Scientific Reports
https://doi.org/10.1038/s41598-026-55076-w
Article in Press

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Received: 12 December 2025
Accepted: 21 May 2026
Published online: 03 June 2026

Cite this article as: Stoltman E., Ludot A., Ziolkowski P. *et al.* Advanced digital skills demands and priorities in wind energy sector. *Sci Rep* (2026). https://doi.org/10.1038/s41598-026-55076-w

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Advanced Digital Skills Demands and Priorities in Wind Energy Sector

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ABSTRACT

In a context of increasing digitalisation within the wind energy sector, the industry is facing a growing need for professionals with advanced digital skills, beyond traditional IT positions. As observed in other major transitions, educational institutions must adapt their curricula accordingly. Before recommending specific curricular updates, this study maps the demand for advanced digital skills in the wind industry using a mixed-method approach that combines expert interviews, survey data, and job-posting analysis. These complementary data sources are integrated to provide a comprehensive and holistic picture, by incorporating quantitative and qualitative data to overcome the usual bias of single-source analysis: job-postings provide a picture of the current labour market demands, surveys enable foresight perspectives, and interviews generate deeper qualitative insights. Interviews and job-postings are analysed using Natural Language Processing, enabling automated analyses that can be repeated in future years to track the evolution of the required skills, while qualitative analysis of the interviews provides additional contextual understanding. The triangulation of survey data, expert interviews, and job-posting analysis suggests a coherent picture of advanced digital skills priorities within the wind energy sector. Across all sources, scientific programming and numerical modelling consistently emerge as cornerstone competencies, while the prominence of machine learning, Internet of Things, and cybersecurity varies depending on organisational context and role requirements. Moreover, job-posting analysis shows that approximately 44% of engineering-related positions in the wind sector require advanced digital skills, while surveys and interviews indicate a broader range of emerging competencies, suggesting that the spectrum of required advanced digital skills is likely to expand in the near future. Interviews expand the analysis on skill gaps and lifelong learning needs, while the survey results also provide insights on preferred training formats. Together, these findings pave the way for a broader skill-gap analysis involving the curricula of educational institutions, with the aim of ultimately bridging this gap and supporting the upskilling and reskilling of wind-energy professionals.

1 Introduction

The wind energy sector is currently experiencing a deep structural transition driven by rapid digitalisation. Value creation in modern wind energy projects increasingly centres on sophisticated data analytics, artificial intelligence applications, and software-driven optimisation across the entire asset lifecycle, from initial site assessment through design, operational management, maintenance, and decommissioning[1]. This digitalisation has created new occupational profiles that blend domain knowledge with data science, machine learning, and software engineering capabilities. Wind farms now operate as complex systems generating large-scale data streams that enable predictive maintenance, performance optimisation, and grid integration through data-driven analytics. Consequently, the sector demands professionals capable of developing, implementing, and maintaining production-grade digital systems rather than only operating existing technologies[1,2]. This is also the distinction between advanced and basic digital skills as defined by the European Commission[3,4].

This structural shift mirrors a broader pattern documented across the wider economy. The International Labour Organisation's review of digitalisation and employment[5] confirms that digital transformation is generating new occupational categories, particularly in data science, artificial intelligence, cybersecurity, and digital systems, while simultaneously rendering routine technical roles increasingly redundant. Recent work on digital transformation and labour markets further shows that advanced digitalisation is reshaping occupational structures by creating hybrid roles that combine domain expertise with data, AI, and programming skills[6]. However, measuring this shift presents its own challenges: occupational classifications of green jobs are difficult to operationalise, as broadly defined categories can include roles whose actual environmental contribution is limited[7]. Moreover, terms such as "AI" or "data-driven methods" are frequently used as overarching labels in industry and policy documents rather than as clearly defined competencies, obscuring the specific skills that professionals actually need to develop and apply[8]. Effective use of these technologies depends on a solid knowledge base that enables professionals to correctly evaluate and contextualise results, underscoring the need to systematically identify and specify advanced digital skills across different occupations and seniority levels.

The rapid evolution of these skill requirements has outpaced workforce development, creating significant gaps between industry demand and available competencies[8,9]. University degrees and standardised training programmes often require years to adjust curricula, leaving students and professionals with knowledge that rapidly becomes outdated, particularly regarding advanced programming languages, data analytics expertise, and cybersecurity[10]. These challenges take different forms across educational profiles, from vocational schools to engineering programmes, both of which face the challenge of bridging theoretical knowledge with rapidly evolving industrial practices that demand immediate application of cutting-edge digital competencies.

Universities and other training providers play an essential role in closing this gap by updating their educational offerings, which requires a detailed and up-to-date understanding of what the market actually demands. Several initiatives have been working to identify the skills required for digitalisation. The BRIDGE 5.0 project focuses on skills for Industry 5.0 and the development of a corresponding learning platform for companies; Industry 5.0 complements the existing Industry 4.0 approach by placing research and innovation at the service of a sustainable, human-centric, and resilient European industry. The SKILLLAB project aims to identify skill gaps between the workforce and industry needs through a shortage-identification platform that enables policymakers to monitor skill supply and demand automatically, generating recommendations for hiring policies, personalised educational plans, and curriculum improvement. In the renewable energy sector, the FLORES project[11] focuses on upskilling and reskilling professionals in the Offshore Renewable Energy sector, identifying necessary skills and promoting relevant training opportunities. Within this broader context, the DigiWind project[12], co-funded under the EU Digital Europe Programme and the main funding source for the present study, aims to address these needs by developing specialised, interdisciplinary educational programmes that promote advanced digital skills.

Despite these efforts, most existing work on skill needs either addresses generic workforce requirements, such as technician availability, health and safety, or basic digital literacy, without systematically analysing advanced digital skills, or relies on a single data source[13,14]. Single-source designs have notable limitations: they tend to under-represent emerging roles and transferable skills, are sensitive to short-term hiring dynamics, and rarely capture organisational foresight regarding future digitalisation trends. At the same time, improvements in natural language processing have opened new possibilities for analysing skill demand at scale, enabling the extraction of skill entities from job postings and the tracking of emerging competency domains[15–18]. Building on these methodological advances and following the approach presented in the Grand Challenges in the Digitalisation of Wind Energy article[1], this study extends the combination of qualitative and quantitative information from two to three data streams: 1) surveys and 2) job postings to gain a broad understanding of current demand, and 3) expert interviews to capture more granular and nuanced industry foresight. The study is descriptive and exploratory, aiming to map patterns of demand for advanced digital skills rather than identifying causal relationships. Data triangulation across these three sources strengthens both the validity and reliability of the findings[19,20].

Using this combined approach, this paper aims to address the following goals:

- Establish an up-to-date understanding of the advanced digital skills in demand in the wind energy sector.
- Identify how skill requirements may differ according to occupation type or seniority level.
- Understand which training formats best facilitate the acquisition of advanced digital skills in the wind energy sector.
- Identify and map gaps or alignments between industry foresight on advanced digital skill needs and current job market demand.

This study contributes to the current state of the art by providing (1) a multi-source empirical mapping of advanced digital skill demands specific to the wind energy sector, (2) occupation- and seniority-specific cross-validation of labour market data with expert experience and foresight, and (3) a repeatable methodology enabling long-term skill demand tracking and curriculum redesign.

The paper is organised as follows: Section 2 outlines the methodology used to collect, process, and analyse data from each source. Section 3 presents the results, beginning with a comparative overview integrating findings from both quantitative and qualitative analyses, followed by detailed insights from each data source.

2 Methodology

The study uses a mixed-methods approach, combining quantitative and qualitative analysis to address the challenges described above. Mixed-methods research combines quantitative and qualitative methods to leverage the strengths of each approach. Quantitative data provides statistical reliability, while qualitative data explains the reasons for results and the context behind them[21]. Figure 1 shows the different data sources used and their expected outcomes. In this methodology section, the studied skills and the taxonomy applied are first defined and described. Next, the analysed data are detailed. Finally, the methods used to process and analyse each data source are presented in the concluding section.

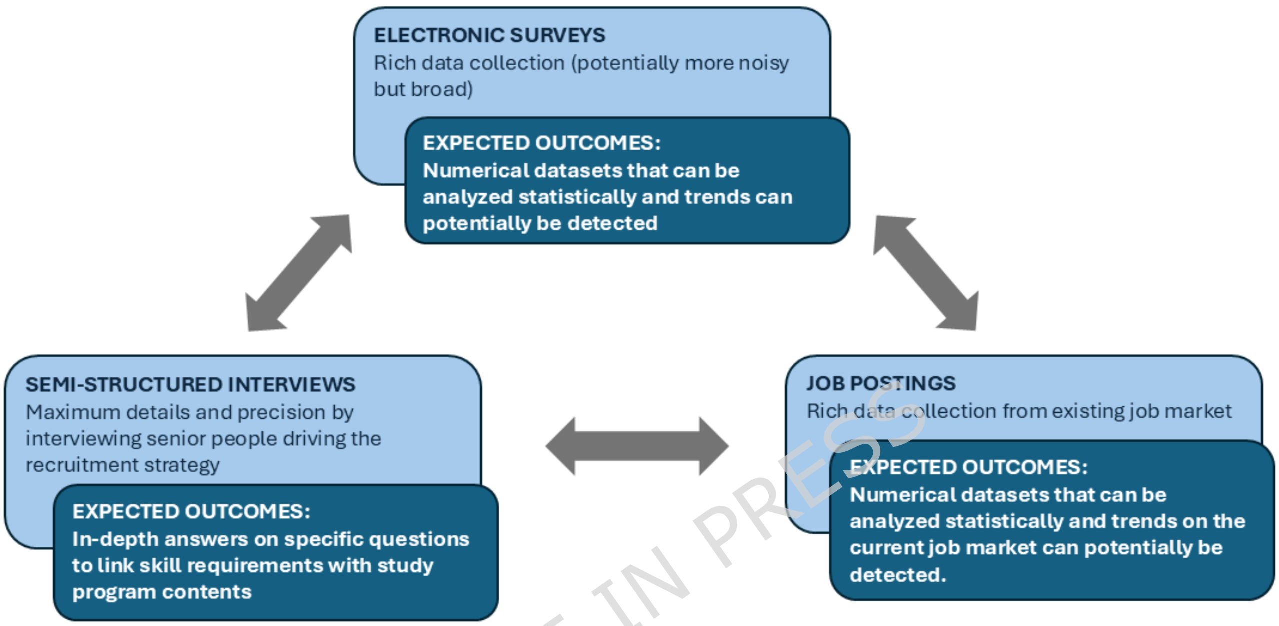

Figure 1. Details on the methods used to collect data in this work

2.1 Definitions of skills and occupation levels under study

Definition of advanced digital skills

To ensure a systematic and consistent analysis of survey results, interviews and job postings, a structured taxonomy of 12 advanced digital skills categories was developed (Table 1). This classification consolidates the Key Capacity Areas from the Digital Europe Programme, specifically adapted for the wind energy domain to ensure relevance and practical applicability. The Digital Europe Programme identifies five Key Capacity Areas: supercomputing, artificial intelligence, cybersecurity, advanced digital skills, and the deployment of digital technologies across the economy and society. To translate these broad areas into actionable, wind-energy-specific categories, a structured adaptation process was conducted within the DigiWind consortium. Each Key Capacity Area was decomposed into more granular competencies based on three inputs: i) the domain expertise of consortium members spanning academic, industry, and training institutions; ii) relevant sector literature, including the Grand Challenges in the Digitalisation of Wind Energy[1,22]; and iii) an iterative review of pilot interview and job-posting data to confirm practical relevance. Specifically, *supercomputing* maps to high-performance computing (HPC); *artificial intelligence* is divided into machine learning & data science and generative AI & large language models, reflecting their distinct technical requirements; *cybersecurity* is retained as a standalone category; and *deployment of digital technologies* is expanded into scientific programming, numerical analysis & simulation, data engineering, cloud computing, IoT & extended reality, robotics & autonomous systems, digital research communication, and blockchain, capturing the breadth of applied digital competencies relevant to the wind energy sector. The fifth Key Capacity Area, *advanced digital skills*, constitutes the overarching aim of the programme rather than a discrete technical competency, and as such underpins the taxonomy as a whole rather than mapping to a single category.

Table 1 summarizes these 12 categories and highlights multiple domain areas to connect advanced digital skills with the specific domain area(s) where they are most critical. Based on the definitions of the advanced digital skills domain, a list of keywords reflecting the skills was created as described in detail in the following sections.

Definition of ESCO occupational levels

The European multilingual classification system for skills, competences, and occupations[23] (ESCO), works like a dictionary, describing, identifying, and categorizing professional occupations and skills that are relevant to the EU labour market, and the education and training sectors. It describes 3,039 occupations and 13,939 skills, translated into 28 languages. ESCO's concepts and relationships are machine readable enabling its use for automated analysis. ESCO aims to create a shared common language between employment, education, and training thus helping to bridge the gap between them. In DigiWind, the primary focus is on occupations. Each ESCO occupation is linked to a code, based on a classification system that organizes jobs based on the tasks performed. Each occupational profile includes the knowledge, skills, and competences that experts define as important for that role. Occupations are organized into a hierarchical structure using a 4-digit code, broken down as shown in Figure 2.

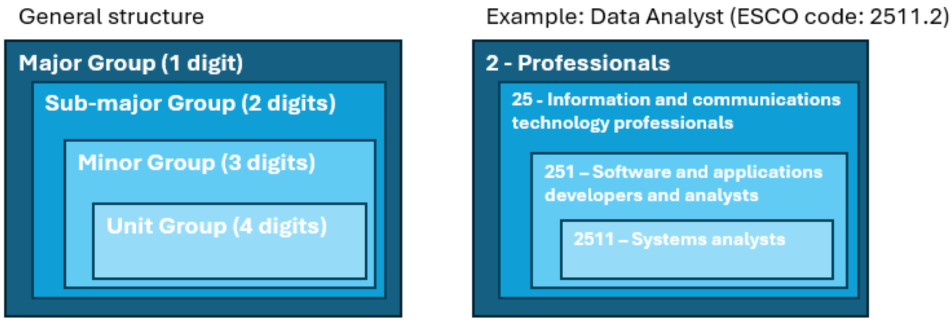

Figure 2. Illustrated example of the hierarchical structure of ESCO occupations taxonomy.

2.2 Data description

The study uses a combination of quantitative and qualitative methods. The various data collection activities where external respondents are involved are outlined in Table 2. The quantitative analysis refers to surveys conducted among the current workforce and an assessment of digital skills requirements in job postings from the wind energy industry. The qualitative part consists of semi-structured interviews with industry professionals. Semi-structured interviews are a flexible way to collect qualitative data. They combine predetermined open-ended questions with additional questions based on the participant's responses[24].

2.3 Survey analysis methodology

Quantitative data collection

A survey instrument was developed via the EU Survey platform, targeting employers, training organisations, and industry experts. We asked respondents to participate through different channels, including LinkedIn posts targeting professionals in the wind energy sector, as well as by making direct contact at industry conferences (e.g., WindEurope). In addition, we used the DigiWind consortium's networks and promoted the survey through our project website. Respondents were asked to rank up to three priority areas of digital skills, where rank 1 indicated the highest priority and rank 3 the lowest. This ranking approach facilitated the identification of relative importance among 12 predefined digital skill categories. In addition, respondents assessed the suitability of various training methods (e.g., online courses, workshops, mentoring) using a 5-point Likert scale, where 5 represented the highest perceived suitability. Cross-sectional variables such as job position, professional experience, organisation type, and national or regional affiliation were also collected. These variables enabled segmentation of the data and comparison of perspectives across stakeholder groups.

Survey data processing methodology

A total of 108 valid responses were collected and processed for quantitative analysis. Data were cleaned, categorised, and coded to ensure consistency across question formats[26]. The initial step was to create an overview of the response distribution across participant categories and countries. To support comparative analysis, the ranking responses were converted into weighted scores. Higher-ranked priorities received greater weights (e.g., rank 1 = 3 points, rank 2 = 2 points, rank 3 = 1 point), allowing an aggregated comparison of the relative skill importance across all respondents. The relative importance scores are derived separately for each data source by dividing the amount of times each skill is mentioned by the total number of times all skills are mentioned. The same process is used in all following analyses. This makes it easy to compare the skills through different data types. The aim was to analyse the relationship between advanced digital skills and different roles and areas within wind energy.

2.4 Interviews analysis methodology

Interview design and execution

Fourteen semi-structured interviews explored industry perspectives on digital skills requirements and training approaches in five countries and seven wind energy sectors (see Table 2). The DigiWind consortium helped in selecting the respondents using purposive sampling. This means that respondents were strategically chosen based on their leadership positions and specialized expertise in the offshore wind sector[27]. Each one-hour online session followed a standardized protocol: pre-interview survey completion, dual-interviewer format (moderator and note-taker), recording with automatic transcription, and structured post-interview summaries. The interview guide comprised 16 questions organized around three themes: current skills gaps, preferred training approaches, and future requirements (5-15 year horizon). Post-interview preliminary summarising analysis documented seven areas: training gaps, future skills, preferred formats, willingness to invest, collaboration preferences, follow-up activities, and key highlights. The complete interview guide can be found in Appendix 5.

Qualitative data analysis

For the interview analysis, transcripts were pre-processed using Python to retain substantive passages containing at least $\geq$60 characters and $\geq$12 tokens. This threshold was implemented to exclude minimal, non-informative remarks (e.g., "yes," "maybe," "I don't know") while preserving segments that convey sufficient semantic and syntactic context for qualitative interpretation. Selecting passages of this length aligns with standard recommendations in qualitative content analysis to define a unit of meaning[28,29]. Text pre-processing used the spaCy en_core_web_md pipeline: punctuation removal, lowercasing, lemmatization, tokenization, and stop-word elimination. This medium-size English model is trained on written web text (blogs, news, and comments) and includes components for vocabulary, syntax, and named entities. Tokenization segmented text into meaningful units, handling punctuation and contractions, while stop words were removed using spaCy's default list[30]. The coding procedure used a primarily deductive thematic approach[31], applying a hierarchically structured keyword database derived from the job-posting analysis and tuned iteratively with the interview data. Indeed, the use of NLP is limited by the need for task-specific databases, and the time required to develop an annotated dataset tailored to the advanced digital skills examined in this paper is prohibitive. Therefore, the methodology focuses on keyword matching based on the defined lists. The database aims to be as exhaustive as possible and has been tuned using interviews' content and reference job postings. This framework is structured around two overarching categories: "Workforce Development & Management" and "Advanced Digital Skills", with eighteen subcategories (Appendix Table 5 and 6).

Sentiment analysis was conducted using the SiEBERT model (prefix for "Sentiment in English")[32]. This model is based on the robust RoBERTa transformer model. Compared to previous Bidirectional Encoder Representations from Transformers (BERT) models, it uses improved pre-training techniques, such as dynamic masking. The model assigns positive, neutral, or negative labels with associated confidence scores, providing a richer and more nuanced understanding of the interviews. The class with the highest probability was selected as the predicted sentiment. Although the original training data mainly used social media texts, the model's sophisticated design can be used to analyse and understand different types of text. In addition to thematic and sentiment analysis, the study incorporated social network analysis (SNA) to provide a deeper relational perspective. Network analysis examines complex systems by analysing the relationships between speakers and topics. In this study, the speakers are respondents and the topics are "Advanced Digital Skills" and "Workforce Development and Management". The respondents are considered as a network, even though they may not have connections outside the context of this study. The level of connectivity within a network can be measured using degree centrality. It measures how frequently topics and respondents appear together. The analysis is further expanded by topic centrality, which identifies the topics that act as important connecting links and influence the flow of knowledge and collaboration between respondents. Centrality can also be calculated from the perspective of the respondents. It shows how many connections a respondent has to a topic, but also how many respondents are connected to each other via topics, which is referred to as betweenness centrality.

2.5 Job postings

This part of the data collection aims to identify trends in the demand for advanced digital skills in the current job market through the automated analysis of a large dataset of job postings. The main question addressed is: *How likely is it that wind-energy job postings require advanced digital skills, and which specific skills are most in demand?* An additional goal is to determine which advanced digital skills are most relevant for specific occupations within the wind industry. This analysis relies on two datasets introduced earlier. The first dataset[25] is a database of 1.3 million job postings from 2024, scraped from LinkedIn (in the remaining of the paper referred to as the *LinkedIn database*). This dataset is broad and is expected to reflect the US and European job market in a given year. It mainly contains offers from the US and the UK. A filtering will be applied to extract wind-related jobs. The second dataset, referred to as the FLORES database, consists of targeted job postings collected for the FLORES project, focused on European countries and well-known wind industry companies vacancies websites (from 2023). Using this more targeted dataset, we aim to validate and compare the results obtained from the broader LinkedIn dataset. The following subsections describe the pre-processing and analysis methods applied to both datasets.

LinkedIn database

This dataset was selected for its open-source availability, large number of job postings, recent scraping year, and its structure (including separate fields for job title, location, description, company, LinkedIn URL, ...). Additionally, a dataset that included the full job description in raw form was needed, to allow the use of automated natural language processing techniques to extract the relevant skills and occupations. The overall methodology to analyse the job postings is illustrated in Figure 3. It relies on four main steps:

- Preprocessing: Each job description was pre-processed in the same way as the interviews, without removing stop words or applying the filtering on short sentences.

- Filtering: Based on a manually compiled set of generic wind energy job postings, a list of relevant keywords was compiled to enable the extraction of wind-related technical job postings from a broader database. These keywords are shown in Figure 3. As some of the selected keywords consist of multiple words, spaCy's rule-based tool *PhraseMatcher* was used to detect whether the lemmatized keywords matched any part of the lemmatized job descriptions. Out of this filtering stage, 544 wind related jobs are extracted.

- Classification using the ESCO Occupation Taxonomy: Out of the extracted wind-related job postings, the corresponding job titles were analysed. The first step involved cleaning the titles by removing additional words (e.g. "senior", "junior", "temporary" ...), converting the text to lowercase, and removing all punctuation as well as non-word or non-whitespace characters. The cleaned titles were then converted into embedding vectors using the *SentenceTransformer* model *all-mpnet-base-v2*, which maps sentences to a 768 dimensional dense vector space suitable for tasks such as clustering or semantic search. This model was selected over other pre-trained models from the *SentenceTransformer* library for its high accuracy (69.57% average performance across 14 diverse tasks[33]) despite its slightly higher computational cost. ESCO occupation titles were also processed and converted into embedding vectors. The cosine similarity between each job posting embedding and each ESCO embedding was then computed, and the most similar ESCO occupation from the *LinkedIn database* was assigned to each job posting based on the highest similarity score. An intermediate step involved checking whether the highest similarity score exceeded a defined threshold. If not, no ESCO occupation was assigned to the job title, as it was assumed that none of the ESCO titles adequately matched the corresponding job. The threshold was determined through a sensitivity analysis examining the trade-off between the number of unassigned jobs and the number of job titles classified under the occupation *Professionals* across different similarity score levels. The objective is to balance coverage (i.e., the share of jobs assigned) and the stability of conclusions (i.e., the consistency of central findings). The same analysis was conducted using an alternative *SentenceTransformer* model to validate the observed trends and assess assignment consistency (Figures 12, 13 and 14). The results indicate that the main finding of the job postings analysis, namely, the estimated share of Professional-level positions requiring advanced digital skills, remains stable across thresholds up to 0.6. Accordingly, a threshold of 0.6 was selected, as it provides a suitable balance between coverage and confidence in match quality.

- Extraction of skill requirements: As described earlier, a list of advanced digital skills and keywords was compiled for the analysis of interviews and job postings. This dictionary was lemmatized using the same model applied to the job descriptions, and each keyword was converted into a regex pattern to enable matching within the lemmatized job descriptions.

FLORES database

The database gathered by the FLORES project is summarized in Table 2. Its structure includes the following columns for each job posting: job title, company, work model, job location, sub-sector addressed (as all ORE technologies are considered), link to the offer, technical skills/competences requested, soft skills requested, knowledge requirements, educational/training requirements, language skills, required experience, job level, working hours, and duration of contract. Since the job descriptions have already been preprocessed to only keep the information listed above, the same methodology used for the LinkedIn database could not be applied. A filter was applied to the "sub-sector addressed" column to keep only wind-related job postings. Technical skills were then manually reviewed to identify postings requiring digital skills. When relevant, these skills were manually classified into the 12 predefined advanced digital skill categories listed in Table 1; otherwise, they were labelled as "Uncategorized". For the mapping of occupations to the ESCO taxonomy, this was performed as part of the FLORES project: each job title was entered into the ESCO "Search occupations" function, and the results were checked to identify the best fit considering both, the occupational profile description and the alternative labels provided.

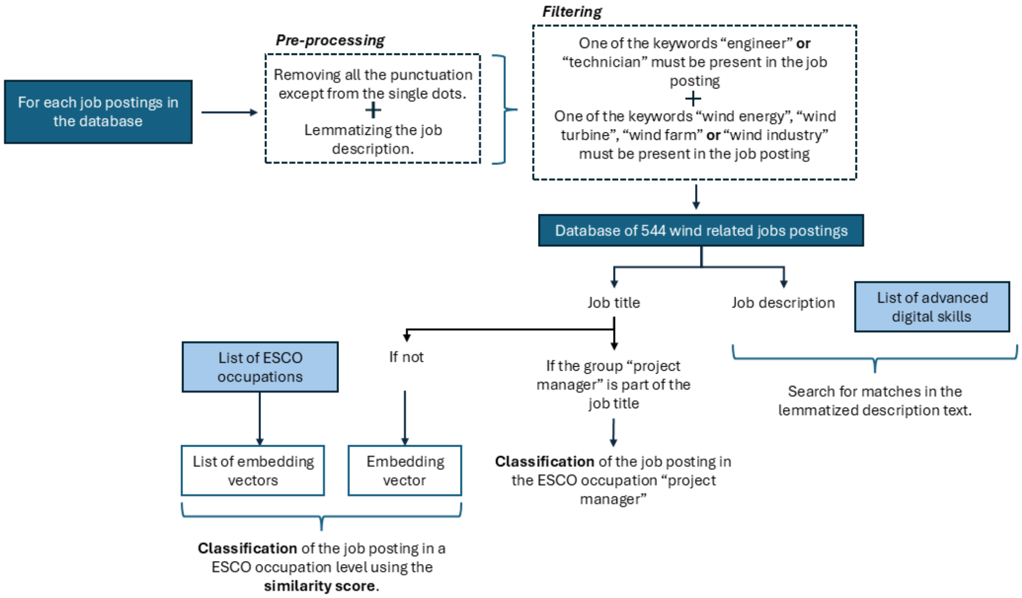

Figure 3. Methodology for filtering and classification of the job postings according to the ESCO occupation taxonomy.

3 Results

This section reports the results from the three sources, starting with the combined findings and then examining each source separately.

3.1 Combined Results

The triangulation of survey data, expert interviews, and job posting analysis shows a coherent and consistent picture of advanced digital skills priorities within the wind energy sector (Figure 5). What emerges is a hierarchy of advanced digital skills illustrated in Figure 4. This hierarchical structure suggests a broad convergence in the wind energy industry on which digital competencies are the most important for innovation, operational excellence and competitiveness.

Across all three data sources, scientific programming, numerical analysis, and machine learning emerge as the key competencies, although organizational context influences the emphasis placed on new or specialized skills. Especially, the analysis of job postings underlines the importance of scientific programming. Looking at Figure 5, the frequency of required programming skills is almost twice as high as in any other category. Survey results and assessments of hiring intentions confirm the leading position of numerical analysis and simulation, and scientific programming representing almost fundamental requirements. Job-posting data provides a more nuanced picture of the wind energy sector when examined independently of the survey data. Among 544 wind-related vacancies, 28.1% explicitly mention at least one advanced digital skill. Looking only at professional-level jobs (i.e., excluding technician and managerial positions), scientific programming appears in 31% of the requirements, indicating that such skills are valued but not yet a universal requirement.

While the job-posting analysis shows a clear predominance of scientific programming and numerical analysis among roles requiring advanced digital skills (leaving other categories largely unrepresented), the survey and interview results highlight the importance of several additional advanced digital skill categories, with multiple relative-importance scores exceeding 0.1. This highlights a gap between the three sources: job postings do not clearly reflect the demand for machine learning or data engineering skills emphasized in the survey and interview findings. This gap can be interpreted through the distinction between revealed demand (what employers are formally requiring today through job advertisements) and anticipated demand (what practitioners and experts foresee as necessary competencies in the near future). It likely arises from the differing time horizons of the sources: job postings reflect current hiring needs, whereas expert interviews and surveys capture anticipated future requirements as well as current needs not yet evident in the job market. This pattern is further corroborated by a recent IEA analysis of digital skills demand in the broader power sector[34], which found that machine learning, artificial intelligence, and IoT remained under-represented in job postings despite attracting growing interest in the research and practitioner community,

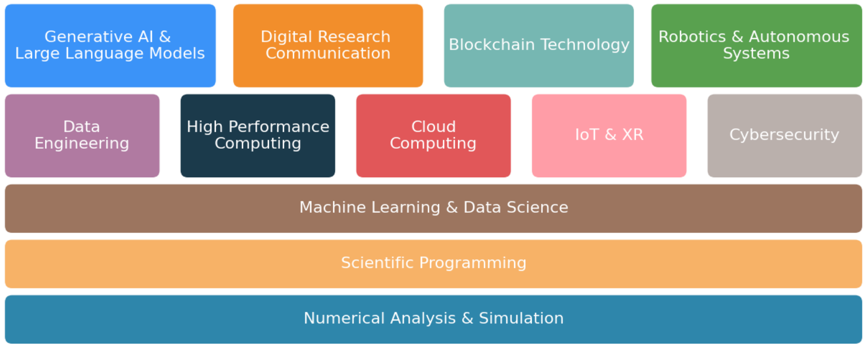

Figure 4. Hierarchical listing of advanced digital skills. The most important (fundamental) skills are at the bottom of the figure, with the importance decreasing for skills higher up in the figure.

suggesting that the lag between anticipated and revealed demand for advanced digital skills is a sector-wide phenomenon rather than specific to wind energy.

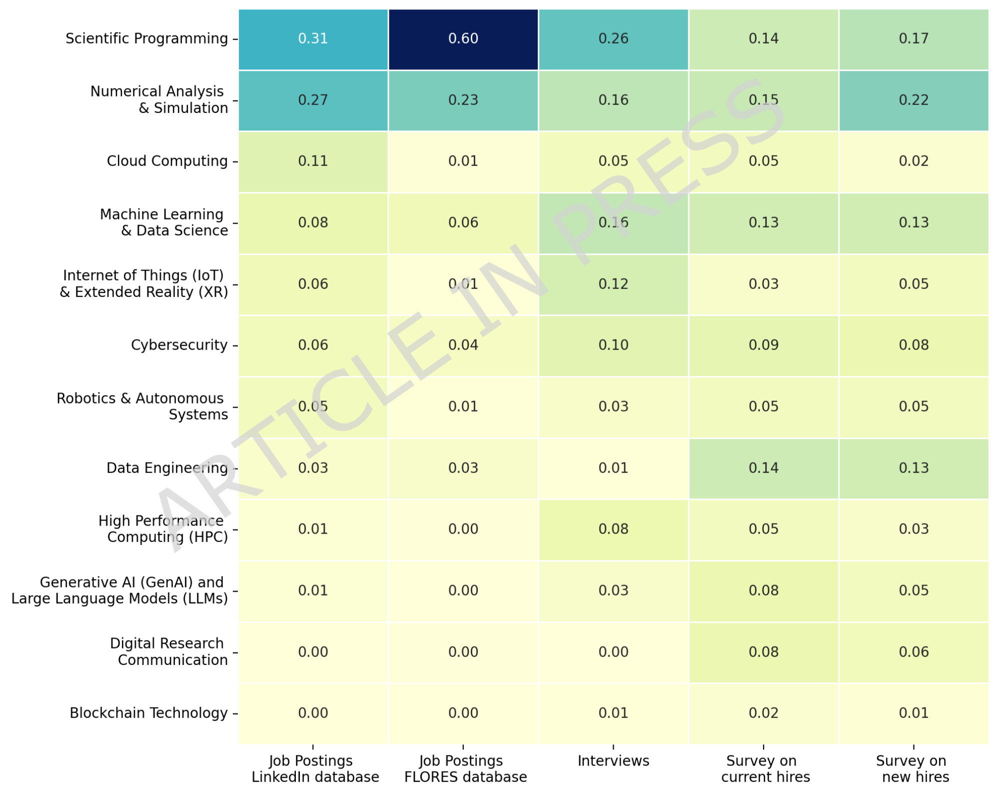

Figure 5. Comparison of relative importance of advanced digital skills from different data sources.

A limitation of importance scores based on the number of hits in keyword-based analysis (for LinkedIn job postings and interview analysis) is their potential bias introduced by the unequal number of keywords included per domain. A domain with a larger keyword list has a higher baseline probability of matching, which may inflate its apparent importance relative to domains with shorter lists. To assess the robustness of the findings presented in Figure 5, an additional weighted importance score has been computed, where the number of hits is multiplied by the ratio of active to defined keywords for each category. This ratio accounts for both the overall coverage of the keyword list and the relevance of the domain vocabulary in the corpus. Table 3 presents the comparison between the unweighted and weighted importance scores across all advanced digital skill categories. The ranking remains largely stable between the two scoring methods, with Scientific Programming and Numerical Analysis & Simulation consistently occupying the top two positions. The most notable shifts are observed for IoT & XR, which drops from 5th to 7th position after weighting, and Scientific Programming, which further increases its lead. This stability across scoring methods strengthens confidence in the overall hierarchy of skill priorities identified in the paper, suggesting that the main conclusions are robust to the choice of importance score computation. The same analysis has been done on interviews results with the same conclusions.

3.2 Survey Specific Results

The survey results further explain how priorities are set in the hiring process and in the current workforce. Across both hiring intentions and current workforce priorities (Figure 5), their relative order varies modestly between contexts; the overall structure remains stable. The core computational skills (numerical analysis and scientific programming) maintain fundamental positions, while the more specialized capabilities (machine learning, data engineering, cybersecurity) show differences in rank, suggesting their importance is more sensitive to organisational context. Cybersecurity occupies an intermediate position. It is recognised as important but not considered to be among the most critical and immediate priorities for either hiring or workforce development. Later, the interviews revealed a potential explanation of this outcome. Most organizations indeed consider cybersecurity as important. However, implementation of cybersecurity solutions was considered a highly specialized job requiring dedicated experts and thus the skills are not a requirement for the more general engineering force but rather a set of competences that can be delivered by another sector.

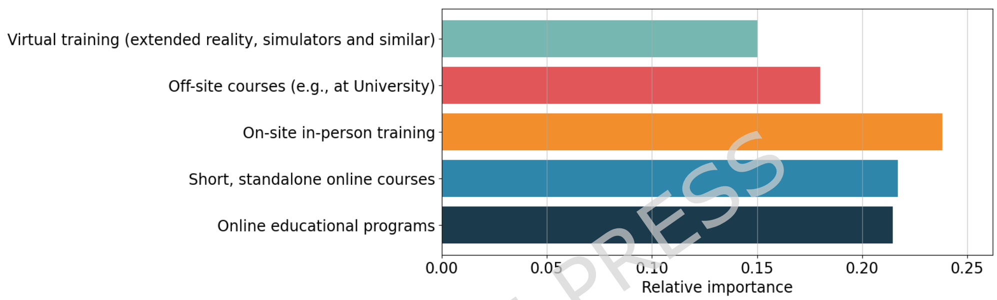

Figure 6. Preferred training formats for learning new advanced digital skills.

Figure 6 presents the distribution of respondents' preferred formats for acquiring new digital skills. University courses and on-site, in-person training emerge as the most valued formats. Then, short, stand-alone online courses follow closely (reflecting strong interest in concise, modular learning with timing compatible with other professional and personal activities), followed by online-based educational programmes, which can be associated with preferences for flexible, self-directed learning opportunities. Virtual training, encompassing extended reality, simulators, and analogous immersive tools, constitutes a smaller but still significant proportion of the total, indicating that while innovation in experiential learning is acknowledged, it is less readily adopted than conventional formats. As the results are very similar and no clear favourite format appears, it can be assumed that no single format is suitable for all learners and situations. Therefore, it is recommended to do a case-by-case assessment of training formats or mixed format, depending on factors such as the type of skills, time constraints and prior knowledge. This is also supported by the interview results.

3.3 Interview Specific Results

Building upon the survey results, expert interviews provide deeper insight into why these competencies are of such fundamental importance and reveal the qualitative nuances that cannot be captured by survey quantitative rankings alone. Industry professionals have shown a high degree of unanimity in their understanding of the definition of advanced digital skills. As articulated by one respondent, "As soon as you move from the world of user interfaces to the world of code, it becomes advanced." This transition signifies a shift from the utilization of software to the development of customized solutions through programming.

Content analysis of interview responses reveals scientific programming as the predominant competency, with frequency nearly double that of other technical skills. Unlike general software development, scientific programming prioritizes mathematical modelling, data analysis, and the implementation of scientific algorithms. The former, on the other hand, often focuses on user-facing features and standard application functionality. This specialized programming enables algorithmic implementation for wind forecasting, turbine control systems, and energy yield prediction models as an example.

A critical distinction emerges between academic proof-of-concept projects and production-ready solutions. As one expert noted, "It is easy to write a notebook to develop a sophisticated machine learning model but making it production-ready requires a whole different set of skills." Production-ready applications require:

- Efficient large-scale data processing capabilities
- Multi-user parallel access functionality
- Maintainable, documented, and tested code architecture
- System integration with existing operational environments
- Reliable operation without human intervention

The ability to develop customized software has become essential as standard applications often cannot meet the specialized requirements of the wind and energy systems sector. Examples include wind farm operations (real-time monitoring and optimization), SCADA (Supervisory Control and Data Acquisition) systems for equipment control, and energy trading processes (managing electricity sales and grid integration).

Skills gap

Despite this technical focus, the sector faces quantitative and qualitative workforce gaps, further highlighted by generational differences (see Table 4).

The most severe shortages are anticipated in operation and maintenance roles, where both technical and digital expertise are required simultaneously. While cybersecurity receives relatively limited mention in advanced digital skills discussions, experts consistently emphasize its critical importance. Wind farms' classification as critical infrastructure necessitates robust security, particularly for SCADA systems and operational technology environments. Cybersecurity implementation varies by organizational scale. Larger developers employ dedicated security teams and multilayered defence systems, while smaller operators embed security practices across all roles. As one respondent observed, "Cybersecurity standards are not abstract—they directly inform how technicians operate in the field."

Lifelong Learning Requirements

Traditional educational pathways prove insufficient for addressing technological change velocity. Dynamic learning approaches, including micro-credentials and industry-integrated programs, have become essential. Effective lifelong learning must integrate:

- Self-paced digital modules for on-demand skill development
- Practical outputs demonstrating applied proficiency
- Interactive components fostering peer networks and collaborative skills

Hybrid delivery models optimize learning outcomes, with recommendations for 70% online content complemented by 25-30% in-person interaction to maintain social learning components.

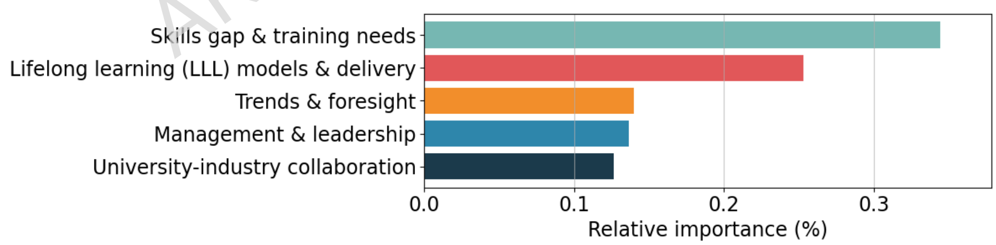

Figure 7. Relative importance of skills gap, lifelong learning, foresight, collaboration

These challenges show just how complex it is to transform a sector. Figure 7 illustrates the relative importance respondents assigned to the skills gap itself, lifelong learning requirements, foresight capabilities, and cross-organizational collaboration. Skills gaps and training needs stand out as the most important issue, suggesting that respondents see immediate capacity constraints in the sector. The industry understands that technological change means that workers need to keep developing their skills, not just learning new skills once but through ongoing learning. The remaining topics, receive lower but still meaningful attention, indicating, pointing to the need for a more coordinated and forward-looking approach to workforce development.

Network and Sentiment Analysis

This section presents the results of the network analysis. The purpose was to reveal insights, patterns and thematic meanings across sectors, that would not emerge through a simple summary of the interview transcripts. By integrating sentiment analysis, respondents' statements can be categorised and prioritised, as detailed below.

Network Analysis Findings

The network analysis shows that this network has a moderate connectivity (24.7%), which is ideal for knowledge exchange and innovation. Scientific programming achieves the highest topic degree centrality (67%), confirming its role as a universal language across engineering disciplines. IoT, sensors technology, and extended reality rank second in centrality (62%), demonstrating their function as connecting technologies across hardware engineering, software development, and operational optimization domains within wind and energy systems. This ranking emphasises the importance of these technologies for cross-functional collaboration (Appendix Table 8).

Table 9 presents the degree and betweenness centrality values for each respondent. Respondents with a 29% degree centrality indicates that these respondents are directly connected to the greatest number of topics. Which means that they talk about many topics and are highly engaged. The remaining respondents, with lower degree centrality, simply mean that they are connected to fewer topics, which may be due to narrower professional interests, expertise or roles.

Overall, most respondents have moderate to low betweenness centrality values, implying a network that is not dominated by a single central participant but rather one in which multiple individuals contribute to knowledge dissemination. However, one individual respondent stands out distinctly, showing a betweenness centrality of 10.8% (Appendix Table 9). This means that this respondent acts as an important bridge or link within the network. This bridging function is particularly important for knowledge dissemination, as it enables the exchange of information, ideas and best practices between otherwise separate communities and prevents them from becoming isolated silos.

Topic Distribution and Industry-Specific Patterns

The analysis of topic prominence and respondents engagement was conducted using a hierarchical representation, where the relative importance of each theme was determined by degree centrality values. Topics with higher centrality occupied proportionally larger positions within the hierarchy, indicating their stronger influence within the overall discourse structure. The distribution follows an industry-based organization, revealing that conversations around advanced digital skills are not evenly dispersed across sectors. Notably, a dense cluster of discussions emerges among original equipment manufacturers (OEMs) of wind turbines, focusing on topics related to programming, IoT, and simulation. This concentration suggests that wind turbine OEMs have developed specialized expertise in these digital skill areas and serve as central actors in broader digital transformation discussions. In other words, they function as hubs where particular digital skills are prioritized and refined.

These sector-specific concentrations provide practical evidence for designing customized training programmes that directly address the skill needs of each industry while ensuring that core digital competences remain transferable across sectors. This approach allows for both specialization (tailored to industry needs) and flexibility (enabling workers to apply skills more broadly).

Sentiment Distribution

The sentiment analysis was conducted on all relevant sentences. Most of the responses were neutral, with a small number of respondents expressing both positive or negative sentiments (Appendix Table 7) However, this neutral dominance could be indicative of a tendency towards caution in discussions about future developments related to advanced digital skills or the technical character of the interviews.

A thorough review and assessment of the initial classification's positive and negative sentiments was conducted to identify underlying patterns. This comprehensive analysis yielded four additional findings. First, persistent frustration with skills gaps identified basic upskilling as the primary obstacle to progress. Second, mixed perspectives on lifelong learning weighed innovative teaching methods against concerns about information overload.

Third, participants shared optimistic thoughts about digital solutions' potential to improve offshore wind farm operations and maintenance. But they also criticized the barriers that organizations faced in implementing these digital solutions. They mentioned barriers like not having enough documentation of digital workflows or relying on old systems.

Fourth, respondents pointed out the tension between celebrating successes in digital upskilling and openly discussing failures. They emphasized the importance of building a fast-failure culture, where failures in digital training, skill competencies, and skill application are treated as learning opportunities rather than problems to hide. But it requires balancing workforce confidence with honest conversations.

3.4 Job postings Specific Results

LinkedIn database

Out of 544 wind-related job postings extracted, 153 included advanced digital skills as explicit requirements in their descriptions, representing 28.1% of the total sample. Based on occupational mapping using the ESCO taxonomy, connections can be drawn between the requirement for advanced digital skills and the type of ESCO Level 1 occupation. Among the postings, 35.2% were classified as *Professionals*, while 19.3% were identified as *Technicians and Associate Professionals*. The remaining postings were distributed among *Managers* (14.3%), *Craft and Related Trades Workers* (7.5%), and unclassified positions (22.6%).

Professionals typically conduct research, develop concepts, teach, provide expert services, and may supervise others. In contrast, *Technicians and Associate Professionals* perform technical tasks, support research and services, and may also hold supervisory responsibilities. Out of the 220 postings identified as Professional occupations, 91 required at least one advanced digital skill, bringing the proportion of professional positions demanding such skills to 44.3%.

Figure 8 illustrates the distribution of advanced digital skills across different occupations. Demand is clearly dominated by the Professionals group. Among Technicians and Associate Professionals, demand for advanced digital skills remains limited in volume but is spread across several categories, with a relatively high share of Robotics & Autonomous Systems compared to other occupation groups, which may reflect the operational and maintenance nature of technician roles in wind energy. Overall, demand is led by the categories Scientific Programming and Numerical Analysis, Simulation, Optimization, and Modelling Tools. The Unknown group (postings that couldn't be assigned an ESCO occupation) is non-trivial in size (60 counts) and shows a broadly similar skill distribution to Professionals. This suggests these unclassified postings likely contain professional-level roles described with non-standard job titles.

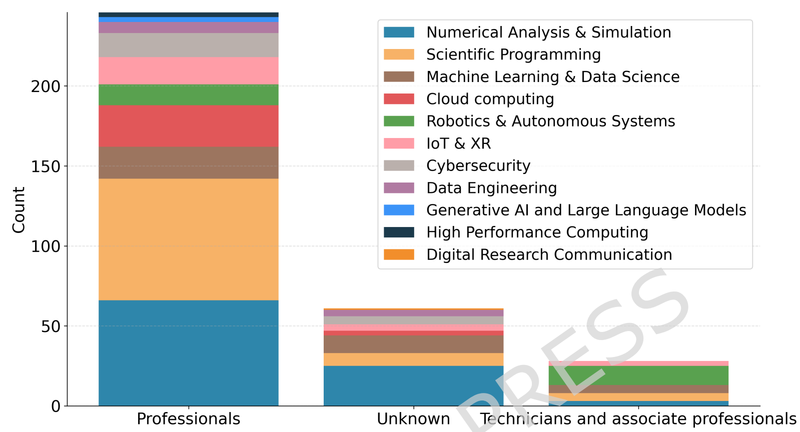

Figure 8. Advanced digital skills per ESCO occupation level 1 from analysis of LinkedIn job postings.

Figure 9 highlights the top five ESCO Level 4 occupations with the highest number of advanced digital skill requirements. The software developer profile is clearly dominant in terms of total skill count, with Scientific Programming accounting for the majority of requirements, reflecting the production-ready software development nature of this role. The energy systems engineer profile displays a different pattern, where the dominance of programming skills is reduced and a more balanced distribution emerges. IoT & XR accounts for an important share of required advanced digital skills in this profile, which may reflect the importance of sensor integration and instrumentation for this occupation. The electrical engineer profile shows an even more balanced distribution, with Numerical Analysis & Simulation forming the largest share, complemented by contributions from Robotics & Autonomous Systems and IoT & XR, suggesting a multidisciplinary digital skill demand consistent with the complexity of electrical systems in wind energy. The onshore wind energy engineer and e-learning developer profiles are broadly similar in total count and both show diversified skill distributions, with Numerical Analysis & Simulation and Scientific Programming prominent in both cases. The presence of e-learning developer among the top five occupations warrants caution in interpretation, as manual inspection suggests that postings mapped to this title frequently correspond to full-stack developer positions, pointing to a limitation of the ESCO Level 4 taxonomy where certain software engineering occupations lack sufficiently specific classification categories. Among the top five specific skills identified from the LinkedIn job postings analysis are Python programming, Numerical Simulations, Computer-Aided Design (CAD), Instrumentation, and Programmable Logic Controller (PLC), listed here in order of importance.

FLORES database

Within the 981 jobs included in the FLORES database, 94 job postings required advanced digital skills as defined in the scope of this paper, representing 9.6% of the total. This database consists exclusively of positions in the Offshore Renewable Energy domain, where Professionals account for 55.3% of all postings. Figures 10 and 11 illustrate the distribution of advanced digital skills by category according to ESCO Level 1 and Level 4, respectively.

Combined results of the two job postings databases: LinkedIn and FLORES

The analysis reveals that the proportion of occupations requiring advanced digital skills is lower in the FLORES database compared to the LinkedIn database. Despite this difference, both analyses consistently identify the same two occupations, software developers and energy system engineers, as those demanding the highest level of advanced digital skills. However,

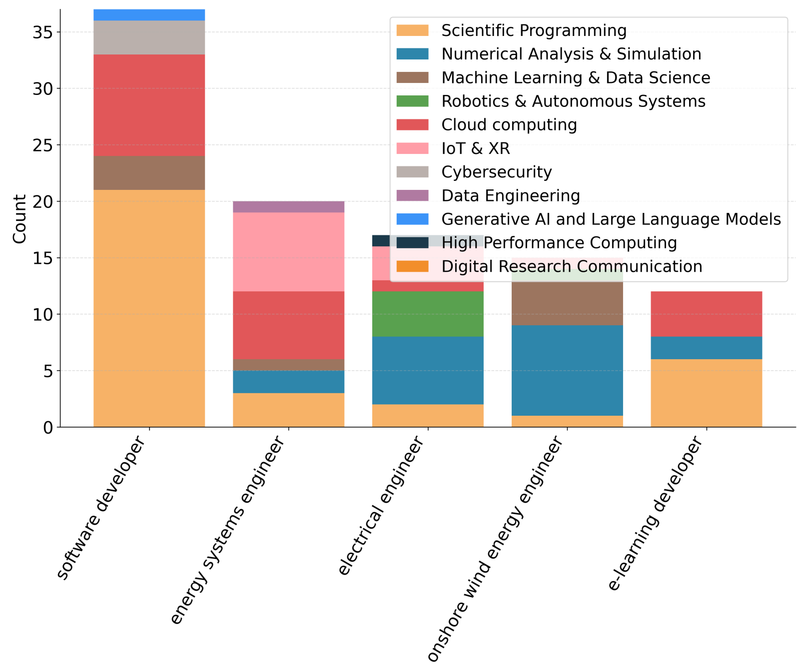

Figure 9. Advanced digital skills per ESCO occupation level from analysis of LinkedIn job postings.

while software developer profiles are largely dominated by expertise in scientific computing, in both databases energy system engineer profiles display a broader distribution across different categories of digital skills, which might indicate a more diversified skill set. Additionally, in both analyses, scientific computing and numerical modelling appear to be as the most prominent categories, surpassing all others in terms of prevalence and importance.

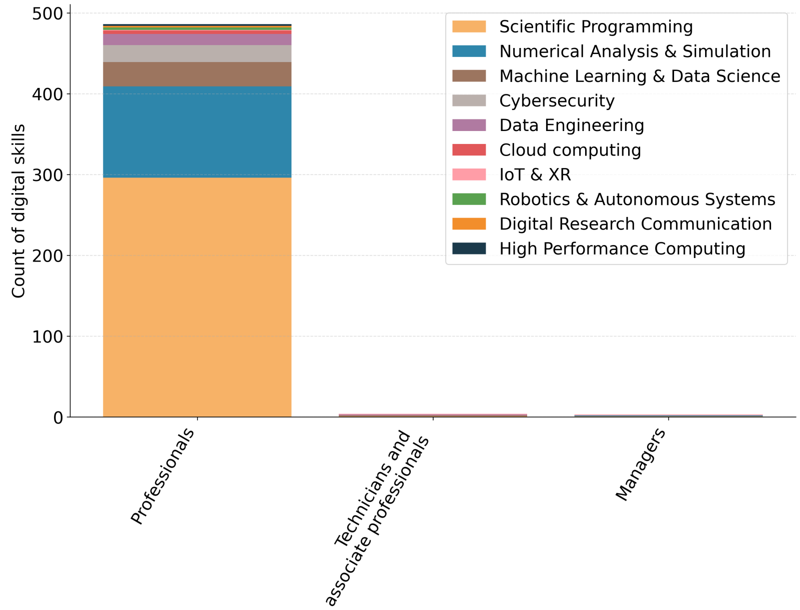

Figure 10. Advanced digital skills per ESCO occupation level 1 from analysis of FLORES database.

4 Further Discussion and Conclusion

This study investigated the importance of advanced digital skills in the wind energy sector using a mixed-method approach. It combines three types of data: survey and interview data of industry professionals, and analysis of job postings. Automated language processing and sentiment analysis were applied to interview transcripts, enabling direct quantitative comparison with survey and job postings data, while qualitative insights from interviews provided contextual depth. The analysis showed consistent patterns across all data sources regarding essential digital skills needed in each sector.

Across all data streams, scientific programming and numerical analysis appear as foundational competencies, consistently ranked at the top of hiring intentions, workforce development priorities, and expert discourses. Scientific programming, in particular, is highlighted, in the interviews, by both network and content analysis as the sector's universal language, underscoring its role in many algorithmic tasks related to wind energy. This finding is supported by the analysis of the two job postings databases, which showed that scientific programming and numerical analysis & simulation skills were the most prominent among the required advanced digital skills. Looking at the LinkedIn database, the findings showed that 28.1% of the wind-related job postings were requiring advanced digital skills. This share goes up to 44.3% when filtered for professional-level occupation (excluding e.g., technician roles). These figures indicate that the importance of advanced digital skills, highlighted in both the survey and the interviews, is not yet fully reflected in current job market demand. However, it is likely to become more pronounced if the survey and interview results are interpreted as foresight indicators for future skill needs in the sector.

While core computational competencies maintain their lead across organizational contexts, the demand for more specialized competencies such as machine learning, data engineering, and cybersecurity demonstrates greater sensitivity to role and company size. Machine learning and data science, for instance, show strong emphasis in survey responses and expert interviews yet appear under-represented in job postings. This discrepancy suggests a lag: professionals anticipating future needs regard these skills as important, yet they are not consistently reflected in current formal hiring requirements. Alternatively, this gap may indicate that machine learning competencies are being sourced through specialized consultancies rather than in-house hiring, or that job descriptions use different terminology that was not captured directly by the categorical classification. Cybersecurity occupies a similar position. Survey results place it in the middle of priorities for recruitment and training, while the analysis of interviews provides a more comprehensive picture. Experts unanimously emphasize the importance of cybersecurity due to the classification of wind farms as critical infrastructure, particularly for SCADA systems. However, implementation varies by company size and sector. Larger companies employ dedicated security teams with multi-layered defence architectures and treat cybersecurity as a specialized function of experts. Smaller companies, lacking the resources for dedicated personnel, integrate security practices into general engineering functions. IoT and sensor technologies act as a bridge between hardware development, software development, and operational optimization. This enables and facilitates cross-functional collaboration and knowledge transfer between traditionally separate disciplines within the wind energy sector.

The remaining advanced digital skills are represented only to a small extent in survey responses. Their low scores show

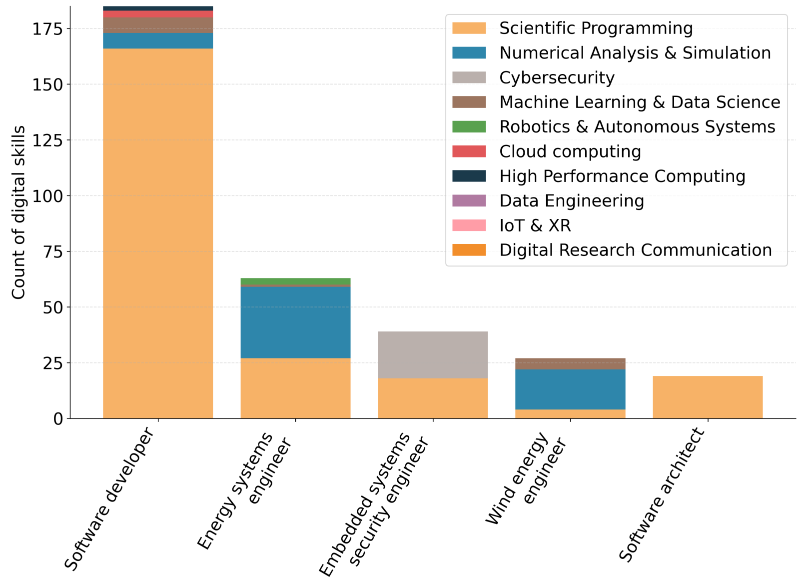

Figure 11. Advanced digital skills per ESCO occupation level 4 from analysis of FLORES database.

that these competencies are not seen as important for the wind energy sector right now, not any more, or that they are too new and too specific to be considered for investment in training. It might also be that there is another delay between a brand new technology being put out to the market and companies employing it, at least on a large scale.

A pronounced skills gap persists between academic proof-of-concept proficiency and the development of production-ready solutions. Industry requirements demand maintainable code architecture, integrated system support and scalable data processing capabilities. Such requirements extend beyond algorithmic complexity and underscore the need for holistic software development. This gap is further highlighted in the areas of operations and maintenance, where the shortage of candidates who combine in-depth technical and digital expertise is a critical issue. A generational analysis shows complementary strengths rather than simple contrasts: younger graduates, digital natives, are highly adaptable to modern programming languages and cloud platforms, while experienced specialists contribute indispensable knowledge of physical fundamentals and pragmatic problem solving refined through decades of practice. Both, however, are crucial to the ongoing digital transformation of the industry. The findings of the study also suggest a perceived misalignment between current educational practices and the pace of digitalisation in the wind energy sector, as expressed by industry professionals and experts. Based on the training format preferences identified in the survey and interviews, hybrid models, with a balanced amount of online teaching and in-person appear promising to combine flexibility with the benefits of collaborative learning. However the optimal design of such programs would need to be validated through direct evidence from educational settings.

As the wind energy sector is undergoing a pivotal transformation, digital competence appears to be an important driver of competitive advantage, operational excellence and sustained innovation in the wind energy sector. The results of surveys, expert interviews and job market data all point to scientific programming and numerical modelling as particularly important skills when advanced digital skills are needed, while also showing that there is more demand for specialised skills in machine learning, IoT and cybersecurity. However, the sector faces not only a skills shortage but a quality gap: current educational pathways may face challenges in preparing students for the transition from academic proficiency to production-ready implementation, as suggested by the industry perspectives collected in this study.

For industry stakeholders, the strong presence of data engineering and scientific programming at the top of the skill rankings suggests that investments should focus on building solid data infrastructures, reliable data pipelines, and production-ready analytics capabilities, rather than concentrating mainly on exploratory AI initiatives. For training institutions, the prominence of Python and scientific programming across all data sources suggests that wind-specific data science and software engineering content may be a valuable addition to existing engineering and MSc programmes. For policymakers, the limited availability of cybersecurity expertise at more senior levels indicates a need for targeted reskilling and upskilling efforts. These could include initiatives supporting secure DevOps practices, cloud security, and the protection of critical infrastructure. This would ensure that increasingly digitalised wind systems remain both competitive and resilient.

5 Limitations and Future work

As is common in multi-source studies, the results were not fully identical across data sources. The differences may be explained by statistical uncertainty, as well as subjective factors such as differences between ideal-profile expectations (as discussed in interviews) vs. practically feasible positions as given by job advertisements. Nevertheless, given the speed and dynamics of the evolution of digital technology, we could have expected even larger differences, especially considering that there is up to one year of time span between the oldest and the newest data analysed. This indicates that some of the dramatic recent changes in technology (such as LLM-based AI applications) had not fully propagated to the skills market at the time of completion of this study. An important future task would be a repetition of this study with new data, to capture the expected evolution of demands in advanced digital skills.

The study's analytical scope is naturally limited by the predefined keyword database of advanced digital skills. While this framework enables systematic comparison across data sources, it may exclude competencies not captured within the initial categorisation or under-represent skills expressed through non-standard terminology. In addition, the number of keywords assigned to each category introduces potential detection bias: skills with more extensive keyword lists yield higher match frequencies, which may distort the perceived hierarchy of skill priorities. These limitations have been reduced as much as possible by defining a list of keywords that are the same order of magnitude regarding their lengths, but some categories are just more relevant to wind industry and more keywords exists. To address this, weighted importance scores have been computed and discussed in Section 3.1, and the robustness of the main findings was confirmed. Nevertheless, this remains a genuine limitation, and results should be interpreted as reflecting the prominence of skills as they are currently listed and discussed within the predefined categories, rather than as an exhaustive mapping of all competencies relevant to the sector. Future iterations of this analysis could further reduce classification bias by incorporating unsupervised clustering techniques applied directly to large-scale textual data, enabling the identification of emergent competency groups without relying on predefined keyword taxonomies.

The heterogeneous formatting and linguistic variability of job postings present additional challenges for standardisation. Skills are formulated inconsistently across postings, some are explicitly named while others are only implied, which complicates automated extraction and classification. This issue is emphasized by implicit biases in job postings, where employers often assume that applicants with a certain educational background are equipped with specific skills without explicitly stating them. For example, machine learning skills are often used in analytical tasks like forecasting, fault detection and predictive maintenance. These tasks combine statistical thinking, analysing time-series data, handling sensor data and using domain knowledge, and may therefore be under reported in job postings. Furthermore, despite the filtering method being designed for maximum precision, it may unintentionally exclude relevant job vacancies or retain false hits. While the performed sensitivity analysis across similarity score thresholds and embedding models provides confidence of classification stability, the lack of systematic uncertainty quantification, such as manual validation of a statistically representative sample of classified job postings with associated confidence scores, limits the scope to formally evaluate classification accuracy.

The survey and interviews provide useful patterns in how skills are prioritised, but their relatively small sample sizes preclude robust subgroup analyses. The geographical concentration, purposive sample selection, and focus on the offshore wind energy subsector further limit the representativeness of the results. Priorities regarding required skills may differ significantly in the onshore sector, among smaller companies, or in the rapidly growing Asian markets, where operating conditions and requirements vary considerably. Network analyses conducted across several institutions introduce further methodological and contextual challenges. While participants from multiple organisations provided valuable diversity, confidentiality obligations and competitive considerations restricted open information exchange. Heterogeneous institutional priorities, legal frameworks, and organisational cultures create additional complexity in collaboration dynamics, and industry interests may inadvertently shape the emphasis given to specific skill areas, leading to potential bias in the representation of knowledge flows and innovation patterns.

Regarding geographical scope, the focus on English-language job postings means that results cannot be extrapolated outside the US and European job markets. The same limitation applies to the interview and survey data. Extending the analysis to Chinese, Indian, or other major global markets would require dedicated data collection in those languages and contexts, which represents a natural direction for future work. Through this paper, we aimed to map the current state of demand for advanced digital skills in the wind energy job market, combining job posting analysis with expert foresight and practitioner perspectives. The natural next step is to examine university course content and learners' perspectives to determine whether they align with the needs identified in the industry. This direction is already being investigated by the authors, and a forthcoming paper will assess university students' preparedness, preferred pedagogical approaches, and competency acquisition pathways in wind energy curricula, using Bloom's Taxonomy as a methodological framework.

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Funding

This research is supported by the DigiWind project, co-funded by the Digital Europe program with grant number 101122836.

Acknowledgements

Special thanks to Karsten Kryger, Fiona Huijie Zeng Skovhøj and Małgorzata Lipska for their contribution to designing the study and carrying out interviews. The authors gratefully acknowledge Brendan Lenihan, Martin Guiton, Morten Willaing Jeppesen, Geert Timmers, and all other industry professionals who participated in the interviews and surveys. Their insights and professional perspectives were invaluable in mapping the digital skills landscape of the industry.

Author contributions statement

E.S. conceptualized the study, conducted the interviews, developed the methodology, and analysed both the interviews and survey data. A.L. analysed and investigated the job-postings, including developing the methodology and code for this section. E.S. and A.L. drafted the manuscript. N.D. and P.Z. contributed to the writing. E. S-M., N.D., P.Z. and T.G. conceptualized the study and supervised it. They were also involved in the design of the methodology (especially the methodology on job-postings). They also conducted interviews and designed the survey. E.Sd. performed the hand-filtering and selection of the FLORES database. O.A-L. assisted with writing and drafting the manuscript. All authors critically reviewed the manuscript.

Additional information

Data availability: The survey and interview datasets generated during the current study are not publicly available due to privacy and GDPR restrictions. Additionally the interviews' data are qualitative and contains respondent identifiers. The contact point for these datasets is Estelle Stoltmann (*estst@dtu.dk*). The LinkedIn datasets analysed in this study are publicly available on Kaggle[25]. The job-posting data from the FLORES project are not publicly available, further information may be obtained from Eleftherios Sdoukopoulos (*sdouk@certh.gr*) upon reasonable request. **Competing interests:** The authors declare no competing interests.

Ethical approval

The survey was prepared regarding the relevant guidelines/regulations, in particular with all the requirements imposed by Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC. Informed consent for participation was obtained from all involved. The surveys were sent to professionals within the wind industry as online forms, or shared during public events. The condition for participation was to confirm consent to use the data obtained in the surveys for further project analyses. Before completing the questionnaire, participants were informed of the survey's purpose, the scope of the study, and how the data would be used. They were assured that no personal or identification information would be disclosed. The survey did not include personal or sensitive questions and posed no more than minimal risk or burden to participants. Moreover, the study's participants expressed their consent for participation consciously and freely and had the opportunity to withdraw before or during the study. Participation was voluntary, and data were handled in compliance with GDPR.

The interview study was conducted in accordance with relevant ethical guidelines and regulations, specifically strictly adhering to the requirements of Regulation (EU) 2016/679. Informed consent was obtained from all participants prior to the interviews. The experts were invited via email or recruited during professional wind industry events. They provided recorded verbal consent to participate and for the interview to be audio-recorded for transcription and analysis. Participants were assured of confidentiality; while their professional role might be relevant to the analysis, no direct personal identification information would be disclosed in published results without explicit permission. The interview guide was designed to avoid sensitive personal topics, posing minimal risk or burden to participants. Participants were free to refuse to answer any questions or withdraw from the study at any time.

For further information on data protection guidelines, please read the following: Communication about collection of personal data by DTU. The need to obtain approval was waived by Technical University of Denmark.

Appendix

Interview guide

1. How would you define “advanced digital skills”?
   We use the term in DigiWind (refer to the supplementary document with survey responses). Does your definition match ours?

2. To what degree is (training in) advanced digital skills relevant for your company’s success?
   How do you see the development of digital competence from a business perspective?

3. In the DigiWind survey, you were asked about prioritizing advanced digital skills. Which one did you choose as number one? Could you explain your choice?

4. In the DigiWind survey, you were also asked to prioritize domain skills that could benefit from combining with digital skills. Could you explain your choices?

5. Can you give us example(s) of a task / role in your organization that would benefit from more digital skills?
   Support questions:
   Maybe there was a case where you saw a delay/missed opportunity due to the people not having enough skills to deal with a problem?

6. How are digital skills of newer graduates different than older ones? Do you see any differences between generations?
   Support questions:
   Any particular skillset that a group (e.g., currently active engineers) is lacking?
   Anything that newly educated employees are natively equipped with, but lacks with the current workforce (or vice versa)?

7. Could you list any course topics that your colleagues would be likely to take?
   Support questions:
   Any particular topics for which you are aware of existing interest? For example, a data science course, or a course in digital tools for resource assessment…

8. Are there any learning topics that are currently missing from the training market?
   Support questions:
   Any situations where your colleagues have been looking for training in a specific topic, but could not find a relevant offer?

9. Which trends do you see in the global wind energy sector when it comes to the need for digital competences?

10. What do you anticipate as the crucial digital skills in the future – 5, 10 or 15 years ahead?

11. Do you see a growing need for lifelong learning offerings tailored to employees in the wind energy sector (within the next 3-6 years)?

12. What would be the ideal teaching method(s), locations, and duration of LLL module(s) for your company?
    Support questions:
    Which forms of LLL would you prefer – online, F2F, hybrid, self-paced, livestream, etc.?
    Do you prefer in-company session, or sessions with a mixed group of people from the wind energy industry (to enhance networking)?
    Do you rather prefer a short module of just one day, a module 2 to 3 days consecutively or multiple days spread over multiple weeks?

13. Is your company planning to or willing to invest in upgrading the digital skills of your employees?
    Support question:
    How much time and money would you invest?

14. How do you see the future role of universities when upgrading the digital skills of employees? Support questions:
    Would you like closer collaboration with universities – e.g., LLL collaboration, guest lectures, supervision, formulation of cases?

15. To what extent do you value input from industry experts in LLL modules? Support questions:
    Who should deliver the module (e.g., universities, commercial providers, guest lecturers/industry experts with best practises, or colleagues with much experience on the matter)?
    Do you value a mixture of theory and industry practises?
16. What is the ideal follow-up to that interview?

Embedding model and threshold selection

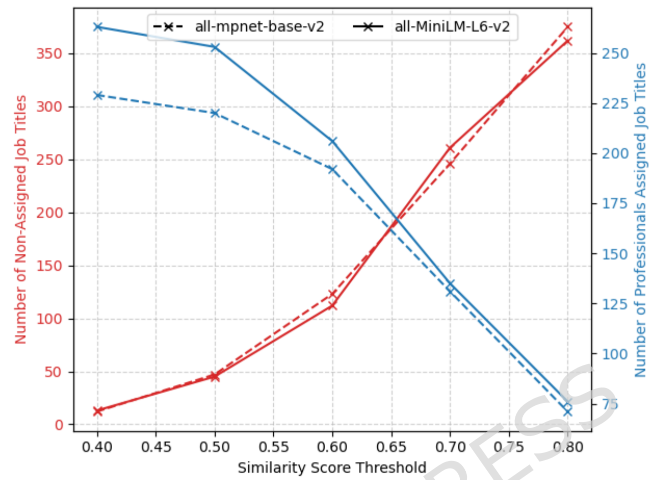

Figure 12. Sensitivity analysis on the number of non assigned job titles and job titles assigned in the *Professionals* occupation from the similarity score threshold choice.

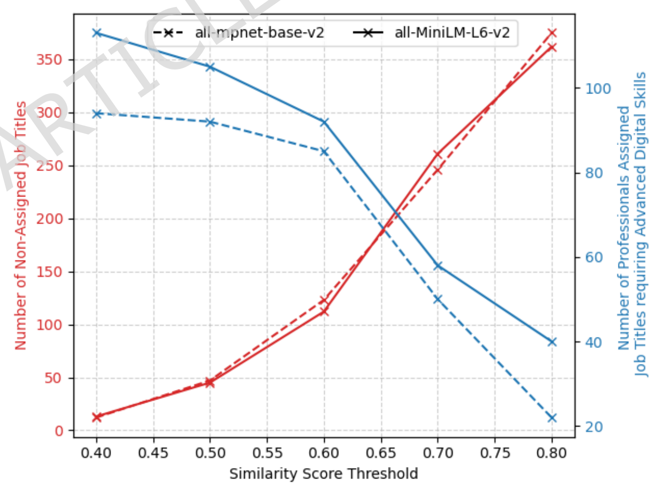

Figure 13. Sensitivity analysis on the number of non assigned job titles and job titles assigned in the *Professionals* occupation, requiring at least one advanced digital skills, from the similarity score threshold choice.

Country Codes and Corresponding Countries

BE Belgium

AR Argentina

LT Lithuania

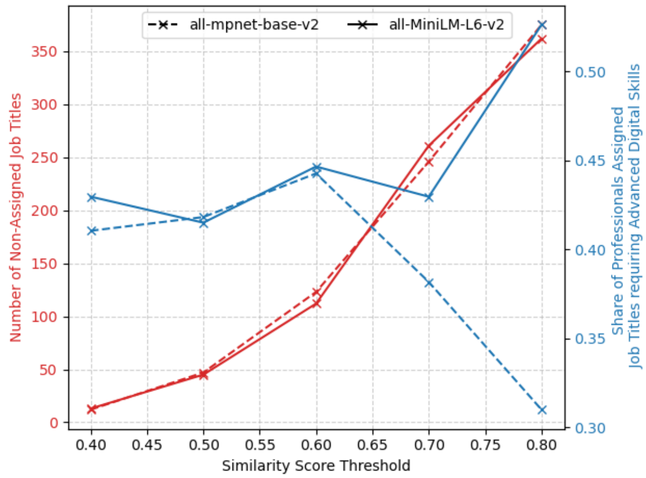

Figure 14. Sensitivity analysis on the number of non assigned job titles and share of job titles assigned in the *Professionals* occupation, requiring at least one advanced digital skills, from the similarity score threshold choice.

NL Netherlands

BR Brazil

BD Bangladesh

IE Ireland

GR Greece

CH Switzerland

CN China

TH Thailand

NO Norway

RS Serbia

FR France

PL Poland

DE Germany

ES Spain

GB United Kingdom

DK Denmark

US United States

IT Italy

PT Portugal

FI Finland

SE Sweden

Table 1. Advanced digital skills categories

Category	Description	Examples
High Performance Computing (HPC)	Central Processing Unit (CPU) and Graphics Processing Unit (GPU) applications for complex computational tasks	Efficient Parallelization to run Computational fluid dynamics (CFD) simulations for wind farm modelling
Scientific Programming	Software development for research and engineering applications	Python-based wind turbine design tools development and updates; development of algorithms for predictive maintenance of wind turbines
Generative Artificial Intelligence (GenAI), including Large Language Models (LLMs)	LLMs and AI-driven content generation	AI-assisted design optimization; automated technical documentation generation
Data Engineering	Data semantics, interoperability, and quality assurance	Supervisory Control and Data Acquisition (SCADA) data preprocessing and standardization
Machine Learning & Data Science	Deep learning, predictive analytics, and data-driven insights	Predictive maintenance using sensor data
Digital Research Communication	Advanced tools for innovation dissemination	Augmented Reality (AR)/Virtual Reality (VR) based dynamic digital ecosystem for learning, ParaView, Dashboards, PowerBI
Robotics & Autonomous Systems	Automated systems and intelligent control	Robotic diagnosis, drone-based, remote control
Internet of Things (IoT) & Extended Reality (XR)	Sensors, connectivity, and immersive technologies	AR/VR for remote maintenance assistance; SCADA sensor networks for real-time performance tracking
Blockchain Technology	Distributed ledger applications and smart contracts	Secure validation green power generation data; transparent energy credit tracking systems
Cybersecurity	Information protection and risk management	Firewall solutions for wind farms; operational technology (OT) security for SCADA systems
Cloud Computing	Distributed computing and scalable infrastructure	Cloud Computing, Development and Operations (DevOps), Azure for wind farm data management; scalable storage for turbine operational data
Numerical Analysis & Simulation	Modelling, optimization, and computational tools	Numerical Analysis, Power Curve Modelling, Finite Element Analysis, Computational Fluid Dynamics

Table 2. Overview of data collection activities

Activity	Description	Quantity	Goals
Online Survey	18-question survey distributed at events and in connection with interviews.	108 respondents from BE, AR, LT, NL, BR, BD, IE, GR, CH, CN, TH, NO, RS, FR, PL, DE, ES, GB, DK and US	Quantify skills gaps, training preferences, and industry perspectives across target groups.
Interviews	16-question in-depth qualitative interviews with industry experts.	14 completed interviews, respondents from DK, NL, US, PL and IE; Industry sectors: Wind turbine OEM, Research and Technology Organization or University, Electrical power generation and large energy consumer, Contractor (wind farm service and operation), Supplier of high-tech products and services, Transmission system operator, Electrical designers	Explore nuanced perspectives on skills requirements, training needs, and future trends.
Job Postings Analysis	Open-source dataset of pre-processed English-language job postings scraped from LinkedIn in 2024, available on Kaggle[25]. Each posting includes job title, location, company, and description.	1.3 million job postings, in the US and the UK	Validate and compare job requirements stated in surveys and interviews with those in the current job market; extract typical Bloom's taxonomy levels linked with advanced digital skills; and categorize the digital skills according to the ESCO hierarchy.
	Forward Looking at the Offshore Renewables (FLORES) database contains job offers in the Offshore Renewable Energy (ORE) sector collected in April-October 2023. For each offer, main details and required skills are manually extracted. Occupations were mapped using ESCO's Search occupations.	981 job postings in 11 European countries (DE, DK, NL, BE, ES, IE, FR, IT, PT, FI, SE)	European dataset; targeted job postings from big industry in EU; another dataset useful to compare results.

Table 3. Comparison of relative importance scores for advanced digital skills in the LinkedIn job postings, weighted and unweighted by ratio of active keywords over total count.

Category	Unweighted score	Weighted score
Scientific Programming	0.309	0.452
Numerical Analysis & Simulation	0.268	0.241
Cloud Computing	0.106	0.104
Machine Learning & Data Science	0.081	0.062
IoT & XR	0.069	0.027
Cybersecurity	0.061	0.042
Robotics & Autonomous Systems	0.053	0.049
Data Engineering	0.028	0.017
Generative AI & LLMs	0.012	0.003
High Performance Computing	0.012	0.002
Digital Research Communication	0.000	0.000

Table 4. Generational skills comparison.

Younger graduates (digital natives)	Experienced specialists (domain experts)
High affinity for modern programming languages (Python vs. MATLAB)	Deep understanding of physical fundamentals and system interrelationships
Quick adaptation to new software tools and cloud platforms	Extensive experience with established analysis methods and Excel-based workflows
Possible weaknesses or inadequacies in fundamental physical principles	Proven problem-solving strategies based on decades of practical experience

Table 5. Digital competency areas and their detailed skills.

Digital competency area	Detailed skills / keywords
High Performance Computing (HPC) with CPU and GPU applications	supercomputing, cluster computing, parallel computing, GPU computing, scientific computing, performance optimization, performance optimisation, MPI, batch processing, distributed systems, embedded systems, OpenMP, GPU acceleration, edge computing, quantum computing, HPC, job scheduling, workflow automation, SLURM job management, containerization, Docker, Singularity, profiling and benchmarking, code optimization for CPU and GPU, code optimisation for CPU and GPU, algorithm optimization for HPC, algorithm optimisation for HPC, GPU programming
Numerical Analysis, Simulation, Optimisation & Modelling Tools	simulation, numerical analysis, numerical optimization, numerical optimisation, design optimisation, design optimization, digital twins, structural analysis, CFD, Computational Flow Dynamics, turbulence modelling, turbulence modeling, load simulation, multi-physics modelling, multi-physics modeling, multi physics modelling, multi physics modeling, multiphysics modelling, multiphysics modeling, layout optimization, layout optimisation, wake effect modelling, wake effect modeling, power curve modelling, power curve modeling, performance simulation, lifetime assessment, reliability assessment, dynamic modelling, dynamic modeling, finite element analysis, FEA, finite element method, FEM, multibody dynamics, fatigue analysis, vibration analysis, OrcaFlex, OpenFAST, PyWake, HAWC2, Ansys, Abaqus, CAD, WindPro, QBlade, WAsP, STAR-CCM+, OpenFOAM, computer model
Advanced Digital Tools for Research & Innovation Communication	ar/vr based dynamic digital ecosystem for learning, ParaView, dashboards, PowerBI, Developing online training modules, Creating interactive simulations and demos, immersive learning, digital learning ecosystems, digital twins for demonstration, ar/vr based presentations
Cloud Computing	cloud computing, Azure, AWS, Kubernetes, DevOps, Infrastructure as Code, IaC, cloud platforms, Google Cloud, Oracle, cloud architecture design, cloud security, cloud migration strategies, hybrid cloud, multi-cloud deployments, multi cloud deployments
Blockchain Technology and Applications	blockchain, distributed ledger technology, DLT, Cryptography, smart contracts, Ethereum, Hyperledger Fabric, Corda, Solana, Polkadot, Avalanche, Algorand, Tezos
Robotics & Autonomous Systems	robotics, autonomous systems, robotic diagnosis, drone-based, drone based, human-robot collaboration, robotic interventions, remote control, remote-control, automation protocols, PLC, M2M, Programmable Logic Controller, Machine-to-Machine, Machine to Machine
Data Engineering, Semantics, Interoperability & Quality Insurance	scalable data management, data management, interoperability, quality insurance, data pipeline design, data quality, data pipeline management, data normalization, semantic modelling, semantic modeling, metadata tagging, metadata cataloging, metadata cataloguing, interoperability standards, quality checks, data validation, data cleaning, Sensor data fusion techniques, data harmonization, ETL pipelines, data warehousing, big data processing, data integration, statistical analysis
IoT, Sensors Technology & Extended Reality (XR)	internet of things, smart sensors & networks, sensor integration, augmented reality, 3D sensor mapping, instrumentation, smart sensors, condition monitoring, digital inspections, sensor calibration, remote monitoring, AR, VR, augmented reality, virtual reality, telemetry
Machine Learning, Deep Learning & Data Science	data science, data analytics, machine learning, deep learning, predictive analysis, predictive maintenance, wind speed forecasting, power forecasting, reinforcement learning, predictive models, natural language processing, NLP, recommendation systems, model training, data labeling, data labelling, time-series forecasting, time series forecasting, timeseries forecasting, anomaly detection, explainable AI, explainable artificial intelligence, XAI
Cyber Security	cyber security, cybersecurity, industrial cyber-physical systems, industrial cyber physical systems, industrial cyberphysical systems, secure data management, privacy preserving modelling, privacy preserving modeling, securing SCADA, threat modelling, threat modeling, intrusion detection systems, vulnerability assessment, secure coding, data protection, encryption, malware, phishing, secure software, IT security, incident response, firewall, penetration testing, intrusion detection, zero trust, network security, security operations center, security operations centre, OT security
Scientific Programming & Software Development	develop algorithms, python, programming skills, Continuous integration, MATLAB, Simulink, develop software, fortran, automated testing, software development, software testing, C/C++, version control, software architecture, Git, GitHub, GitLab, Java, Julia, C++, JavaScript, TypeScript, Jupyter, VS Code, SQL, NoSQL
Generative AI & Large Language Models (LLMs)	recommender systems, computer vision, ar/vr, using LLMs, using Large Language Models, natural language processing, NLP, chatbots, text-to-speech, text to speech, speech-to-text, speech to text, trustworthy AI, trustworthy artificial intelligence, generative AI, AI ethics, generative artificial intelligence, artificial intelligence ethics, chatbot, text generation, image generation

Table 6. Keywords for Workforce Development & Management.

Category	Keywords
Lifelong Learning Models & Delivery	lifelong learning, LLL, module, blended learning, hybrid, online, self-paced, interactive learning, short module, peer learning, face-to-face, face to face, virtual classroom, ideal teaching method, duration, certificates, micro-credentials, micro credentials, e-learning, e learning, continuous education, personalized learning, adaptive learning, gamification, learning analytics, learning outcomes, assessment, learning path, digital badge, competency-based, competency based, skills development, mobile learning, webinar, flipped classroom, knowledge transfer, learning management system, MOOCs, open educational resources, live stream
University–Industry Collaboration	university, guest lecture, supervision, case study, internships, research projects, curriculum development, knowledge exchange, industry expert, guest speaker, real-world insights, real world insights, mentorship, commercial provider, academic collaboration, workshops, consulting, professional networks, theory and practice mix, joint ventures, technology transfer, spin-off, spin off, industry partnership, collaborative research, funding, innovation hubs, co-creation, co creation, strategic alliance, laboratory sharing, intellectual property, applied research, networking events
Skills Gap & Training Needs	skills gap, talent shortage, competency gap, training deficiency, upskilling, reskilling, training topic, course, demand, missing, e-learning, e learning, workshops, certification, skills development, training formats, barrier, lack, delay, problem, missed opportunity, not enough skills, knowledge gap, digital literacy, training needs analysis, on-the-job training, on the job training, career development, lifelong learning, learning curve, employee readiness, insufficient knowledge, training programs, technical skills gap, soft skills gap
Management & Leadership	leadership, decision making, business processes, strategic planning, resource allocation, risk management, stakeholder engagement, change management, team building, KPI tracking, communication skills, people management, organizational development, organisational development, performance management, conflict resolution, coaching, mentoring, delegation, vision setting, executive leadership, business acumen, cross-functional collaboration, cross functional collaboration, emotional intelligence, employee engagement, succession planning, agile leadership
Trends & Foresight	in 5 years, in 10 years, future, anticipated, trend, next 3–6 years, crucial digital skills, emerging technologies, digital disruption, AI impact, automation, remote work, continuous education, technological foresight, future workforce, labour market trends, workforce of the future, economic shifts, sustainability trends, future competencies, skills of tomorrow, digital transformation, resilience, scenario planning, demographic change, future-readiness, innovation roadmap, workplace evolution

Table 7. Sentiment distribution - topics vs. non-topics

Category	Positive	Neutral	Negative
Topics	6	596	18
Non-Topics	36	2140	88

Table 8. Degree centrality of advanced digital skills.

Node	Degree Centrality
Scientific programming and software development	0.67
IoT, sensors technology, extended reality	0.62
Numerical analysis, simulation, optimization, modelling tools	0.43
Cyber security	0.38
Cloud computing	0.29
Robotics and autonomous systems	0.14
High-Performance Computing (HPC)	0.14
Data engineering, semantics, interoperability and quality insurance	0.05

Table 9. Network centralities respondents

Node	Industry	Degree Centrality	Betweenness Centrality
John Smith	Electrical Power Generation and Large Energy Consumer	0.29	0.054
David Johnson	Wind Turbine OEM	0.29	0.050
Michael Brown	Research and Technology Organization (RTO) or University	0.29	0.050
Robert Davis	Research and Technology Organization (RTO) or University	0.29	0.050
William Miller	Supplier of high-tech products and services	0.24	0.108
James Wilson	Wind Turbine OEM	0.24	0.039
Thomas Moore	Wind Turbine OEM	0.24	0.040
Christopher Taylor	Transmission System Operator (TSO) or Distribution System Operator (DSO)	0.19	0.011
Daniel Anderson	Contractor - wind farm service and operation	0.14	0.004
Matthew Thomas	Electrical Designers and Power systems studies	0.14	0.004
Anthony Jackson	Contractor - wind farm service and operation	0.10	0.002
Joshua White	Research and Technology Organization (RTO) or University	0.10	0.001
Ryan Harris	Research and Technology Organization (RTO) or University	0.10	0.001
Jonathan Martin	National laboratory	0.10	0.001