

Article

Towards Proactive Higher Education: Drivers for Future-Ready Learning Ecosystems

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Abstract

Higher education is undergoing a profound transformation driven by online and generative learning environment expansion, rapidly evolving labour market demands, and the emergence of new educational providers offering flexible, industry-aligned learning activities. Universities are responding by redesigning and expanding their degree programmes, even though institutional rigidity sometimes limits their ability to change. This study investigates how higher education institutions can shift from reactive adaptation to proactive leadership in shaping the future of skills and jobs. We propose a skills mapping approach, applying text mining to syllabi using the European Skills, Competences, Qualifications and Occupations (ESCO) classification. The resulting course–skill–occupation map can support communication among stakeholders and update learning objectives, enabling modular curriculum design and micro-credential development. The educational offer of one of the leading technical universities in Europe is presented as a case study. Findings demonstrate how systematic skills extraction can enhance career guidance for students, curriculum development for teachers, and provide actionable insights for upskilling and reskilling.

Keywords: competences; learning objectives; job profiles; cosine similarity; BERT; large language models

1. Introduction

Today, higher education systems are undergoing a profound transformation. Universities, once regarded as the primary gatekeepers of knowledge and professional expertise, are increasingly challenged by declining attractiveness (Jackson, 2021; Harvey, 2000). This shift signals a deep tension between the traditional academic models and the evolving systems for knowledge sharing (Komljenovic, 2019). The rapidly evolving demands in labour markets require a near-constant update of the educational offer (Mukul & Büyükožkan, 2023), pushing the 21st Century Skills and the lifelong learning attitude (Kotsiou et al., 2022). A constant gap is registered among what companies need, what current workers are able to do, and what educational providers offer (Karakolis et al., 2022; Goulart et al., 2022). And recent evidence underscores the urgency of this challenge: half of graduates work in positions misaligned with their credentials, revealing a structural disconnection between study and career paths (Strohl et al., 2024). In this scenario, the concept of employability takes on a central role. It is no longer a question of delivering up-to-date courses, but of developing in graduates the ability to adapt, continuously learn and translate their



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skills into a changing professional context (Dlamini & Dlamini, 2025; Cheng et al., 2022). These dynamics are increasingly relevant for companies as well: training programmes for upskilling and reskilling can be developed through generative AI solutions, e.g., AI-driven chatbots and personalised learning systems aligned with employees' roles, aspirations, and evolving skill needs (Ooi et al., 2025). We are witnessing occupational upgrading, with a growth in the demand for labour concentrated in highly qualified professions, as highlighted by the Joint Research Centre (JRC; Torrejón Pérez et al., 2024). The Future of Jobs Report 2025 (Leopold et al., 2025) even expects a job churn of 22% by 2030 due to the strong turbulence and profound instability in demand, and it is estimated that 39% of current competences will become obsolete or be transformed by the end of the decade. The difficulties in effectively addressing this organisational transformation derive from a persistent skills-mismatch and critical skill-gaps (European Training Foundation, 2025).

In these challenging times, universities must ensure educational goals that are relevant to the ever-changing demand, gaining new agility to deal with unpredictable and ongoing transformations. A redefinition of learning ecosystems is taking place, where universities risk being sidelined under the pressing labour market trends. There is therefore a pressing need to understand which drivers can guide higher education institutions from reactive adaptation to proactive leadership in shaping the future of skills and work. Instead of the current demand–offer alignment, universities can find new strategies to strengthen the employability of graduates in rapidly changing professional ecosystems. This research seeks to operationalise this objective in the following research question: how can evidence of labour market needs be integrated into higher education processes to enable proactive action by universities in strengthening the employability of graduates?

We propose course–skill–occupation mapping by applying text mining techniques to course syllabi and by using the European Skills, Competences, Qualifications and Occupations (ESCO) classification. A comprehensive map linking knowledge (i.e., theory and principles) and skills (i.e., applying know-how), occupations, and courses can be a solution in a three-part logic: (1) student-oriented logic to clearly communicate which skills and knowledge would be acquired with a given course and for which possible professional role, (2) teacher-oriented logic to support teachers in the process of syllabus updates, and (3) labour market-oriented logic to improve the connection between universities and the labour market, leveraging terminology and descriptors of educational offers.

This terminology lever is being adopted by the European Union to support mobility and matching between supply and demand at the European level. Indeed, the universities' curricula are part of the broader context of the European Qualifications Framework (EQF), a framework for comparing qualifications of different countries (European Commission, 2018). This framework is divided into eight levels based on learning objectives (knowledge, skills, and responsibility/autonomy), and covers from basic education to the highest academic and professional levels. Each Member State develops its own national qualifications framework and aligns it with the EQF system to identify synergies between different training paths and guarantee the quality of the qualifications awarded (Méhaut & Winch, 2012). This framework interacts with the ESCO classification, reinforcing the common language for universities and the labour market. Indeed, ESCO includes the qualifications pillar, connecting the qualification information reported in Europass and referenced to the EQF system¹. Harmonisation efforts at national and European levels are an ongoing priority (Mikulec, 2017; Ure, 2023), encouraging studies on systems that favour the terminological alignment enabled by these reference structures.

We adopt a single-case study design approach for validating the proposed tool in a controlled and well-defined context (Thomas, 2011). We mainly take the Technical University of Denmark (DTU) as a case study for the following reasons, which will be

further explained in Section 2: the polytechnic nature of this university, characterised by a strong integration with the industrial reality, makes it a privileged context to analyse the employability and its relation with curricula (Bronstein & Reihlen, 2014), and the location in Denmark, where universities are characterised by a strong focus on preparedness, and institutional reforms are attributed to universities with a strategic role in building the country's future (Kallo & Välimaa, 2025). In addition, the institutional strategy and policy of the university, namely the vocation for innovation and the importance of societal challenges², and the high position of DTU in Europe's technical university EngiRank in recent years³, make it an authoritative reference point and a benchmark for future competence-oriented education. Finally, the syllabi of the courses are written directly in English by the teachers, not translated, thus ensuring a high linguistic and conceptual quality of the input data, an essential condition for the reliable application of text mining techniques (Ferreira-Mello et al., 2019). For the sake of consistency in the analysis and results, we select one department only, i.e., Dept. of Civil and Mechanical Engineering (aka DTU Construct), to ensure a proper scale for robust and manageable analysis (De Silva et al., 2025; Chong et al., 2022).

The algorithm extracted 995 different ESCO skills and knowledge from the 8341 learning objectives. We analysed the ESCO's hierarchical relationships to identify the most common types and the distribution of courses by occupation category. We also explored the specialisation/transversality of courses through the number of different occupations associated with them. Finally, we constructed a map of courses, skills/knowledge, and occupations, representing a measure of the connection between training offers and the labour market.

This study contributes to the stream of educational data mining, learning analytics and educational text mining (Romero & Ventura, 2007, 2017). Our approach allows the identification of competences (i.e., skills and knowledge) embedded in the LOs and the integration of occupation-related information into the educational offer. Such a strong and explicit connection offers valuable insights to enhance employability, support curriculum innovation, and inform institutional and policy responses to skill shortages. The text mining approach we propose is particularly relevant for systematically acquiring empirical data on the competences actually developed in training courses, of which we have limited direct evidence. Indeed, statistics on education usually regard quantitative output, e.g., the number of graduate students (Moshtaghi & Sotudeh, 2023). These measures are ex-post by design, but a proactive strategy demands ex-ante tools to inform decision-making processes.

As previously noted, the solution follows a three-part logic. Findings can help students in their educational and career choices; teachers can use the information in curriculum design, while companies can leverage educational activities for upskilling and reskilling. Fostering students' skills development from a lifelong learning perspective, ensuring a deeper understanding of educational experience, is indeed one of the biggest challenges for engineering education, and in general for higher education (Winkens et al., 2025).

The implications of this work extend beyond alignment with labour market trends. We argue that higher education institutions could embrace proactive vision-building, positioning themselves as a central actor in learning ecosystems. By integrating modular structures and micro-credentials into curricula, universities can enhance their attractiveness, foster resilience in the face of emerging competitors, and strengthen their relevance for both students and employers. In addition, we develop a robust knowledge base which can be used for further development and integration with other data resources addressing labour market intelligence and other applications exploiting LLMs, as we will demonstrate in the following sections of the paper. This work provides an informed evaluation of the links between academic offerings and industry demands, enabling the explicit labelling

and integration of competences within educational frameworks. Aimed at ensuring an improved alignment between the educational initiatives and the dynamic demands of the labour market, the present work uses the ESCO classification and course syllabi. The proposed approach demonstrates how universities can systematically extract and analyse the competences being taught. Such a detailed overview of the educational offer can enable a quantifiable comparison between academic curricula and job market requirements, supporting the matchmaking and improving employability.

2. Background Literature

Recent analyses of the labour market are highlighting multiple structural changes in response to the current technological and social transformation. Universities' reactions are characterised by two main tendencies. Firstly, educational institutions have progressively introduced a large number of courses into their offerings, trying to keep pace with the labour market, aiming to satisfy companies with skilled graduates and attracting students with a wide educational portfolio (Biagi et al., 2024). This caused a stronger focus on measurable outputs, such as graduation rates and student enrolment rates (Moshtagh & Sotudeh, 2023). Secondly, universities embraced the learner-centred approach, prioritising learners' needs, interests, and learning styles over the teacher's role beyond the sole transmission of knowledge. Despite its strong pedagogical foundation, students were to some extent perceived less as learners engaged in a demanding intellectual journey and more as clients of educational services, shifting towards a marketing logic (Nicolescu, 2009), and in the end leading to a student-focused and metrics-centred approach (Williamson, 2019). Such a reaction clashed with institutional overload and bureaucratic rigidity and constraints, slowing down responsiveness (Lašáková et al., 2017). This shift was even pushed by the market entry of massive open online course providers (Kaplan & Haenlein, 2016), who set a new pace of developing and updating content. Students begin to favour short-term logic, choosing more attractive and immediately expendable courses and certifications (Watted & Barak, 2018).

In such a context, the difference between public and private educational organisations is further increasing (Alam et al., 2020), and new providers of education and training are proliferating (Kaplan & Haenlein, 2016), offering flexible and industry-recognised certifications that compete directly with university degrees (Kato & Galán-Muros, 2020). Their ability to deliver targeted and short courses aligned with immediate job demands and technological and organisational changes attracts both students seeking employability advantages and companies developing upskilling and reskilling strategies (Thi Ngoc Ha et al., 2023). An intensified competition among educational providers emerges also at international level, thanks to the improvement of mobility programmes and facilities (Altbach & Knight, 2007).

Regarding the method, this study relates to the stream of educational data mining, learning analytics and educational text mining (Romero & Ventura, 2007, 2017), regarding the application of text/data-driven approaches in the education domain. Usually, educational-related textual data include programme descriptions, curricula, lesson transcriptions, job vacancies, and job descriptions, and the main applications regard analysis of educational literature, tools to support students and teachers during learning activities, methods and processes for improving pedagogy and curriculum, and finally explorations of the opinions from social media (Yang et al., 2023). However, an effective implementation is still a challenging task for teachers and faculty staff, requiring clear guidelines and practical support (Gaftandzhieva et al., 2023; Wolf, 2007).

The analysis of syllabi with taxonomies and classifications is well-established in the educational literature for mapping skills, occupations, and courses, for identifying

specific profiles to guide student career development, and for attracting companies to upskilling and reskilling initiatives. Studies adopting text analysis typically leverage both local and international classifications (Lan et al., 2025). For example, Javadian Sabet et al. (2024) leverage O*NET, the US-based classification of industrial activities, jobs, and skills, for developing the ‘Course-Skill Atlas’. Ferreira et al. (2025) exploit natural language processing (NLP), semantic similarity, and large language model (LLM) extraction to map ESCO competences onto Portuguese course descriptions or learning objectives, demonstrating the promising avenue of using LLMs, while highlighting some limitations in accuracy. They found that LLMs only outperform when used in combination with NLP, as demonstrated by Kavargyris et al. (2025b) with ESCOX, which exploits LLMs and similarity of text embeddings to map unstructured text into standardised skill and knowledge. Preliminary examples with LLM-only are being presented as well: Romão et al. (2025) used DeepSeek to map ESCO competences in courses, obtaining a retention rate of 74% over a test sample of 22 course descriptions.

3. Materials and Methods

3.1. Case Study

We adopt a single-case study design approach for validating the proposed tool in a controlled and well-defined context. The use of a single-case study design approach, which sets a well-defined and controlled context, is linked to the following methodological reasons. In a well-defined context, a single case can serve to explore the dynamics of the phenomenon under clear circumstances while also facilitating the logic of replication of the tested theory/application (Eisenhardt & Graebner, 2007). In a controlled context, a single case represents an ideal environment through which the developed theory or application can be precisely validated, exploring various perspectives (Eisenhardt, 1989; Thomas, 2011). In this sense, a single case does not aim to provide a representative sample, but a specific context to relate facts and concepts explored in the theory/application in a holistic way (Thomas, 2011). These characteristics make the single-case study design a rigorous tool for validating the approach proposed here, as a fundamental step in being able to expand adoption to a broader context.

We selected the Technical University of Denmark (DTU) as a case study, specifically the Dept. of Civil and Mechanical Engineering (aka DTU Construct).

The choice of this university as a case study is due to two main reasons, already mentioned in the introductory section and further detailed here: its nature as a polytechnic, and the Danish national context and cultural characteristics. Being a polytechnic university with a strong technical–scientific vocation, DTU is configured as a so-called entrepreneurial university (Bronstein & Reihlen, 2014), following the techni–preneurial model, i.e., strongly oriented towards technical expertise and applied science, collaboration with industry, and the pursuit of technological innovation. It also integrates some elements of the research–preneurial model, for its intense applied research activity and the transfer of knowledge to companies. Next, Denmark represents a particularly interesting context to study the evolution of university systems given the strong Nordic focus on preparedness and long-term vision (Wright, 2025). The recent literature on the Nordic context highlights how Denmark, Finland, Norway and Sweden have developed advanced approaches to address global uncertainty, investing in foresight techniques, resilience policies, educational systems capable of adapting to various scenarios, and universities acting as central actors in the training of resilient citizens and professionals, also with a high degree of autonomy (Kallo & Välimaa, 2025). Such an approach is reflected in the institutional strategy and policy of the university, which place an emphasis on societal challenges and innovation.

Moreover, DTU is an authoritative reference point and a reference point for education, especially for engineering education. Being the top technical university in Europe according to EngiRank for three consecutive years, as well as holding consistently high positions in other well-established university quality assessment rankings.

The choice of one department only makes the analysis and the results more homogeneous (Chong et al., 2022). Significant patterns can be observed in a coherent context, neither vast nor hyper-specialised, highlighting the drivers for employability instead of the variety of the educational offer of an entire university (De Silva et al., 2025; Orellana et al., 2018).

Among the various departments, the case of the DTU Construct was selected as it combines interdisciplinarity integration with industry and technical skills that are in high demand. Indeed, the Civil and Mechanical Engineering sector is a sector with a very high demand for skills and is changing for the green transition, with updated regulations on energy, safety, and tools like BIM and advanced materials, among others (Van den Beemt et al., 2020). The teaching programmes included three Bachelor of Engineering degrees (Architectural Engineering, Mechanical Engineering, Naval Architecture and Maritime Engineering), four Bachelor of Science degrees (Architectural Engineering, Civil Engineering, Design and Innovation, and Mechanical Engineering), four Master of Science degrees (Architectural Engineering, Design and Innovation, Materials and Manufacturing Engineering, and Mechanical Engineering), and two Master degrees (Master of Fire Safety and Master of Sustainable Construction), leading to a wide educational range in terms of courses.

3.2. Data Collection

Syllabi were retrieved from the DTU Course Base (<https://kurser.dtu.dk/search>, last accessed 28 July 2026). All courses belonging to the teaching programmes of the selected department (DTU Construct) and that were available in English were manually collected, for a total of 215 documents. The number of syllabi is given by the number of programmes offered by the selected department. This quantity covers the training offer of the case study analysed. It allows us to grasp, in text mining analysis, the internal variability of the teaching contents and to evaluate the robustness, effectiveness and replicability of the proposed approach. In the frame of a single case study, this quantity allows us to reasonably consider the results obtained transferable to other training contexts. The amount is considered reasonable considering the average number of degree study programmes offered in polytechnics in Europe, on average from 50 to 130, leading to 6000 courses in the largest cases and 3000 in the smallest cases. Thus, the selection of one department only with over 200 courses ensures a sizeable set of data for the purpose of the present analysis on educational offer⁴.

We specify that the syllabi are directly written both in English and in Danish by the teachers; thus, the analysed texts are both English texts and non-translated texts. This feature is very relevant in text mining techniques: linguistic consistency and a high conceptual quality of the input data have a positive impact on the application of techniques, which perform better in the English language and on the results (Ferreira-Mello et al., 2019).

A syllabus is a structured document describing scope, learning objectives, content, learning activities, assessment methods, and organisational details of a course (Parkes & Harris, 2002). Learning objectives (LOs) are concise statements describing what a student is expected to know, understand, or be able to do at the end of a learning process; each LO must consist of a single, self-contained sentence (Orr et al., 2022).

Syllabi were used to map the LOs with the European Classification of Skills and Occupation (ESCO)⁵, aiming at supporting students, teachers, and policy makers in learning, teaching and educational design tasks. ESCO is a multilingual classification of competences, qualifications and occupations developed by the European Commission since 2008. It is a

constantly evolving system: after a demo version in 2013 and the first full version in 2017, the current version v1.2.1 (last update on 10 December 2025) includes descriptions of 3039 professions and 13,939 skills/knowledge, concepts linked to each other and organised in a hierarchy, as well as associated with the qualifications required for a certain profession or attesting to the possession of a certain competence. It is designed as a broad resource to improve the matching of skills supply and demand: it supports employers, individuals, training institutions and guidance counsellors. Its update is also based on European studies dedicated to identifying skills needs in different sectors and on research that monitors the emergence of new skills. ESCO is largely used in the literature, primarily in the field of labour market intelligence (Colombo et al., 2019; Chiarello et al., 2021), and also in the education domain (De Silva et al., 2025; Spada et al., 2022).

Following the aim of the paper on terminology alignment, we provide here the definition of the concepts used here to ensure consistency in the reading. We refer to the definitions provided by ESCOpedia, i.e., the reference guide for understanding ESCO classification. In addition, in line with the EU strength of terminology harmonisation, ESCO applies the same definitions as the European Qualification Framework (EQF). The terms used in this work refer to competence, knowledge and skill and are defined as follows:

- “Competence means the proven ability to use knowledge, skills and personal, social and/or methodological abilities, in work or study situations and in professional and personal development”.⁶
- “Knowledge means the outcome of the assimilation of information through learning. Knowledge is the body of facts, principles, theories and practices that is related to a field of work or study”.⁷
- “Skill means the ability to apply knowledge and use know-how to complete tasks and solve problems”.⁸

Therefore, skills and knowledge are used specifically for the two items identified in the analysed syllabi, whereas competence is adopted as a general term including both skills and knowledge. Although competence typically also refers to the degree of responsibility and autonomy in applying skills and knowledge in a given work or study context, here we do not have any specific references to these dimensions.

3.3. Data Analysis

The textual information in the syllabi was first pre-processed. Texts from the available sections general course objectives, learning objectives, content, and course literature were joined in one string. The underlying assumption for this decision is that general course objectives and learning objectives explicitly mention the learning goals of the course and thus competences can be referred to. While content and course literature provide a general description, topics, and references, those might include information that can implicitly refer to competences, such as theoretical knowledge, activities to be performed in the class, expected behaviour of the students, and prerequisite skills. Even the details on exam procedures, which can be described in these sections, can be related to competences, as it is widely recognised the formative value of the assessment (Clark, 2012). After joining sections, the sentences, identified with a full stop or line-end, were separated to list the single statement of each LO.

Next, the cosine similarity is implemented with a pre-trained BERT model for embeddings (Devlin et al., 2019). The BERT embeddings are obtained with the ‘paraphrase-multilingual-mpnet-base-v2’ model, and next the similarity between each LO and the ESCO concept is computed with ‘cosine distance’. ESCO provides alternative labels for each concept that are like synonyms, and uses AI and machine learning to compute the similarity between preferred and alternative labels. So, it is reasonable to assume the vectorial

representation of alternative labels is close to the vectorial representation of preferred labels; consequently, we do not consider the alternative labels in the similarity scores calculation. For each LO, the three most similar skills or knowledge are ranked. We evaluated the trend of similarity scores against rank to define the similarity threshold at 0.75, reaching a precision of 85.54%, in line with the recent works in the literature stream (Khan et al., 2025; Kavargyris et al., 2025a). The explanation of the process for the identification of the semantic similarity threshold and the estimation of precision is provided in Appendix A.

Finally, the information available on ESCO is joined to the extracted competences. Those include tags for type (knowledge or skill) and reuse levels (vertical specialisation or cross-sector diversification), and occupations to which the extracted skills/knowledge are marked as essential in the taxonomy. For both competence and occupation, the different levels of the ESCO classification are included in the final dataset.

3.4. Validation of the Approach

We validated our approach by comparing it with other extraction techniques to measure the effectiveness of our semantic similarity method. The other techniques include (i) the newest approach in the field, i.e., extraction with a large language model⁹, (ii) the clue extraction based on rules and patterns, and (iii) the old-fashioned basic string search for exact match. Figure 1 reports the results of the comparison in a Venn diagram, highlighting the semantic coverage of the different techniques and their convergence.

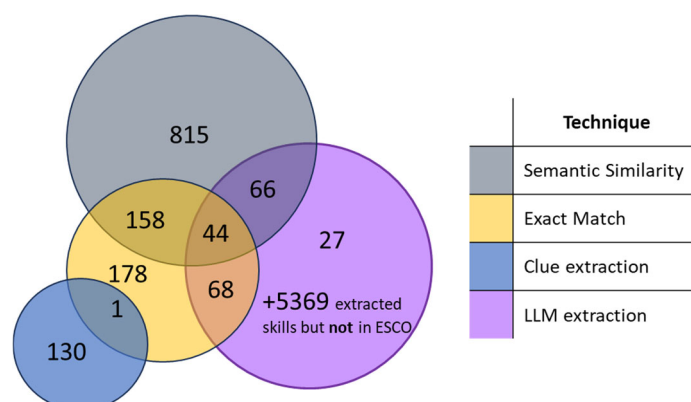


Figure 1. Comparison of skills extracted with different techniques.

The semantic similarity approach appears to be the most complete and reliable among the different techniques: it is the only method that has identified the largest number of correct items (i.e., 1083 skills), suggesting a greater capacity for semantic recognition than other approaches, which tend to identify a more limited number of items. The overlap with other techniques shows its ability to capture both explicit and implicit skills. Moreover, the intersections with all the different techniques reinforce methodological soundness. Clue extraction and exact match show a very limited coverage, still anchored to explicit mention of skill. LLM extraction is the method with the highest absolute number of skills extracted (5574): the great part is not present in ESCO, but is semantically consistent with the domain of skills.

We would like to specify that the LLM extraction relies on a single open-weight model queried with a single-shot prompt, while we acknowledge that authors in the literature are testing different models with different prompting strategies, as referenced in Section 2. Background Literature. Our approach in this validation procedure may have produced a distortion towards relatively unstable LLM extraction, which could instead have been affected by model and prompt selection. However, this initial result can represent promising evidence for the development of more flexible and adaptive approaches to skills

extraction, while showing the effect of hallucination, i.e., the production of elements that cannot be verified or are not supported by evidence. The LLM extraction suffers from structural limitations in processing large datasets (Gómez & Fillottrani, 2024) and currently, studies in the literature use LLMs in combination with other approaches for skills extraction (Kavargyris et al., 2025b). Therefore, the results are promising and open the possibility of advancing towards using only LLMs for skills extraction.

4. Results

This section describes the experimental results of our analysis. The collected syllabi were 215 from the courses offered by the Department of Civil and Mechanical Engineering of the DTU (DTU Construct). At least one skill was found in 208 syllabi. This initial result proves the consistency of the proposed approach, which is able to find a skill in almost every syllabus. The algorithm extracted 1083 ESCO competences from the 8341 LOs (i.e., intended goals of the course, each expressed in one line/sentence of the syllabus). The count of distinct ESCO competences is 995 (i.e., items counted without repetition), indicating the variety of the training offer.

A total of 2441 different occupations were related to the competences, based on the ESCO classification. Figures 2 and 3 present the most recurrent skills and knowledge and an analysis of the occupations in the courses.

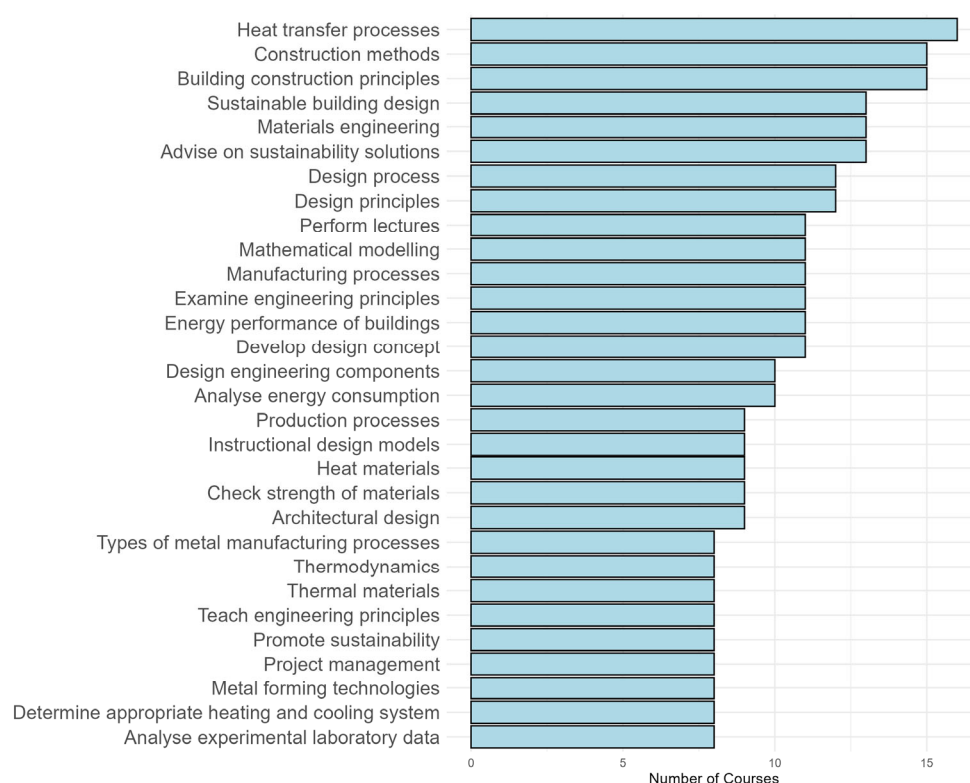


Figure 2. Top 30 skills and knowledge per number of courses.

The results in Figure 2 show a strong integration between technical-engineering skills, design skills and sensitivity to sustainability; the professional profiles are the most frequently associated with the learning objectives of the courses offered by DTU Construct. Figure 3 consolidates this overview with a strong variety of engineering roles, mentioning occupations related to design, materials, energy and mechatronics.

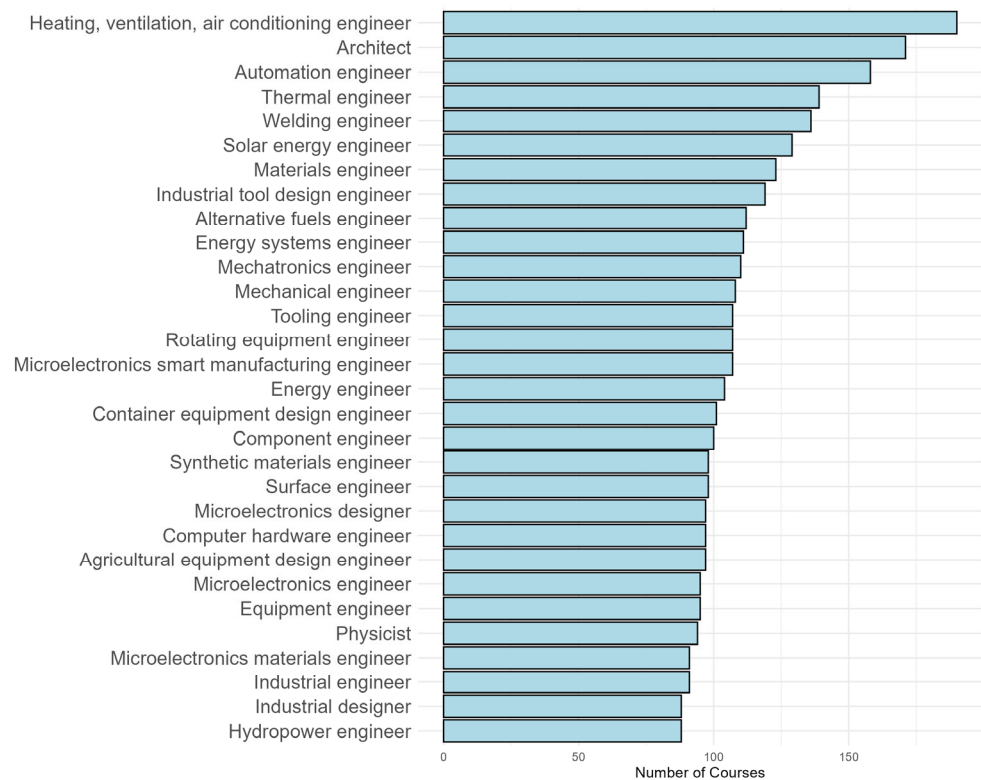


Figure 3. Top 30 occupations per number of courses.

The most recurrent competences (Figure 2) concern technical and engineering skills. First of all, the field of thermodynamics and heat transfer appears to be fundamental, with theoretical knowledge such as *heat transfer processes*, *thermal materials*, *thermodynamics* and *heat materials*. Another relevant topic for the department's training activity concerns production technologies and materials, with reference to *metal forming technologies*, *types of metal manufacturing processes*, *materials engineering* and *production processes*. The importance of an analytical approach is given by modelling and analysis skills, such as *mathematical modelling*, *analyse experimental laboratory data*, *check strength of materials* and *examine engineering principles*. There are also design and construction skills related to architectural and engineering design (*architectural design*, *design engineering components*, *develop design concepts*, *design principles*, and *design process*). Another building block pertains to the analysis of energy performance, indicating a connection with building/industrial practice and energy efficiency (*energy performance of buildings*, *advice on sustainability solutions*, *analysis of energy consumption*). In addition, transversal skills also play an important role in the training of engineering profiles, even though only communication and managerial skills appear in the reported top chart. Indeed, despite growing interest in transversal and soft skills and attempts to introduce them into engineering curricula, it remains difficult to determine which skills are truly prioritised and, above all, how to teach and evaluate them consistently; thus, those are not frequently mentioned in the syllabus (Caeiro-Rodríguez et al., 2021).

Among the most recurrent profiles (Figure 3), we find those related to mechanical and materials engineering, such as *mechanical engineer*, *materials engineer*, *thermal engineer*, *welding engineer*, and *component engineer*. The connection with the optimisation of production processes is found in figures like *industrial engineer*, *industrial tool design engineer*, *mechatronics engineer*, *automation engineer*, *microelectronics engineer*, and *computer hardware engineer*. These profiles reflect the integration of electronics, automation and engineering. There are also many profiles oriented towards energy and sustainability (e.g., *energy engineer*, *solar energy engineer*, *energy systems engineer*, *hydropower engineer*), which highlight

the attention to energy efficiency, renewable sources and the design of sustainable systems. The distribution includes profiles related to design and architecture (*architect, industrial designer*) as well as purely transversal ones (*physicist*).

Figure 4 depicts a tree map with the number of skills extracted by learning objectives across the hierarchical categories of ESCO. Figure 5 presents a similar map for the hierarchical categories of occupations of ESCO. The maps show a balanced mix of technical and transversal competences and profiles.

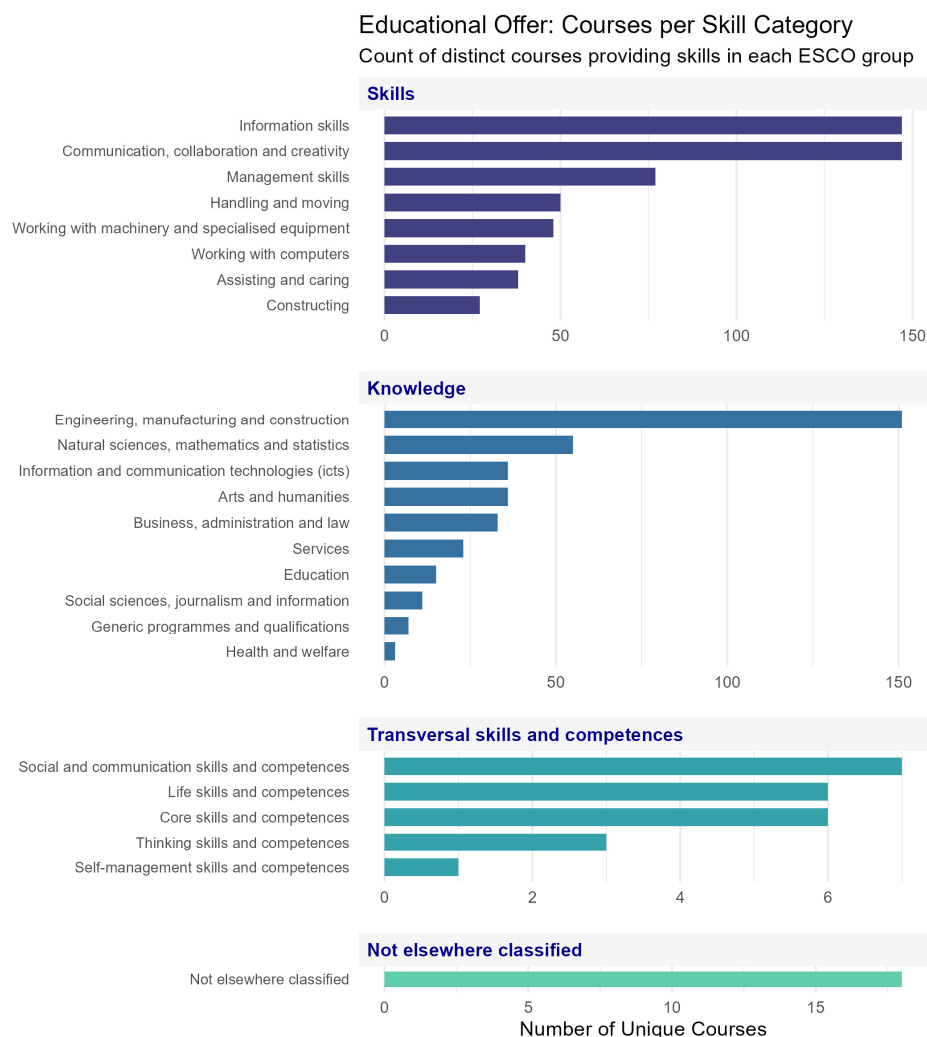


Figure 4. Competences extracted from the syllabi distributed in ESCO hierarchical categories.

In Figure 4, the *skills* section for practical and transversal skills is the predominant one compared to the *knowledge* section, which describes the basic theoretical knowledge addressed. The most relevant skills categories are *information skills* and *communication, collaboration and creativity*. The former regards the abilities to collect, analyse and manage technical and design information, essential for data-driven engineering. The latter includes the ability to manage technical complexity thanks to interdisciplinary integration in innovation and design processes. Then we find the *management skills* and the other practical components linked to the use of technical tools in laboratories and operational contexts. The most relevant knowledge areas are *engineering, manufacturing and construction*, to which the other areas contribute to strengthening their effectiveness. A small part of extracted elements belongs to the category of transversal skills; although transversal skills are frequently encouraged in teaching activities, they are rarely formally expressed in course design, leading to their limited presence in syllabuses.

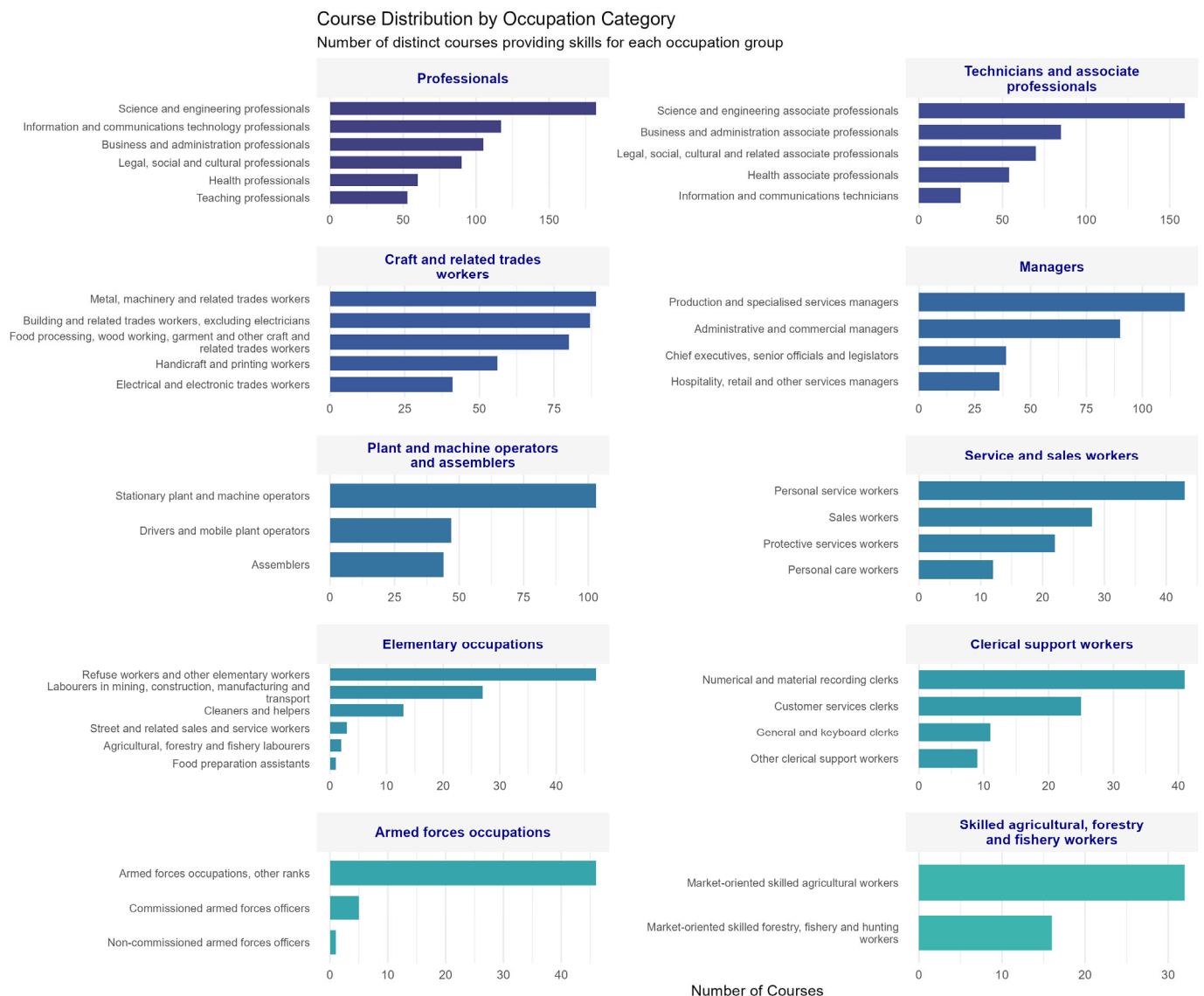


Figure 5. Occupations related to the skills extracted from the syllabus and distributed in ESCO hierarchical categories.

Figure 5 shows the distribution of occupational profiles and career opportunities related to the educational offer. The most relevant occupation groups relate to science and engineering (professionals and technicians), confirming the centrality of advanced STEM profiles. Another large group is plant and machinery operators, which reflects the relevance of practical and operational skills, especially in industry and manufacturing. A growing integration between engineering, digitalisation and management is suggested by the presence of ICT professionals and business/administration professionals. Distribution also encompasses categories such as production and specialised services managers, metal and machine trades workers, and partly plant and machine operators. This reflects the cross-cutting nature of engineering skills, capable of supporting roles ranging from advanced design to operational management and production process supervision.

The two maps of Figures 4 and 5 in combination suggest a strong relevance of applied technical skills, but also suggest management and digital skills that are in line with the transformations of Industry 4.0.

We can further explore the intersection, changing the perspective on courses and occupation groups in terms of specialisation or transversality, counting the course and shared skills. Figure 6 presents the degree of specialisation of courses, measured by the

number of different occupations associated with the course. The heatmap in Figure 7 allows for visualising the intersections between skills and occupational groups based on the number of courses which mention the competences in their syllabi.

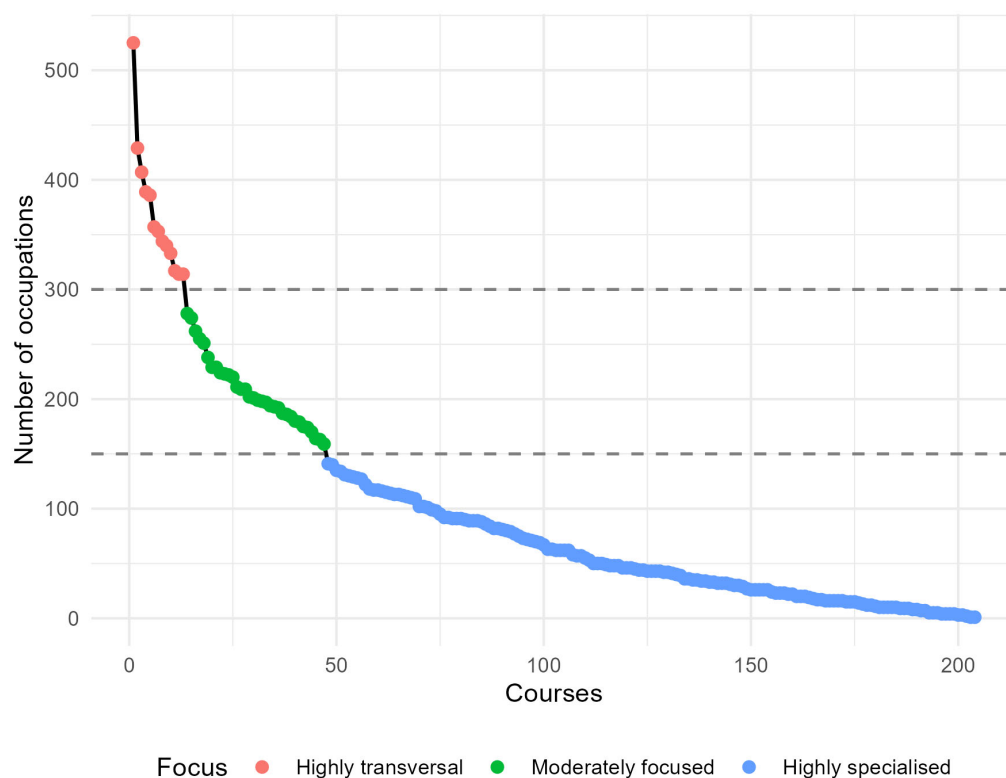


Figure 6. Trend in the number of occupations associated with courses. The horizontal dotted lines indicate thresholds, which divide the courses into three areas based on their focus: highly specialised (courses with ≤ 150 occupations), moderately focused (150–300), and highly transversal (>300).

The chart in Figure 6 reveals how the educational offer of DTU Construct covers a wide range of specialisation levels. The number of different occupational profiles linked to each course can serve as a proxy for the degree of specialisation of the educational offer. The highly transversal courses are 13 courses associated with over 300 occupations. They reflect broadly applicable training, preparing students for a wide range of professional roles. This pattern of highly transversal courses is partly due to the underlying connectivity structure of the ESCO skill-to-occupation matrix. ESCO has several generic competences associated with a large number of occupations. Yet, the courses in the category deemed “highly transversal” present LOs intended for a wide student population, independently of the specific disciplinary context. Therefore, this pattern emerges due to the adopted interpretative lens of ESCO and, due to the intrinsic transversality of some courses, simultaneously signals the structural connectivity in the two sources. In the middle, we find moderately focused courses (150–300 occupations), with 47 courses maintaining a core disciplinary identity while enabling access to diverse careers. Finally, the highly specialised courses (below 150 occupations) are tailored to specific professional niches. This suggests an educational offer that mixes technical depth with cross-sector relevance, supporting both specialisation and adaptability.

Figure 7 provides a measure of the connection between training offers and the labour market. The heatmap reveals how educational offers distribute skill categories across occupational groups.

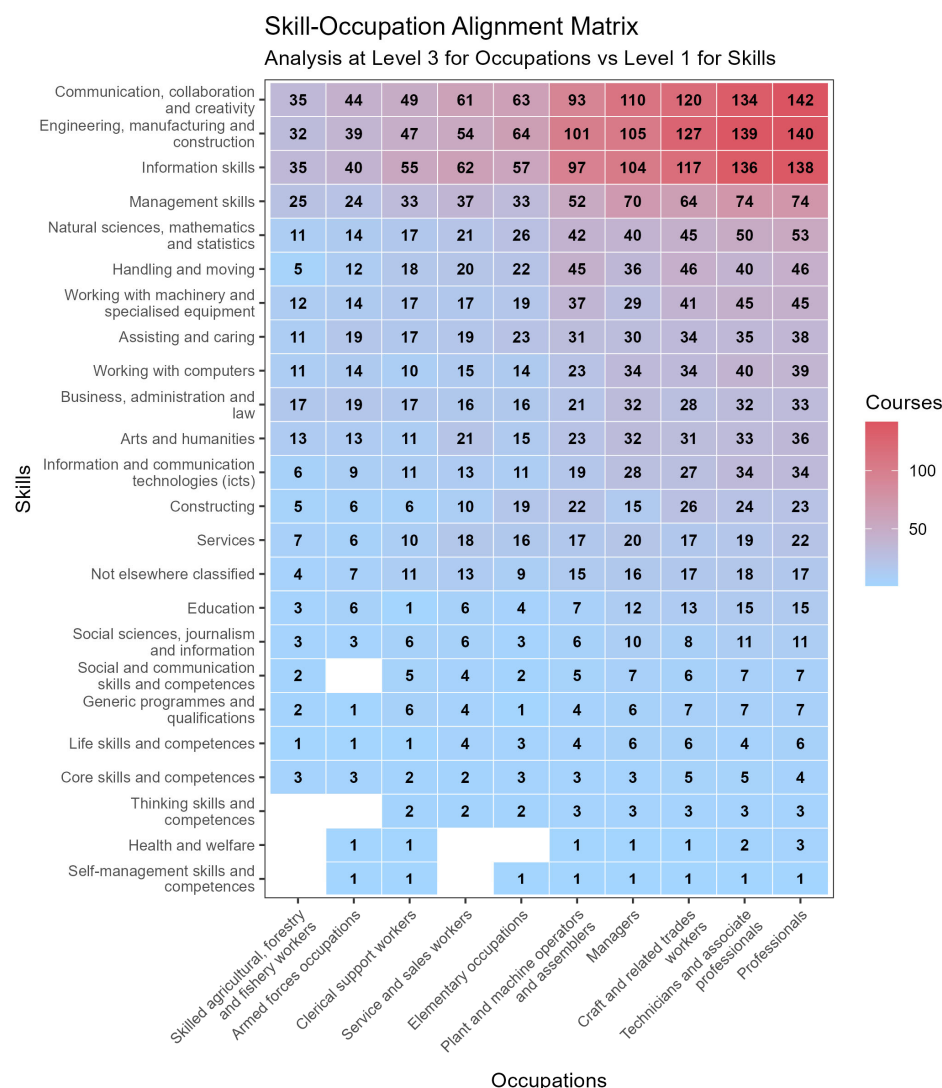


Figure 7. Heatmap showing the number of courses mentioning the skill categories (on the vertical axis) and the related group of occupations (on the horizontal axis). The intensity of the colour indicates the number of courses for each skill-occupation pair. Unlabelled cells correspond to zero.

The “hottest” areas, i.e., the ones with the highest intensity of red colour, located at the bottom right, represent courses focusing on the intersection between technical-engineering competences (e.g., *engineering, manufacturing and construction; working with machinery and specialised equipment; natural sciences; and mathematics and statistics*) and the target occupational groups of *professionals and technicians*. Most courses naturally reinforce competences required in advanced engineering roles and technical positions. Such positions also register warm intersections with transversal skills, such as the categories of *communication, collaboration and creativity, management skills, and information skills*. This suggests engineering education helps prepare students for leadership, coordination, and problem-solving tasks typical of engineering careers.

The “colder” regions, i.e., cells with low or zero values, positioned in the bottom left area, correspond to courses also referring to occupation groups and skills categories that are not directly related to the engineering field. Some of those marginal pairs may indicate unavoidable noise; others can suggest some weak signals of skills expansion or unexpected professional development. For example, *service and sales workers* and *clerical support workers* can indicate hybrid roles of emerging professional niches, addressing skills of technical or personal support in interface functions.

Overall, the heatmap depicts the educational offer and can be read as a course–labour market map. Students can use it to understand which competences they are most likely developing by taking the courses in their educational path. The connection of skills categories to occupational groups indicates potential career trajectories aligned with their learning profile. Similarly, workers can identify engineering-related competences to acquire in career development or in up/re-skilling activities. Teachers may reflect on the explicit and implicit profile of their courses and verify whether it aligns with the intended occupational outcomes.

5. Discussion

The findings present evidence on skills needs related to university courses in the analysed case study. The single-case study approach adopted in the analysis represents the analytical frame for validating our proposal of course–skill–occupation mapping by applying text mining techniques to course syllabi and by using the European Skills, Competences, Qualifications and Occupations (ESCO) classification. Such an application uses terminology consistency as a lever to support proactive action of universities in shaping the future of skills and work. The generalizability of the results presented here does not derive from the statistical representativeness of the case itself, but from the possibility of being applied to a broader class of cases, namely the analysis of education and training offer in rapidly changing professional contexts. The mapping of skills categories and occupation groups associated with an educational offer can be useful in several complementary ways for students, teachers, educational institutions, and labour-market stakeholders.

By highlighting the most relevant skills and occupations related to course syllabi, Figures 2 and 3 provide an overview of the educational offer of the department. This can improve students' awareness of knowledge and skills acquired during their studies and of career opportunities upon completing their degree, consolidating their background. Teachers can clearly describe their training activity, focusing not only on the specific learning objectives but also integrating the perspective of the labour market. The labour market and education system operate in two different languages in terms of descriptions for competences and learning goals (Aguayo-Arrabal, 2023). The terminology lever here bridges the two languages in a systemic way. HE institutions can integrate evidence on key competences and occupations covered by the proposed courses, making their relevance to labour market needs more transparent and verifiable. In this sense, the proposed standard reference can improve effectiveness in communication. The findings are also a valid support for the motivation of students. Moreover, students sometimes struggle in finding the purpose in their study, searching for the alignment between the training course and their career intentions or aspirations and the support of career guidance and teachers (Bandura, 1993). In this sense, improved communication can help. For example, a student may not intuitively associate studying a given topic with acquiring a given skill or being employed in a given occupation, while they may easily understand such a connection if clearly stated in the educational offering. Thus, both students and career guidance counsellors can benefit from such mapping. The utilisation of common terminology makes it possible to use the European Union's labour market intelligence tools, such as Cedefop¹⁰, laying the foundations for even deeper data integration to be able to speak the same language and refer to objective and timely data on market trends.

The charts provided in Figures 4 and 5 depict the most relevant categories of skills and occupations related to the course syllabi, providing details on the underlying patterns linking course content to labour-market skill demands. Indeed, it is possible to identify the skills addressed and the professional roles targeted as output. The terminology lever here allows framing the educational offer in terms of potential employment opportunities. This

evidence can support teaching planning. For a civil and industrial engineering department, the relevance of practical vs. theoretical content (Figure 4) and the growing integration of engineering, digitalisation and management (Figure 5) imply that strengthening the training offers automation and process control, production management and project management, an integration between technical design and sustainability, and transversal skills (ICT, communication, regulations).

Next, the exploration of semantic correspondences among syllabi, categories of competences and groups of occupations, presented in the graphs of Figures 6 and 7, allows recognising transversal patterns and making explicit the latent structures of the training offer. The cross-counts of the three observed dimensions (competence, occupation, course) presented in Figure 6 allow discovering the various modules of the training offer. The map in Figure 7, depicting the synergies in courses in terms of skills/knowledge or occupations, allows us to monitor both the variety and the consistency of the training offer, identifying areas of improvement and thus supporting strategic educational plans. Here, the terminology lever shows how the course content is organised into thematic and professional modules. This evidence can support career path development and indicate opportunities for up/re-skilling, but also verify coherence of the educational offer and timely identify possible improvements or gaps.

With respect to the field of literature reviewed in Section 2, evidence on course content translated into labour market terminology can support trainers to refocus their attention on curriculum and learning topics rather than mainly on performance outcomes. This proposed shift measures content; therefore, it counters the risk of overemphasis on quantitative parameters (Moshtagh & Sotudeh, 2023; Nicolescu, 2009; Williamson, 2019). Timely information and clear explanation can mitigate the overload highlighted by Lašáková et al. (2017). Therefore, the evidence proposed in graphs and visualisations can offer clear guidelines, consistent with the approaches proposed by Wolf (2007) and Gaftandzhieva et al. (2023).

This increased awareness can enhance employability thanks to a clearer understanding of learning possibilities (Bennett, 2019). It clarifies what kind of knowledge and skills are developed during the educational programmes and which professional roles they enable, so students better understand what they can offer to the labour market, and educators can better leverage how academic activities contribute to building a coherent experience portfolio and learning ecosystem. This fine-grain information enables the development of modular and synergistic programme designs based on links to common competences or occupations.

The evidence on skills categories and occupational groups opens up possibilities for future development toward more modular and flexible models of curricular design, in line with the recent design practices in the field (Ward et al., 2024). We propose here an interpretation of the indicators as structural components of a modular model: competence with frequency describes the relevance of modules, occupation with frequency sets the target of modules, categories of skills or occupations with their size constitute the architecture of modules, and the shared skills or occupations measure the degree of specialisation/transversality. Indeed, the skills embedded in LOs can be intended as the core modules building the educational offer. Such “bricks” can be combined considering the specific needs of a given professional profile and based on the degree of specialisation/transversality. This can support higher education for a modular design of the offer, drawing information from the skills–occupations catalogue. The categories of skills and occupations can constitute an informative layer in the architecture of the educational offer, in addition to the formal requirement of the qualification degree, which enables the identification of macro-areas overcoming boundaries of different educational fields and

promoting multi/inter-disciplinary and niche specialised content. Shared skills can become hubs for building stackable modules, combining different courses while maintaining general coherence.

Scholars are highlighting both the promise and the complexity of micro-credentials in higher education. As compelling as that sounds, the potential increase in flexibility of educational offer and labour-market responsiveness of universities, such approaches are still at an early stage of development, and their effectiveness depends on the availability of clear, evidence-based structures capable of linking learning to employability outcomes development (Thi Ngoc Ha et al., 2023). Our findings and the modular architecture outlined above provide initial insights and inspiration in response to this call, offering an evidence-based foundation documenting skills acquisition and ultimately enhancing graduate employability while supporting lifelong learning.

6. Conclusions

In conclusion, the proposed approach and the related findings can support the design of curricula based on frequent, emerging or distinctive skills, tailored to various professional roles to enhance employability. The obtained evidence and insights represent a strategic driver for employability, offering students, teachers, and institutions an actionable insight to proactively align learning with the competencies most valued in the labour market. The use of the ESCO classification with its structure makes it possible to highlight cognitive bridges to organise a stackable learning experience. Students can define their personalised learning pathways aligned with their inclinations and attitudes and identify leverage points that enhance their adaptive capacity. Teachers can identify how their course fits within the broader educational offer, facilitating modular or integrated course design even across disciplinary boundaries. The integration of ESCO skill tagging into syllabi can be incorporated into the syllabus revision plan, so that skills and occupations mapping would be systematically included during each review cycle, ensuring consistent adoption and long-term curricular development. Moreover, companies can identify opportunities for training current workers in upskilling and reskilling plans. Employers gain a clearer view of the competencies cultivated within specific programmes, enabling a specific talent identification and recruitment programme. The paper describes and implements a replicable and scalable pipeline (preprocessing, embedding, similarity, and mapping) with the European ESCO classification, contributing to the streams of educational text mining and labour market intelligence. The empirical results can be generalised and are thus useful for future studies on employability, curriculum design, and labour market intelligence. Finally, the study demonstrates how universities can use evidence on course content to proactively shape future learning ecosystems.

Despite these contributions, some limitations should be acknowledged. First, we analysed one university in one academic year, following the single-case study design approach; however, the results are grounded in the selected context, and by not having a cross-case comparison, it may be possible that some specificities will not be found in other contexts of use. We adopted course syllabi and ESCO as sources of data. However, the former only captures the declared learning objectives, which may not fully reflect the learning experience; the latter is the European reference framework, thus further expandable with other international references (e.g., O*NET). Concerning the methodological component, we exploit similarity extraction, with a single embedding model ('paraphrase-multilingual-mpnet-base-v2'), and only evaluated the use of LLMs. Possible improvements can include a workshop with domain experts or course instructors in order to refine the association among courses, skills and occupations. The approach directly depends on the linguistic quality and consistency of syllabi. The possibility of relying on natively English texts (and

not translated ones) is not common; the use of a multiline classification helps a bit, but we must always consider that performance may degrade in multilingual or less formal contexts. Our study does not involve any end users, neither students nor teachers or professionals, who are the potential beneficiaries. Therefore, future studies may address empirical assessment of usability, interpretability, or effectiveness.

Finally, the difficulties in systematic integration of skills-based evidence into institutional processes are still limiting the operationalisation of the results presented so far, which can be intended as strategic insights and not yet operational guidelines.

Therefore, this work can serve as a set of robust evidence for benchmarking exercises and future research. Cross-national and longitudinal analysis, even across different types of organisations (e.g., universities, polytechnics, vocational schools), as well as within multiple departments of the same institution, can be further explored. These insights can enable proactive support for higher education institutions in shaping the future of skills and work.

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Institutional Review Board Statement: This study did not involve human subjects, human material, human tissues, or human data. The dataset consists of publicly available university syllabi. No surveys, interviews, experiments, or social-media data collection were performed; we rely on the use of exclusively public institutional documents.

Data Availability Statement: The data presented in this study are available in the ESCO repository at <https://esco.ec.europa.eu/en>, reference number skills collection and occupation collection v1.2.1 (last update on 10 December 2025), and in DTU Course Base, reference number syllabi in the Academic Year 2025/2026. These data were derived from the following online resources available in the public domain: ESCO repository at <https://esco.ec.europa.eu/en> (last accessed 28 July 2026), DTU Course Base at <https://kurser.dtu.dk/search> (last accessed 28 July 2026).

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Appendix A explains the process for the identification of the semantic similarity threshold of 0.75 and the associated precision estimate of 85.54%, which is divided into four main phases: exploratory analysis, sample determination, precision evaluation, and refinement.

First, the frequency distribution of similarity scores was analysed, both overall (Figure A1) and by rank (Figure A2). The rank indicates the position of each similarity score within the five most similar skills identified for each sentence, with rank 1 indicating the highest similarity. The scores typically stabilise between 0.6 and 0.7, while below 0.6 the lowest values are found. This analysis guides the initial definition of the acceptability threshold.

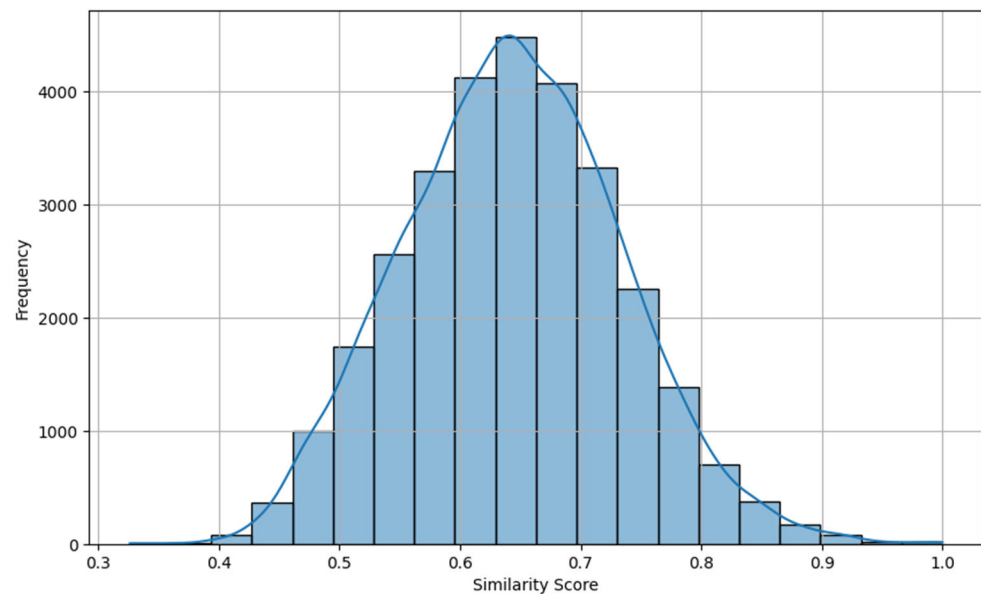


Figure A1. Frequency distribution of similarity scores in the population dataset.

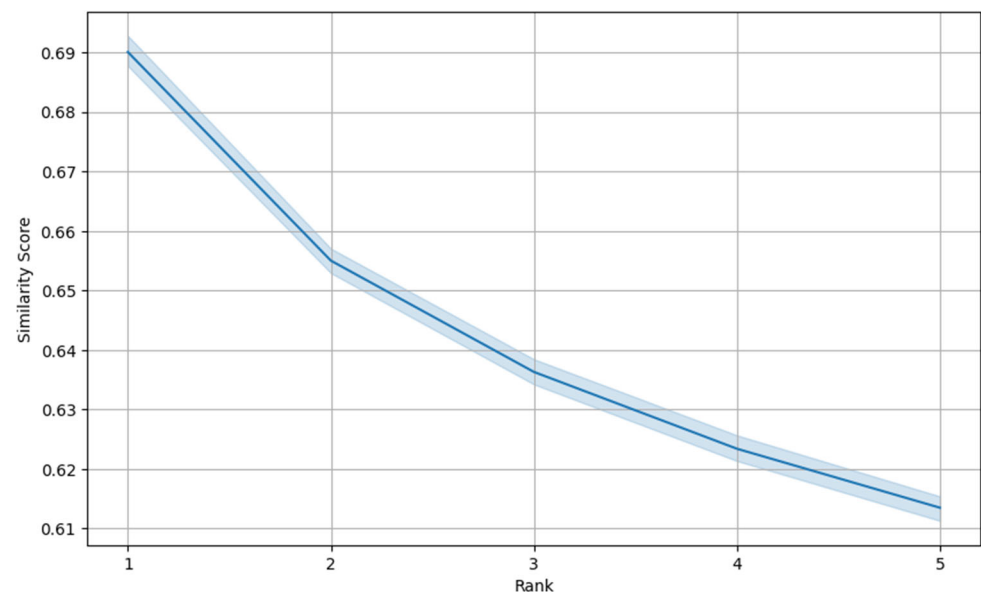


Figure A2. Trend of the similarity score by rank.

To ensure that the accuracy estimate is statistically significant, the sample size is determined using the formula for proportion in a population (Equation (A1)) and correction since it is a finite population (Equation (A2)), with the following parameters: 95% confidence level (corresponding to $Z \simeq 1.96$), margin of error at 5% (corresponding to $E = 0.05$), estimated variability $p = 0.5$, and population size $N = 30.055$.

$$n_0 = \frac{Z^2 \cdot p \cdot (1 - p)}{E^2} \quad (\text{A1})$$

$$n = \frac{n_0}{1 + \frac{n_0 - 1}{N}} \quad (\text{A2})$$

The initial sample was 380 units. To ensure a homogeneous representation of all ranks, a stratified sampling based on the rank variable is adopted, initially considering five groups, with 76 items per group. The equal amount was set to avoid bias toward the strongest matches, as higher ranks have higher similarity scores. The first estimate of

precision (correct matches compared to the total number of matches in the sample) was calculated as 48.68%. Figure A3 reports the trend of the parameter for the five groups.

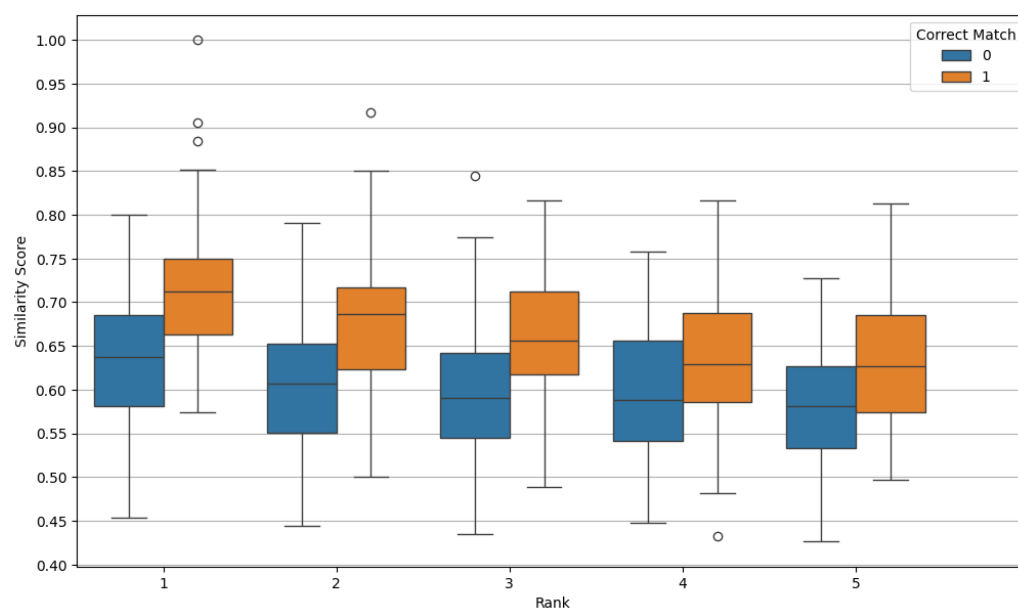


Figure A3. Boxplot of match comparison among similarity scores by rank (1–5).

An iterative approach follows to optimise the balance between precision and recall. First, a similarity threshold was set at 0.65, and the analysis was limited to the first three ranks, so the precision increased to 69.92%. Next, further increasing the similarity threshold to 0.70 with ranks 1–3, the precision was estimated as 77.77%. Finally, by setting the similarity threshold to 0.75 and keeping ranks 1, 2 and 3, the precision reached the value of 85.54%, as shown in Figure A4. The results of this process represent the validated dataset that minimises false positives by ensuring a significant portion of correct matches, with a confidence of more than 85% and a confidence level of 95%.

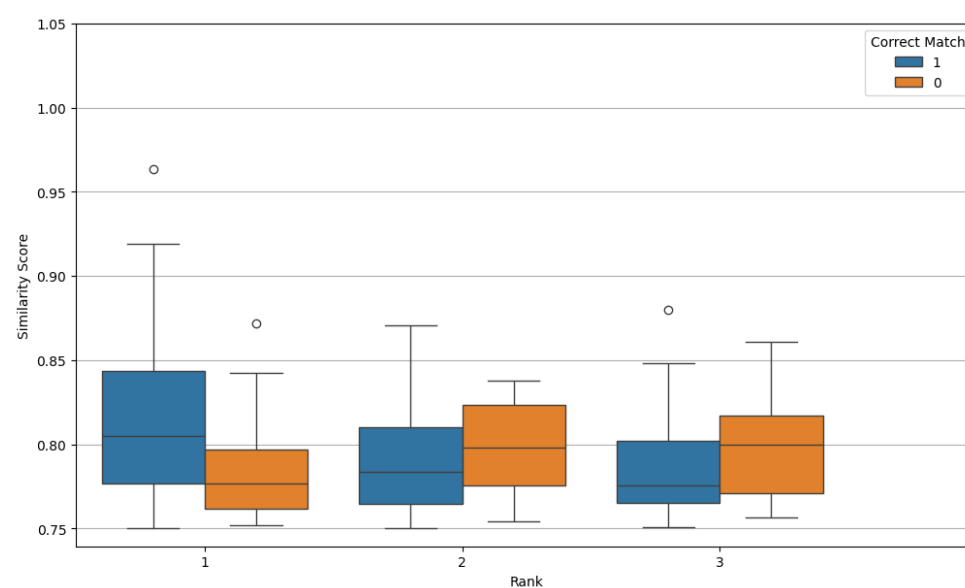


Figure A4. Boxplot of match comparison among similarity scores by rank (1–3).

Notes

- ¹ Qualification and ESCO on ESCOpedia <https://esco.ec.europa.eu/en/about-esco/escopedia/escopedia/qualifications-and-esco?id=222>, last accessed 28 July 2026.

- ² DTU Strategy 2026–2031 available online at <https://www.dtu.dk/english/about/strategy-policy/strategy-2026-2031>, link last accessed July 2026.
- ³ DTU rankings available online at <https://www.dtu.dk/english/newsarchive/2025/12/dtu-once-again-on-top-as-europes-best-technical-university> and at <https://www.dtu.dk/english/about/facts-and-figures/rankings#academic-ranking-of-world-universities>, links last accessed 28 July 2026.
- ⁴ The average values have been estimated selecting the largest and smallest polytechnics in Europe, based on the size of the institution in terms of number of students (reported on university key stats pages in <https://www.timeshighereducation.com/world-university-rankings/latest/world-ranking>, last accessed 28 July 2026) and the amount of degrees they are offering (reported on universities websites), next the number of syllabi is estimated considering the number of University Educational Credits (CFU), i.e., an average 6 CFU per course, 180 credits in three-year degrees and 120 credits in master's degrees.
- ⁵ <https://esco.ec.europa.eu/en>, last accessed 28 July 2026.
- ⁶ <https://esco.ec.europa.eu/en/about-esco/escopedia/escopedia/competence>, last accessed 28 July 2026.
- ⁷ <https://esco.ec.europa.eu/en/about-esco/escopedia/escopedia/knowledge>, last accessed 28 July 2026.
- ⁸ <https://esco.ec.europa.eu/en/about-esco/escopedia/escopedia/skill>, last accessed 28 July 2026.
- ⁹ We used Ollama Gemma3, available for download at <https://ollama.com/library/gemma3> (last accessed 28 July 2026). The experiments were conducted using Gemma3 4B (4.3B parameters), served locally through Ollama (version 0.14.3), in GGUF format with Q4_K_M quantization, with the following prompt: “You are an expert on skills analysis for higher education and the labour market. You are an expert in the European Skills, Competences, Qualifications and Occupations (ESCO) taxonomy. Based on this expertise and your knowledge, analyse the learning objective and select the most relevant ESCO skill or knowledge, meaning that it is most similar to, most aligned with, and most appropriate for the learning objective. If no ESCO item is relevant, output an empty array. Do not include any other text, explanations, or markdown.”
- ¹⁰ European platform collecting intelligence from experts and data on megatrends and aspirations of key stakeholders at national, regional, local and sectoral level into labour market trends and skill needs. It provides several dashboards of trends and prospects on the jobs and skills employers demand, based on online job advertisements (OJAs) in 32 European countries. The sources include private job portals, public employment service portals, recruitment agencies, online newspapers and corporate websites. The online tools are available at: <https://www.cedefop.europa.eu/en/online-tools>, last accessed 28 July 2026.

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