, projects and workshops in AI education,
- insufficient mathematical preparation of students to learn AI;
- poor access to good-quality study materials and modern AI tools, which will be constantly updated in line with emerging novelties,
- too little emphasis on a good understanding of the basics of AI during education.

The last question in the AI section was about **things that could support students in AI learning process**. The students most often mentioned the need to put more emphasis on:

- practical examples of AI application,
- increasing the number of project classes, workshops, and labs, learning by doing, team work, additional classes for non-advanced (teaching step by step with a large number of examples and case studies),
- teaching programming (especially in Python).

Several respondents pointed to the usefulness of internships, learning with individual assistance, and also indicated specific solutions to support learning (IBM Labs, Coursera, virtual machines with implemented CUDA graphic cards).

**Some students need:**

- more materials and tutorials available online,
- the state of the art about techniques in every domain of AI,
- books that don't only focus on the AI structure, but also on the problem AI can solve.

Students suggest that materials and exercises for studying AI could be collected in the form of a consistent platform.

**Also important for students are:**

- access to open-source software,
- access to large quantities of computing resources,
- centralized place to receive proven tested techniques,
- infrastructure (e.g. robots) on which AI applications can be tested.

There is also a proposal to organize competitions for solving some problems with AI (such as on the Kaggle).

Students also paid attention to **general learning needs**: access to qualified teachers and to professionals (interaction with companies), financial support, funded projects that can provide students with the necessary equipment in learning the AI process, structured learning paths with theoretical references for a deeper AI understanding, summer schools, and access to more free time.

**<u>Summing up, apart from the needs mentioned in the previous question, the students in this question pointed to the following needs:</u>**

- participation in internships, joint international projects, and competitions;
- infrastructure for testing AI applications,
- appropriate equipment (more computing resources),
- contact with companies and professionals,
- online base of educational materials and AI tools;
- more programming lessons.

In another opened question, students were asked **what is missing in the IoT education process.** The most common answer is the lack of an adequate number of project-based learning and laboratory classes, as well as too little emphasis on teaching practical skills related to IoT (too few solving real-world problems, too little variety of case studies, the lack of application driven education). Showing complex designs from scratch is also lacking.

Students pay attention to the shortcomings in educating the basics of IoT, which makes it difficult to understand what IoT is and what is its essence.

There is also a lack of practice on hardware, so students do not have the necessary experience to deal with IoT.

Some respondents indicate specific issues that receive insufficient attention in the education process. These are: privacy, OS, practice on sensors.

IoT learning is also hampered by:

- the low availability of IoT in the content of courses at universities,
- insufficient access to the standard documentation,
- lack of adequate resources,
- poor quality of code found online,
- difficulty in applying concepts in a real environment to see how it could work.

**<u>In turn, according to the students, following needs arise from the students' responses that could facilitate the learning process of IoT:</u>**

- teaching the theory behind IoT to understand when and why IoT is useful,
- more project-based learning and workshops (e.g. small weekly projects or projects combining all IoT techniques) including examples and practical activities (real scenarios and cases),
- more information on sensors, energy consumption, circuitry,
- increasing the availability of IoT devices (digital twins, simulators) and easy to use technologies,
- more accessible information, materials and online courses,
- teaching C ++, Python, JavaScript,
- introducing subjects at universities entirely dedicated to IoT.

In the case of EC, two students replied that online seminars and placing the EC at an earlier stage of education learning EC could **facilitate the learning process of EC**.

**Based on results from the <u>AI</u> section of the survey, it can be summarized that the student need:**

- a better understanding of the mathematical issues behind AI (a better explanation of the fundamental mathematics and how they relate to the algorithm implementations);

- a better explanation of AI theoretical issues to understand the concept and intuition accompanying AI methods, in particular in the initial stage of AI education;
- a better balance of the amount of information provided during classes (problem of overloading courses—too much information provided during one class);
- a right balance between theory and practice during AI teaching;
- providing access to data sets and hardware facilitating studying AI;
- highlighting aspects of preparing data for AI, e.g. data transformation in such a way that a computer can interpret the data;
- putting more emphasis on teaching practical AI applications, especially in AI areas such as cognitive computing (interactive task learning, game playing agents, meta-algorithms), natural language processing (speech recognition, natural language generation, natural language translation), computer vision (domain adaptation and neural style transfer);
- a greater emphasis on teaching more advanced machine learning techniques, in particular reinforcement learning;
- enriching the content of courses at universities with issues related to real-life examples based on real-world datasets;
- enriching the content of courses at universities with issues related to deep learning;
- more information on the first and last steps of CRISP-DM (business understanding and deployment), which means the need to familiarize students with the business context of the analyzed data and also draws attention to the implementation issues of the developed models in the business field;
- more information on fuzzy logic when teaching computation intelligence aspects;
- more programming classes (especially in Python and Matlab);
- information on the use of Matlab and Jupyter Notebook software in the context of AI;
- showing how to apply AI especially in processes monitoring, deliveries, scheduling problems, cognitive systems and robots;
- greater involvement in projects, especially in areas such as autonomous cars and robots, chatbot development, computer vision, healthcare, text mining, natural language processing, finance, risk prediction, game development, time series analysis, signal processing;
- better access to right resources of tutorials and other materials to study: articles, books and other materials to deepen knowledge (especially in native languages);
- more free time to study AI, IoT and EC;
- a centralized place to receive proven tested techniques;
- an environment to experiment the projects students are working on;
- a well-organized online site with projects to work on for self-study and to work in groups;
- increasing the number of laboratory and design hours at universities;
- education in partnership with business, companies, and professionals;
- better access to sophisticated AI software and modern AI tools;
- showing the basic things of AI in earlier years of education (high school);
- starting AI teaching from bachelor level;
- introducing performance-based learning;
- more lessons about neural networks;
- education process which is more specialized in specific fields of AI;
- exercises that based on real problems which students has to face in everyday life;
- the content of education which is updated to keep up with any novelties;
- more committed and competent teachers for AI education;
- emphasis on a good understanding of AI algorithms;
- increasing the number of project classes, workshops, and labs, learning by doing, team work, additional classes for non-advanced;

- access to open-source software and appropriate equipment (more computing resources);
- participation in internships, joint international projects, and competitions;
- infrastructure for testing AI applications;
- online base of educational materials and AI tools.

**Based on results from the IoT section of the survey, it can be summarized that the student need:**

- a better explanation of IoT concepts;
- better understanding when something in IoT should be used and how to choose between different IoT solutions;
- better access to infrastructure for IoT;
- more attention on integration of multiple technologies and platforms of IoT;
- adequate resources and right documentation about IoT technologies;
- more emphasis on applying IoT concepts in a real-world environment;
- adequate number of project-based learning and laboratory classes for teaching IoT;
- more emphasis on teaching practical skills related to IoT (increasing the diversity of case studies, application driven education);
- better teaching the basics of IoT which will help you understand what IoT is and what is its essence;
- more attention in the education process on privacy, OS, energy consumption, circuitry, practice on sensors, and practice on hardware;
- better availability of IoT in the content of courses at universities (introducing subjects at universities entirely dedicated to IoT);
- increasing the availability of IoT devices (digital twins, simulators) and easy to use technologies;
- more accessible information, materials and online courses about IoT;
- teaching C ++, Python, JavaScript in the context of IoT;
- focusing especially on M2M industrial IoT protocols, searching for vulnerabilities, distribution of computing processes in IoT networks, IoT maintenance, and cryptography;
- place special attention on IoT applications in market behavior, logistics, and deliveries;
- the presence of education in the field of Application Programming Interface, data processing, data transformation, and big data management which are most helpful in mastering IoT;
- the presence of Arudino IoT in the education process.

**Based on results from the EC section of the survey, it can be summarized that the student need:**

- increasing education in the field of privacy and security, scalability and reliability, speed and efficiency in the context of EC;
- increasing education in the field of mobile EC, fog computing, service composition and service-oriented computing;
- enhancing education on algorithms / techniques used in EC implementation;
- pay particular attention in the education process to designing an edge computing architecture, implementing software solutions using EC middlewares as well as doing data analytics in EC environments;
- broad the skills of using hardware and software that enabling EC platforms;
- putting more emphasis on EC applications, especially in autonomous products, autonomous production planning system, augmented reality, autonomy in energy networks;

- access to online EC seminars;
- emphasis on implementations of algorithms related to EC;
- teaching EC at an earlier stage of education.

Moreover, **interdisciplinary teams can be created** between the students who study different engineering fields. It is important to identify the possibilities to realize joint projects. This can be difficult when the programs of the study are different in different courses. The courses of the students in different fields should be the same length, should start and finish in the same moment. This can be difficult because the rules can be different for different courses, in different universities and in different countries.

Therefore, for the academics, who would like to apply the presented here recommendations it will be necessary to find the possible collaborators from other fields, other universities or other countries

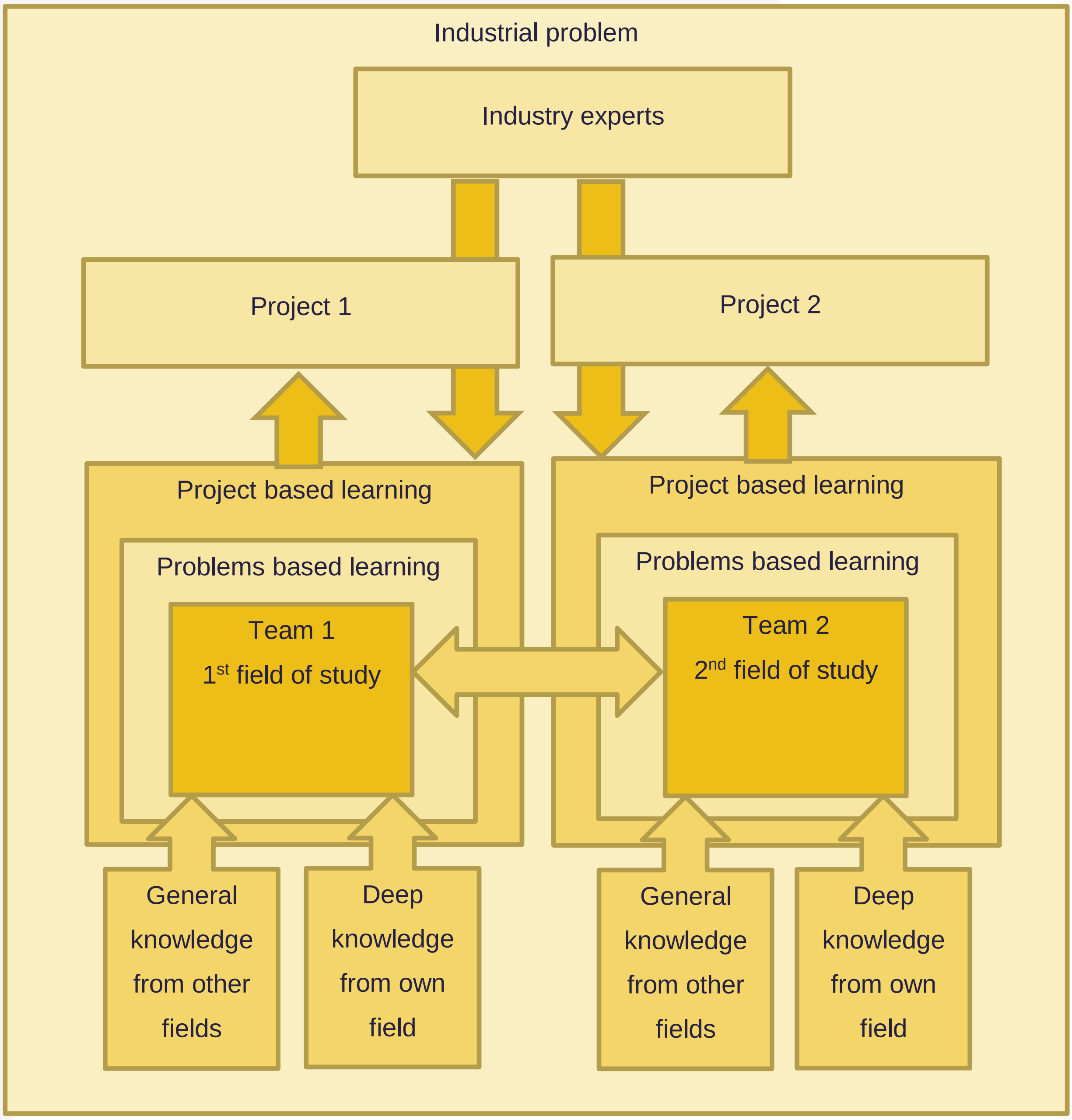


Figure 30 Scheme of the interdisciplinary teams collaboration in order to solve the same studied industrial problem

Learning by doing is one of the most effective way of teaching. To solve a certain industrial problem the students must focus on what is important, must gain needed knowledge, must improve needed skills, must collaborate to achieve a goal. It is because in many cases the problems are complex and need expertise from different disciplines. If additionally industry is presenting to the students the current problem which have to solve, the industrial experts will be interested in supporting students who will analyze the problem. This way a win-win situation is created.

## 1.7 Statistical analysis

The results obtained in the student's surveys were subjected to statistical analysis what is presented in this document. The results were detailed to the answers for the bachelor and master level of studies. The results of the survey were stored in a dataset which enabled its further statistical analysis. With the use of the statistical analysis the hypotheses developed was tested. The attribute data coming from Likert scale were used: Not at all; To a small extent; To some extent; To a moderate extent; To a great extent; To a very great extent. The goal of this bachelor/master level of knowledge comparison was to show where is the biggest students level gap, to what level bachelor/master students know the researched topics.
In the analysis Chi$^2$ test was used. A general structure of the tested hypotheses was as follow: **H0: There is no difference between the knowledge of bachelor level of studies and masters' students.** The level of confidence was assumed equal to 0.05. So that every p-value result of lower values than 0.05 reject the assumed hypothesis, that means that there is significant difference of the level of knowledge possessed by bachelor and masters' students. Also, the average level of knowledge was calculated to show the actual level of knowledge possessed by bachelor and master students.
Table 15 presents the results of Chi2 test highlighting where is statistically justified difference between bachelor or master students average level of knowledge an whose knowledge is higher (in green).

Table 15 Statistical analysis results: Is there a statistically justified difference between the knowledge of engineering and master's students? Green color indicates higher average value of knowledge level; "-"sign means not enough data to perform statistical analysis

| Topic/Technology | p-value | Average level of knowledge (Bachelor, Master) |
|---|---|---|
| **AI Areas** | | |
| Machine Learning | **0,048** | **Bachelor – 3.3, Master – 3.8** |
| Deep Learning | 0,129 | Bachelor – 2.8, Master – 3.3 |
| Data mining | **0,013** | **Bachelor – 2.7, Master – 3.2** |
| Computation intelligence | 0,440 | Bachelor – 2.7, Master – 2.9 |
| Natural language processing | 0,947 | Bachelor – 2.5, Master – 2.6 |

| | | |
|---|---|---|
| Computer vision | **0,022** | **Bachelor – 2.4, Master – 2.9** |
| Cognitive computing | - | Bachelor – 1.9, Master – 2.0 |
| **AI applications** | | |
| Quality problems | 0,211 | Bachelor – 2.2, Master – 2.5 |
| Predictive maintenance | 0,186 | Bachelor – 2.1, Master – 2.5 |
| Deliveries | 0,385 | Bachelor – 1.8, Master – 1.9 |
| Supply chains management | - | Bachelor – 1.7, Master – 1.9 |
| Scheduling problems | 0,748 | Bachelor – 2, Master – 2.1 |
| Manufacturing processes monitoring | - | Bachelor – 1.7, Master – 2.0 |
| Anomaly detection | **0,001** | **Bachelor – 2.0, Master – 2.7** |
| Computer vision | 0,417 | Bachelor – 2.3, Master – 2.7 |
| Optimization | 0,217 | Bachelor – 2.6, Master – 3.0 |
| Cognitive systems | 0,912 | Bachelor – 1.9, Master – 2.0 |
| Autonomous systems | 0,531 | Bachelor – 2.2, Master – 2.3 |
| Robots | 0,495 | Bachelor – 2.3, Master – 2.2 |
| **IoT context** | | |
| Quality problems | - | Bachelor – 2.7, Master – 2.3 |
| Machine condition monitoring | 0,908 | Bachelor – 2.4, Master – 2.5 |
| Robotics | 0,506 | Bachelor – 2.6, Master – 2.5 |
| Deliveries | - | Bachelor – 2.2, Master – 2.0 |
| Market behavior | - | Bachelor – 2.0, Master – 2.1 |
| Data management | - | Bachelor – 2.5, Master – 2.6 |
| Support decision-making | | Bachelor – 2.2, Master – 2.6 |
| Process parameters monitoring | 0,934 | Bachelor – 2.2, Master – 2.3 |
| Logistics | - | Bachelor – 2.2, Master – 1.9 |
| **EC topics** | | |
| General concept | - | Bachelor – 3.4, Master – 3 |
| Privacy and security | - | Bachelor – 2.8, Master – 2.8 |
| Scalability and reliability | - | Bachelor – 2.9, Master – 2.8 |
| Speed and efficiency | - | Bachelor – 3.3, Master – 2.4 |
| Applications | - | Bachelor – 3.4, Master – 3,0 |

Besides calculating the p-value to confirm or reject assumed hypothesis, there has been calculated average level of knowledge for bachelor and master students. For most of the analyzed topics an average level of knowledge was higher for Master students, so that it can be assumed that Master students are better prepared in the area at least of AI. However, for some of the topics an average level of knowledge was higher for **bachelor students**, particularly for, **AI applications: Robotics; IoT context: Quality problems, Robotics, Deliveries, Logistics; EC topics: General concept, Scalability and reliability, Speed and efficiency, Applications.** Based on the average value of knowledge of bachelor and master students it can be seen that the lowest average value is for AI applications: Supply chain management (Bachelor – 1.7, Master – 1.9), Deliveries (Bachelor – 1.8, Master – 1.9) and Manufacturing processes monitoring (Bachelor – 1.7, Master – 2.0), while the highest average value is for AI Areas: Machine Learning Bachelor – 3.3, Master – 3.8, EC topics: General concept (Bachelor – 3.4, Master – 3) and Applications (Bachelor – 3.4, Master – 3,0).

Based on the obtained statistical analyses results we can see in what areas there is the significant statistical difference and because of that there is some gap in the knowledge possessed by bachelor and master students.

It can be seen that the p-value lower than 0.05 is within the following topics:

- **AI Areas:**
  - **Machine Learning,**
  - **Data mining,**
  - **Computer Vision.**
- **AI applications:**
  - **Anomaly detection.**

For the above areas where there is the highest difference in the knowledge of bachelor and master students, an additional graphical analysis has been performed. **Figures 31-34** present detailed bachelor and master students' responses to see within which options there is the most significant difference. There are also some topics for which there have not been enough data to perform statistical analyses and those topics are indicated as "-" for the p-value.

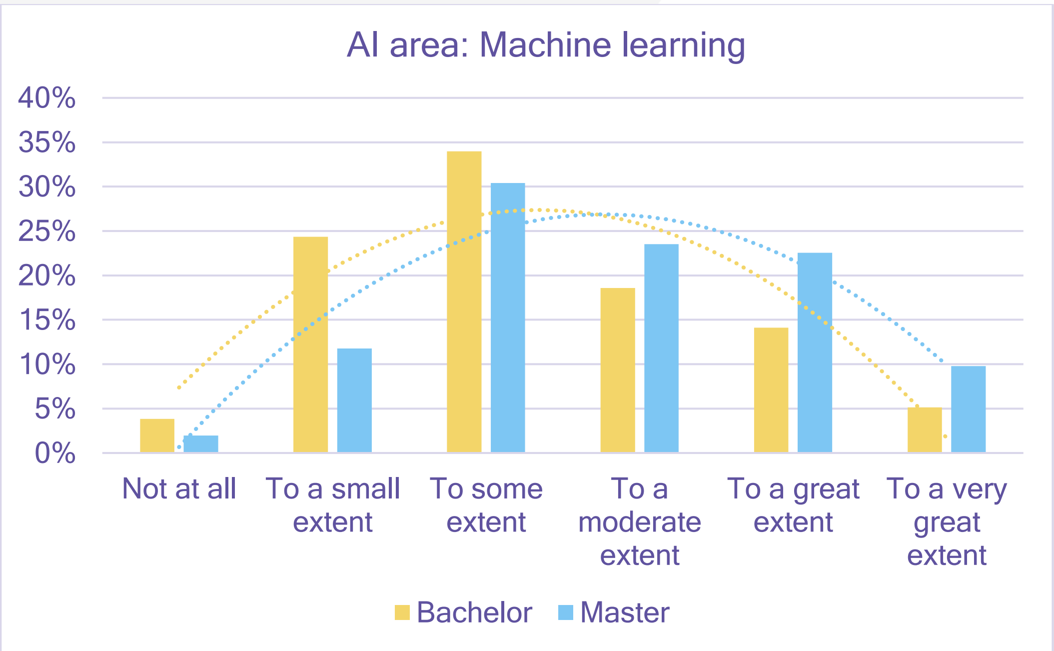


**Figure 31** AI area: Machine Learning detailed responses of bachelor and master students

Based on **Figure 31** it can be seen that for the Machine learning, the most bachelor and master students indicate to some extent answer, while the lowest number of students choose not at all. The highest difference is within to a small extent option and is about 13%.

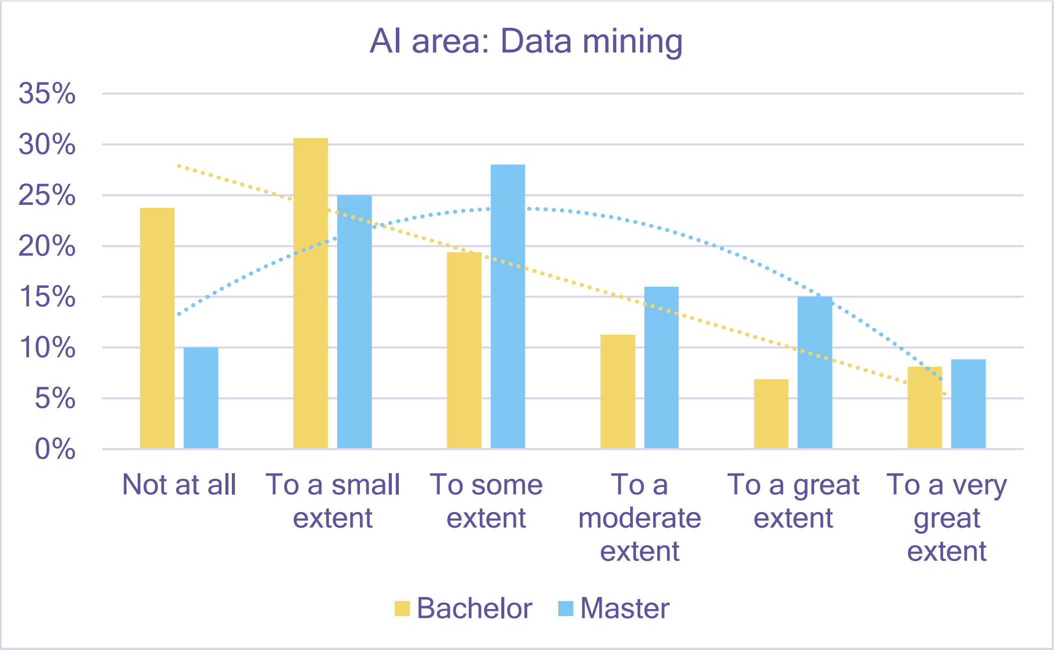


**Figure 32** AI area: Data mining detailed responses of bachelor and master students

**Figure 32** indicates that most of the bachelor students choose not at all (over 20%) or to a small extent response (30%), while master student mostly indicates to some extent (over 25%) and to a small extent (25%). Also, in the area of an answer to a moderate, great and very great extent there is higher value of master student's percentage that choose those option in comparison to bachelor student, so that it can be conclude that master students have more knowledge in this researched area.

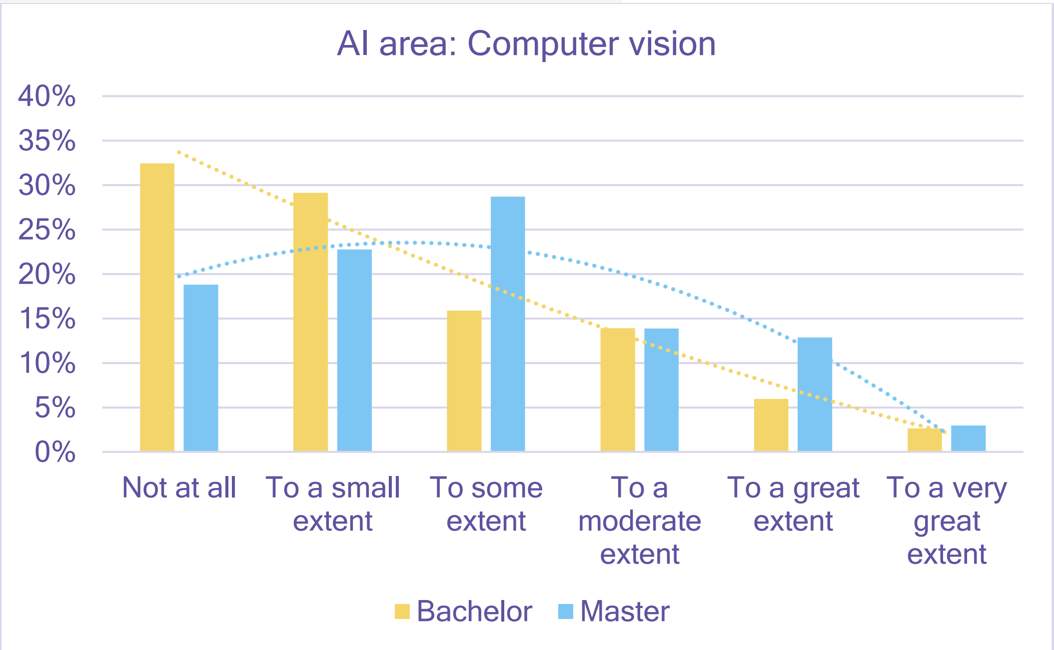


**Figure 33** AI area: Computer vision detailed responses of bachelor and master students

Similarly, to the previous **Figure 32,** the **Figure 33** presents that more master students know the topic of computer vision. Most of the bachelor students choose not at all (over 30%), while masters to some extent (about 30%).

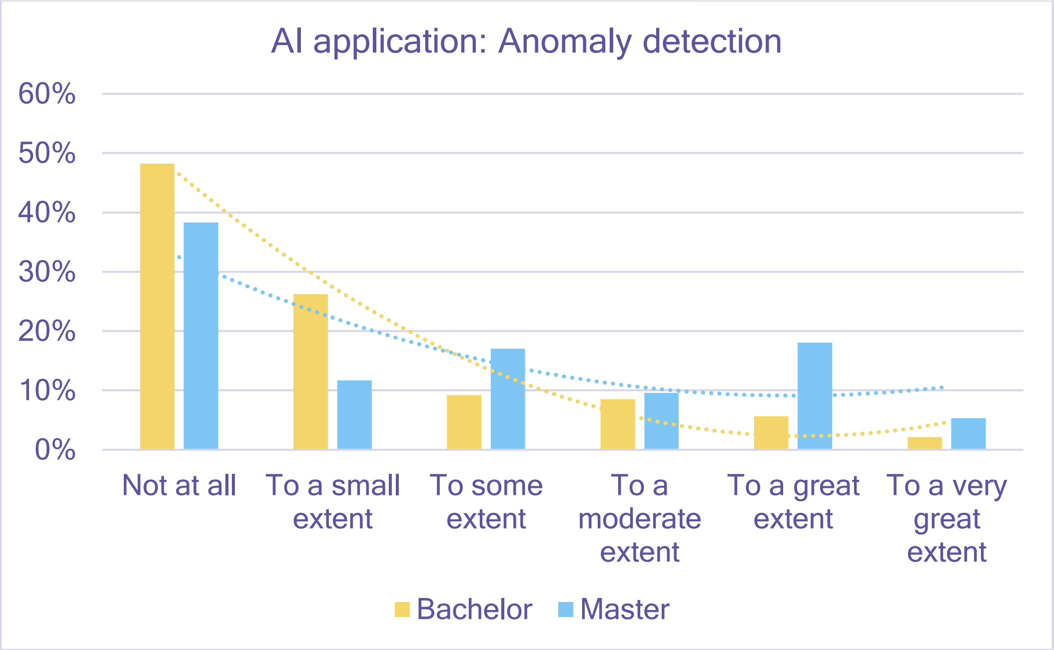


**Figure 34**. AI application: Anomaly detection detailed responses of bachelor and master students

The highest differences in the area of AI application for Anomaly detection for bachelor and master students according to **Figure 34** are in the scope for the answer to a small extent (about 15%) and to a great extent (about 8%). Based on this figure it can be seen that a greater number of master students know the topic of Anomaly detection.

The obtained results show the level of students' knowledge in the analyzed area of AI, IoT and ET topics and also it can be seen where is the biggest gap in the knowledge possessed by bachelor and master students. Naturally, the level of knowledge should be higher for master students, but according to the results this is not true. This state of affair can be caused by **curriculum of studies**, because some topics can be more teach on the bachelor level, and some can be more on master level of studies. The result of implementing the **current** curriculum may be that the analyzed topic is more current (fresher) and better recognizable, e.g., for bachelor students.

# 2 THE SUMMARY

## 2.1 Why training is needed?

There are several causes why the training is needed:

- There are differences in what the academics teach and what the students know.
- There are cases in which students knowledge is lower that it is expected based on what the academics teach. The reasons of this situations can be ineffective learning tools. Academics indicate lectures as the main teaching techniques. While, students rate the effectiveness of the lectures the worst. They indicate project based learning and problem based learning as the most effective learning tool.
- There are also cases in which students knowledge is wider that the academics teach. The reason of this can be that some up-to-date topics are not included widely or not at all in the educational programs. However, as students have nowadays easy access to information about innovative technologies, they may learn from sources other than university courses. Moreover, more and more online courses are easily accessible to students, and in many cases open and free, allowing the student to gain the knowledge individually. In many cases they learn from movies available on line. The question is, what is the quality of the courses offered on Internet? Can students distinguish between valuable and worthless knowledge? What will be the consequences if students have inadequate knowledge and apply it to industry?

That is why it is necessary to develop new or improve the current courses to ensure that the students will receive the valuable knowledge during the educational process. Therefore, it is important:

- To motivate academics to improve their courses.
- To support the academics with the case studies to allow them to explain better the industrial problems and solutions used AI, IoT and EC.
- To pick up the topics which are related to the current industrial problems and introduce them into the educational programs.

## 2.2 How will training cure the problems identified?

The trainings will deliver to students knowledge and skills needed to solve industrial problems. If the academics are aware of the industrial problems and have access to industrial sample data and case studies they can explain better the technologies which can be applied to use these problems.

The newly developed training plans should focus on solving most common problems identified in the industry. These problems are collected in the Table 13 and marked with the priority 1. In the Table 14 there is a relation between priority 1 problems and industry problems identified in the bibliographical research. With the help of Table 10 and Table 11 it is possible to detect which technologies are used to solve priority 1 problems and evaluate degree of teaching of these technologies. So we identified five main problems presented in the Table 16 and eleven technologies that are taught insufficiently (when the sum of answers “not at all” and “to small extent” is greater than 50%). Nine technologies are taught sufficiently (when the sum of answers “not at all” and “to small extent” is less than 50%). Eleven technologies were not found in the curricula.

Table 16 The most important industry problems and their solving technologies

| Issue from bibliographic research | Solving technology from bibliographic research | Technology exists in training program |
|---|---|---|
| Vertical interconnection and integration (between departments in a factory)<br><br>Horizontal interconnection and integration (between different actors of the supply chain) | Data Visualization and Dashboarding | No |
| | Data Analytics | Sufficient |
| | Data Mining | Sufficient |
| | Databases | Insufficient |
| | Time series DB | No |
| | Serverless programming | Insufficient |
| | device management | No |
| | Connectivity | Insufficient |
| Production on demand enabling technology | Data Visualization and Dashboarding | No |
| | Data Analytics | Sufficient |
| | Non SQL DB | No |
| | Time series DB | No |
| | Data engines | No |
| | Machine learning | Sufficient |
| | Cloud Data Storage | Sufficient |
| | Industrial communication protocols | Sufficient |
| | Microcontroller programming and RTOS | Insufficient |
| | Microprocessor programming and embedded Linux | No |
| | Sensors (hardware) | Sufficient |
| | Signal Processing | No |
| | Connectivity | Insufficient |
| Product servitization | Databases | Insufficient |
| | Connectivity | Insufficient |
| Automatic consumables reorder | Data Visualization and Dashboarding | No |
| | Data Analytics | Sufficient |
| | device management | No |
| | Industrial communication protocols | Sufficient |
| | Connectivity | Insufficient |

These problems are:

1. Vertical interconnection and integration (between departments in a factory).
2. Horizontal interconnection and integration (between different actors of the supply chain).
3. Production on demand enabling technology.
4. Product servitization.
5. Automatic consumables reorder.

The summary of the above discussion is following: if we want to help to solve 20% of the problems that industry partners signaled in their surveys then new training programs should focus on technologies given below:

1. Connectivity.
2. Data engines.
3. Databases
   a. Non SQL DB.
   b. Time series DB.
4. Microcontroller programming and RTOS.
5. Microprocessor programming and embedded Linux.
6. Serverless programming.
7. Data Visualization and Dashboarding.
8. Device management.
9. Signal Processing.

## 2.3 What is the best way to get the best results?

To get the main understanding of the industrial problems and possible ways of their elimination it is necessary to present to student wide general knowledge to allow them to understand the wide context.

Then, depending on the field of the study the dipper knowledge and skills should be delivered to students.

It was assumed that project based learning and problem based learning are the most important techniques to learn AI, IoT and EC in practical applications.

Moreover, it was assumed that interdisciplinary collaboration is indispensable to understand the problems and design solutions for them.

Therefore, the following methodology is proposed:

4. Identification of general knowledge needed to students in different fields of study.
5. Identification of topics needed to be discussed in at a greater level of detail in the educational process of students. This should give better understanding of possible utilization of the knowledge from the field in industrial practice.
6. Identification of topics for exercising the practical applications. Based on the current industrial needs the skills needed to solve the most crucial industrial problems are identified and described for the students.

7. Identification of effective learning techniques to gain the knowledge and acquire the skills. It is important to find the best way to present the knowledge and the best mean for gaining the skills by the students.
8. Organizing the work in the interdisciplinary teams. As, the problems existing in Industry 4.0 are complex and need knowledge and skills from different disciplines, it is indispensable to teach students how to work in the interdisciplinary teams and how to communicate with the people from other fields. The additional value can give international collaboration.

Regardless of the observations that result from the conducted quantitative research, it is also worth paying attention to one more issue related to the practical side of education. It seems that even the best selection of the content of classes and the methods and tools used in education will not bring the expected results if we do not have properly prepared teaching staff. All persons conducting classes in the field of new technologies, regardless of their previous experience and skill level, must acquire appropriate industrial experience. The application of artificial intelligence, the Internet of Things and edge computing in the implementation of the concept of industry 4.0 is a typical example in this context. This is especially confirmed by the high competences of these teachers who have intensive contacts with industry and even work outside the university, solving everyday practical problems. For other people, it would certainly be useful to undergo additional industrial training, e.g. in the form of at least a six-month internship.

## 2.4 When training should take place?

As, the studied topics are complex and difficult as well as need established mathematical knowledge the training should have place during master course. However, passing basic information and general understanding of the industrial problems as well as at least general overview of I4.0 methods is also expected for bachelor students.

To know what is an actual level of knowledge of bachelor and master students there has been made an additional statistical analysis (1.7 Statistical analyses). These analyses based on p-value calculations to see where is the biggest difference between the knowledge of bachelor and master students. Besides this, there has been also calculated an average value of students' knowledge.

Based on the performed analyzes there can be concluded some general points:

- Because of additional statistical analyses we can see the topics and areas and an average value of knowledge possessed by bachelor and master students for them, and because of that we can see what topics need **more attention** in the process of teaching because of **low average value.**
- **Higher average values** of knowledge for **bachelor students** usually indicates higher average values for **master students**, so that it can be concluded that teaching of AI, IoT and EC topics is important also for bachelor students for **later expansion** of this knowledge on master studies.

- However, for some of the topics an average level of knowledge was higher for **bachelor** students, particularly for, **AI applications: Robotics; IoT context: Quality problems, Robotics, Deliveries, Logistics; EC topics: General concept, Scalability and reliability, Speed and efficiency, Applications**. Based on these results we see probably that the curriculum for bachelor studies among mentioned topics is probably more focused on these areas.
- Because some topics can be more teach on the bachelor level, and some can be more on master level of studies. The result of implementing the **current curriculum** may be that the analyzed topic is more current (fresher) and better recognizable, e.g., for bachelor students.

More detailed conclusions can be as follows:

- Based on the average value of knowledge of bachelor and master students it can be seen that the lowest average value is for AI applications: **Supply chain management (Bachelor – 1.7, Master – 1.9), Deliveries (Bachelor – 1.8, Master – 1.9) and Manufacturing processes monitoring (Bachelor – 1.7, Master – 2.0), while the highest average value is for AI Areas: Machine Learning Bachelor – 3.3, Master – 3.8, EC topics: General concept (Bachelor – 3.4, Master – 3) and Applications (Bachelor – 3.4, Master – 3.0).**
- Analyzing particularly in detail the results for the highest priority challenges pointed by industry, such us: **Production/operations planning, Forecasting, Relations with customers, Business analysis,** which are included in the educational programs such as following topics: **Deliveries, Supply chains management,** based on the average knowledge values we can see that these topics are teach on relatively low level, particular these topics have **the lowest average knowledge ratios** – **Deliveries (Bachelor – 1.8, Master – 1.9); Supply chains management (Bachelor – 1.7, Master – 1.9)**. So that it can be concluded that the new curriculum for the existed subjects need an update to be more focused on these areas, or the new subjects with the completely new curriculum are needed to be create. Also, the highest priority for the industrial problems has **Production/operations planning** which has an equivalent as **Logistics** topic included in the educational program. Again, this area has also one of the lowest average levels of knowledge as well as for bachelor and master students **(Bachelor – 2.2, Master – 1.9).** Furthermore, there has been indicated that bachelor students have higher average value of knowledge in this area thank masters. Also, as for the above mention's areas, also for this one there is an emergence to include an update or to create a whole new subject for the curriculum of master studies.

## 2.5 Knowledge transfer

Research conducted in industry has shown that companies still need to have the knowledge about the I4.0 solutions and how to implement them. At least 20% of the companies want to implement, among others, SCADA systems, big data analytics, intelligent process supervision and diagnosis, intelligent tools, Business Intelligence and decision support systems (see **Figure** 2). However, the practical skills of employees of these enterprises needed to implement and operate I4.0 solutions are largely insufficient. As Figure 3 shows, **less than 30% of companies assessed that they have**

**at least an average degree of practical skills related to AI, ML, IoT, EC and autonomous systems**. Therefore, it is crucial to provide knowledge in this field to students who will become employees of these companies in the future. The student should:

- acquire knowledge of existing IT systems and technologies that support I4.0 solutions both in the technical and soft areas,
- be aware that existing technologies should be constantly developed,
- know that new technologies should be created (e.g. cognitive systems) in order to fully meet the needs of businesses in the future.

The surveyed companies indicated their needs that may suggest what to focus on in educating students. These needs mainly concern:

- implementation of integrated IT systems (MES, MIS), implementation of automatic data collection systems and intelligent condition monitoring systems, implementation of integrated platforms for automatic data exchange between IT systems,
- skills connected with programming, data science, industrial automatons, data security,
- soft competences required for the implementation of I4.0.

**The issues listed above should be treated as a priority when creating courses for students.**

Moreover, Table 5 lists the technologies related to AI, IoT and EC, which were identified during bibliographical research and which are also important from the point of view of modern enterprises. Therefore, all the technologies listed in the table should be included in the courses preparing students to work in todays' companies. Some of these technologies already exist in university education programs (Table 6 shows to what extent teachers teach a specific technology). However, **some of crucial technologies are not present in the educational content or are present insufficiently**. They are: data visualization, dashboarding, advanced reporting, self-service business intelligence tools, device management in cloud computing signal processing and blockchain in the IoT domain, Internet of Everything, Non-SQL DB, time series DB, data engines, computer vision, serverless programming, microcontroller programming and RTOS, microprocessor programming and embedded Linux as well as connectivity (M2M industrial protocols).

The bibliographical research also showed some problems that are relevant to modern enterprises. They are divided into two groups: process optimization problems (see Table 7) and product innovation problems (see Table 8). Surveys conducted among academic teachers revealed that only three of the problems exist directly in the content of education at universities. They are: real-time production monitoring analysis and supervision, predictive maintenance, as well as supply chain transparency and reliability improvement. However, the analyses also attempted to answer the question if training programs contain topics dedicated to the technologies came from bibliographical research so that a solution of the problems found in the industry exists indirectly in the training programs. For this purpose, connections between the problems and the technologies used to solve these problems are found (see Table 10 and Table 11). This showed that only in the case of two problems (smart PPE and product servitization), students have knowledge about technologies required to solve them. **The remaining issues are still a challenge for universities and indicate future directions in which research and education of students may follow.**

Due to the fact that there are many issues present in the industry, it is worthwhile to rank their importance. Such a ranking was also developed as part of the conducted research, using the results of the survey of the companies (see Table 13). The highest priority in the created ranking was assigned to: business analysis, relations with customers, customer service, business process monitoring, production/operation planning, obtaining data from the market, and forecasting. **These listed challenges should necessarily be present in the education of students.**

The analyses revealed that the topics existing in teaching programs do not cover the problems pointed by industry (see Table 14). Therefore, the problems cannot be solved because of lack of necessary trainings. **In order to improve knowledge transfer, based on the analyzes carried out, we proposed 14 topics significant for teachers** (see section 1.4).

In addition to the issues identified by industry, **student surveys also provide a picture of knowledge transfer needs.** Student surveys showed which areas and applications of AI, IoT and EC are better known to students, and which are less known. This information is provided in section 1.5 of this report. **Increasing the level of students' knowledge in the areas and applications that are currently less known may be the most desirable due to implementation of the Industry 4.0 concept in today's enterprises.**

Moreover, the students indicated what, in their opinion, is important for the effective transfer of knowledge. Recommendations from students are listed in section 1.6. One of the many recommendations relates to teaching techniques. The survey revealed which forms of education are most appropriate for teaching AI, ML, IoT and EC. Figure 28 shows that, according to students, **laboratory classes are the most useful**. Following are Project Based Learning (individual work), Project Based Learning (team work) and workshops. **Practical realization of some tasks (e.g. in a project) gives students the most knowledge and skills** in the field of AI. The conducted research shows that students participating in AI-projects are characterized by a greater level of knowledge in the field of AI compared to other students (see Figure 29). Moreover, it was assumed, that digital presentations can substitute the lectures as they can be enriched with the animations, movies, practical industrial examples.

A good way to apply project-based learning can be the creation of interdisciplinary project groups (see Figure 30). That kind of teams can be created between the students who study different engineering fields. Moreover, these students may come from different universities or even different countries, and the work of the students could be supervised by representatives of the industry.

## 2.6 Skills development

For the skills it was assumed that the best way to ensure that the student will acquire the necessary skills is problem based learning and project based learning. When the student have to solve a certain problem have to reach a goal. Therefore, there are focused to achieve the certain target by inventing a solution. Project based learning approach allows the students to follow a certain methodology which minimalize a risk of failure.

## 2.7 Interdisciplinary teams

The interdisciplinary teams are recommended to be worked on the joint projects or collaborate to each other in the form of knowledge exchange. This will create the awareness of a wider context of the analyzed problems.

# APPENDIX A – LIST OF RESOURCES IDENTIFIED IN THE LITERATURE REVIEW

1. https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/ai-in-production-a-game-changer-for-manufacturers-with-heavy-assets#
2. http://scientiairanica.sharif.edu/article_21299_7178257779f1119484087880ef786335.pdf
3. https://mobidev.biz/blog/ai-visual-inspection-deep-learning-computer-vision-defect-detection
4. https://www.digiteum.com/iot-supply-chain/
5. https://www.researchgate.net/publication/326823239_Industry_40_Smart_Scheduling
6. https://www.digiteum.com/internet-of-things-logistics/
7. https://mobidev.biz/blog/machine-learning-methods-demand-forecasting-retail
8. https://www.visiononline.org/blog-article.cfm/Embedded-Vision-Applications-in-Supply-Chain-Management/110#:~:text=Embedded%20vision%20technology%20is%20finding%20use%20throughout%20the%20supply%20chain%20management%20process.&text=In%20a%20variety%20of%20forms,the%20process%20of%20moving%20goods.
9. https://stlpartners.com/edge-computing/edge-insights-service/
10. https://docs.microsoft.com/en-us/azure/architecture/example-scenario/predictive-maintenance/iot-predictive-maintenance
11. https://www.st.com/content/dam/artificial-intelligence/edge-ai/stmicroelectronics-stlivedays-low-power-predictive-maintenance-Lacroix-marketing-presentation-2171.pdf
12. https://www.merckgroup.com/en/research/science-space/envisioning-tomorrow/smarter-connected-world/5g.html
13. https://www.insightsip.com/news/what-s-new/606-smart-ppe-and-iot-to-improve-workplace-safety
14. https://www.researchgate.net/publication/2511046_Predicting_Defects_in_Disk_Drive_Manufacturing_A_Case_Study_in_High-Dimensional_Classification
15. https://flashglobal.com/blog/how-to-improve-inventory-cost-management/
16. Real-Time Production Performance Monitoring (Zerynth)
17. Smart Warehouse System (Zerynth)
18. Blockchain-enabled IoT shipment tracking system (Zerynth)
19. Vehicle Tracking and Fleet Management (Zerynth)
20. Smart Tracking Solution (Libelium)
21. IoT Retail with Consumer Smartphone detection (Libelium)
22. IoT Industry Solution (Libelium)
23. Tracking System (Particle)
24. IoT Order Fulfillment (Particle)
25. Asset Tracking (Particle)
26. Predictive Maintenance (Particle)
27. https://www.researchgate.net/publication/257001844_A_Web-based_Product_Service_System_for_aerospace_maintenance_repair_and_overhaul_services
28. https://www.researchgate.net/publication/280722890_Reducing_Complexity_with_Simplicity_-_Usability_Methods_for_Industry_40
29. https://www.st.com/content/st_com/en/campaigns/artificial-intelligence-at-the-edge.html#edge-ai-counting-sensor
30. https://www.oreilly.com/library/view/predictive-analytics-using/9781784395803/

31. https://www.reach-incubator.eu/project/energy-sources-optimization/
32. https://www.reach-incubator.eu/project/improving-stores-efficiency-using-clients-shopping-times/
33. https://www.reach-incubator.eu/project/predictive-maintenance-and-production-optimisation-in-industry/
34. https://www.reach-incubator.eu/project/data-driven-technology-for-efficiency-in-energy-intensive-industries/
35. https://new.siemens.com/global/en/products/automation/industry-software/automation-software/scada/simatic-wincc-oa/simatic-wincc-oa-iot-suite.html
36. https://www.igi-global.com/chapter/leveraging-iot-framework-to-enhance-smart-mobility/249114
37. https://edincubator.eu/2019/03/13/iot-in-retail/
38. https://edincubator.eu/2019/03/13/remote-measurements-control/
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44. Peter Gorm Larsen, Smart products with focus on Cyber-Physical Systems, 25.03.2021 https://digit.au.dk/research/smart-products-with-focus-on-cyber-physical-systems/
45. What is Process Mining? https://www.celonis.com/process-mining/what-is-process-mining
46. Hiriyannaiah, S., Matt, S. G., Srinivasa, K. G., & Patnaik, L. M. (2020). A Multi-layered Framework for Internet of Everything (IoE) via Wireless Communication and Distributed Computing in Industry 4.0. Recent Patents on Engineering, 14(4), 521-529. https://www.eurekaselect.com/node/172949/article/a-multi-layered-framework-for-internet-of-everything-ioe-via-wireless-communication-and-distributed-computing-in-industry-40

Lead Partner:

Partners: