The Quantum Technology Job Market: Data Driven Analysis of 3641 Job Posts

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Abstract

The rapid advancement of Quantum Technology (QT) has created a growing demand for a specialized workforce, spanning across academia and industry. This study presents a quantitative analysis of the QT job market by systematically extracting and classifying thousands of job postings worldwide. The classification pipeline leverages large language models (LLMs) whilst incorporating a "human-in-the-loop" validation process to ensure reliability, achieving an F1-score of 89%: a high level of accuracy. The research identifies key trends in regional job distribution, degree and skill requirements, and the evolving demand for QT-related roles. Findings reveal a strong presence of the QT job market in the United States and Europe, with increasing corporate demand for engineers, software developers, and PhD-level researchers. Despite growing industry applications, the sector remains in its early stages, dominated by large technology firms and requiring significant investment in education and workforce development. The study highlights the need for targeted educational programs, interdisciplinary collaboration, and industry-academic partnerships to bridge the QT workforce gap.

1. Introduction

The potential applications of QT, in particular quantum computing, have been demonstrated in areas such as cybersecurity, materials and pharmaceuticals, banking and finance and advanced manufacturing [1]. Despite this progress, the commercial applications and maturity of QT, require “significant investment, expertise and cultural change” [2] Due to its potential impact to revolutionise society and economy, a quantum-ready ecosystem is needed to accelerate advancements in the emerging quantum industry, with strategic decisions from governments worldwide [2].

Industrial and national assessments have highlighted the need for standards and benchmarking of new developments [3], greater international collaboration allowing free international trade, increasing awareness of the value of quantum technologies over traditional solutions, and a stronger pipeline for workforce development to provide talent to the industry worldwide [4]. Interdisciplinary jobs in QT are increasing in number [5-7] because supplying the industry with a highly skilled workforce and talent pipeline is an important concern. This includes a workforce composed not only of PhD graduates, but of bachelor and master graduates from diverse backgrounds, as Quantum Technology (QT) becomes increasingly diversified [5].

The characteristics of the workforce that are needed have been investigated in several previous studies [5-13]. One of the main challenges addressed is the “workforce gap” as more QTs are progressively moving from theory and lab experimentation towards commercial applications [8] and, are expected to gain relevance in the future [9]. In overcoming that gap, it is essential to understand, which are the competencies and skills needed for entering the quantum industry [8-9, 11, 13-16] and to serve as a foundational guide for future educational programs [17-18].

In shedding light about what are the most important skills required for the quantum industry, from an industrial perspective, Fox et al. [11], through interviews with 21 companies, reported that 90% of companies considered coding skills and statistical methods for data analysis to be highly valuable , followed by laboratory experience (81%), electronics (76%), troubleshooting and problem solving (71%), knowledge of material science and properties (67%) and quantum algorithms and computer science (62%) [11].

Apart from mastering technical skills, the need for “enterprise skills” and therefore more soft business skills is growing across suppliers and end users of QT [13]. This trend aligns with the progressive commercialization of QTs, requiring diverse profiles to transmit the value and potential use cases of QTs. However, the skills needed may not be the same for every role and would differ from one to another, as stated by Hughes et al. [5]. In their analysis, they identified 3 distinct skills clusters (hardware, software and business) valuable to industry. It is notable that these clusters are not necessarily all overlapping, and universities could structure their programs to align with one or more of them to better prepare students for specialised roles in the quantum industry. The authors also suggested that personnel with a non-quantum background should be encouraged to enter the quantum industry in order to diversify the pool of skills available to employers [5] and to manage the shortage of trained talent. For example, upskilling programs have been effective for employing photonic technicians [8]. Similarly, a recent study from Greinert et al. [6] with 34 interviews coming from a wide diversity of companies, identified the need of competencies and upskilling programs to be formed based on different projected job roles, from engineers or technicians needing technical skills to marketing and sales roles able to have a greater holistic understanding of QT and the market [6].

The relevance of hands-on experience as reported by companies is undoubtedly a great asset for entering the quantum industry [5-13], a trend that has been observed both in interview studies and in the structure of educational programs [8]. Hence, the quantum educational landscape is evolving rapidly with an increasing diversity of opportunities emerging, from certificates [19-22], minors [23-26], industry training [27], educational resources [12], along with different training possibilities across sectors [6].

As for the most desired roles for the quantum industry, there is a distinction depending on the level of specialisation and skills, ranging from specialists focusing on research and development of new devices or theory, to non-quantum engineers (with increasing number of job positions) employed in areas such as electronics, software, pharmaceuticals or sales [17]. Higher levels of specialisation may likely require a PhD, while master students or bachelors will contribute to the workforce pipeline in roles demanding less specialisation [17].

Fox et al identified engineering roles as the most desired ones (95% of surveyed companies), although within these roles there may also be differences between companies in the specific skills required [11]. In the same way, Hughes et al reported about growing demand for engineering (95%) but a high grade of experimentation and research, with roles such as “experimental physicist” (86%) and “theorists” (56%) will still be needed in the following years [5]. Finally, in a later study, Greinert et al suggested that we could expect a shifting from hardware to software roles as the industry matures [6].

An important development toward improving communication between industry and education programs is the Competence Framework in Quantum Technologies (CFQT) [16]. The CFQT is a continuous effort in mapping the landscape of skills in QT, aiming to be a comprehensive guide covering topic areas which may appear in education programs, and competences which may be required for certain jobs. It has been developed over several years within the EU, incorporating multiple rounds of stakeholder interviews and community feedback. While the first versions comprised primarily a topic map, later versions have included proficiency levels [28] , which can be mapped to educational program levels, and qualification profiles, which can frame the job roles in terms of their educational needs. While as yet the CFQT has not reached complete adoption, it is beginning to appear in educational programs in the EU [27,29]. The extent to which it represents the day-to-day of jobs, however, is less clear, and this can only be established by a large scale study of the skills involved in the industry. This research is beyond the scope of the present article, however this may be a fruitful direction for future work.

In summary, the need for a skilled quantum workforce is now well known. However, the best route to this workforce is not. It is of paramount importance to develop more education programs worldwide. But at what level? And what job roles should the graduates be going into? Answers to these questions are needed in order to smoothly address the growing issue of talent worldwide. As of now, nations across the world are differing in their approaches.

Here we summarise the major educational efforts and regional developments worldwide.

USA: The United States, under the National Science and Technology Council (NSTC) Subcommittee on Quantum Information Science (SCQIS), released in 2021 a Workforce National Plan addressing actions such as “evaluate the QIST workforce landscape, prepare more people for jobs with quantum technology, enhance STEM education at all levels, accelerate exploration of quantum frontiers, and expand the talent pool for industries of the future” [30]. As a result, a different set of educational initiatives composed of multiple partners has been launched to address these objectives, spanning from school education to higher education [14, 31-33].

EU: Several initiatives regarding quantum education span from Middle school to higher education curricula through the educational community of QTedu [34]. As for higher education, DigiQ [29], coordinated by Aarhus University, is enhancing 16 master-level programs among 24 educational institutions, offering adapted learning materials, networking and internship opportunities. At the national level, there are also educational consortia aimed at training the quantum workforce [35-38].

The efforts regarding quantum education are not only about higher educational programs with a well-grounded quantum curriculum but also, as stressed in the latest Strategic Research and Industry Agenda, there is a growing need for upskilling programs within different stakeholders as the quantum industry evolves, several employees without quantum expertise will be needed to fill the demands “such as project and product and innovation managers, CXO’s, business analysts, marketing and sales, and human resources” [39]. One of these examples is the QTindu project [27], which offers specialised training tailored to the diverse needs of business sectors. To this end, the European Quantum Readiness Center has been assigned to coordinate, among other initiatives, the “Continuous qualitative and quantitative tracking of the emergent workforce needs” [39].

Canada: The Canadian Quantum National Strategy recognises the following programmes geared toward facilitating the flow of skilled professionals in quantum technologies delivered by Mitacs [40] and CREATE [41] from the National Science and Engineering Research Council (NSERC). The Université de Sherbrooke, funded by the CREATE programme is at the forefront of implementing “QSciTech - Bridging the Gap between Quantum Science and Quantum Technologies-” a training program for future quantum scientists, engineers, and entrepreneurs [42].

UK: The United Kingdom, through the UK National Technologies Programme (NQTP) identified as a priority the creation of "Skills hubs" to nurture industrial requirements through high specialised training [43]. Apart from fellowships and specialised centres for Doctoral Training (CDTs), the so-called "Training and Skills Hubs in Quantum Systems Engineering" are part of the national network of Quantum Technology Hubs and provide fellowships, mobility programs, and career development opportunities [44]. As stated by the National Physics Laboratory in 2023, while investigating the quantum industry, the demand for PhD students is decreasing while the need for engineers or related professionals increases as the industry evolves [4].

Australia: Among the key initiatives to train the quantum workforce, Australia aims to offer scholarships to Phd students, investigate skills taxonomies for quantum profesionals and other related professions and include quantum into STEM programs, in Schools, Universities and Vocational Education and Training (VET), as well as attrach global talent. These initiatives are part of theme 3, “A skilles and growing quantum workforce”, as part of their national quantum strategy [45].

Japan: The long-lasting research efforts in Japan backed by several programs such as FIRST or ImPact and, more recently, Q-LEAP [46] provides a good overview of the quantum technology ecosystem in Japan. In concrete, the latest program (Q-LEAP) oversees the implementation of the Human Resource Development program, which aims to develop educational and training programs targeted to higher education and companies [47].The project Quantum Academy of Science and Technology (Qacademy) serves as a connector, enabling learning opportunities and internship experiences for quantum students as well as opportunities for educators [48].

South Korea: South Korea established its Quantum National Strategy in 2023, outlining the need to reach and educate over 2,500 people and 10.000 professional workers by 2035 [49]. Two centres are established to educate and to train their quantum workforce the “School of Quantum at Korea University” [50] and “QCenter Quantum Information Research Center Support Center” [51].

Singapore: In Singapore, apart from the scholarships to PhD and master students and outreach initiatives, the Quantum Talent program [52] supported by the National Quantum Office [53] offers a wide range of educational opportunities such as open courses and resources. As for India, as part of the National Quantum Mission (NQM), students and teachers will benefit from educational opportunities in quantum technologies [54].

Russia: In Russia, an international school on quantum technologies is organised annually by the Quantum Technologies Center of the Lomonosov Moscow State University about QT to disseminate to different students from undergraduates and graduate students and postgraduates the field of quantum technologies [55]. Similarly, the Quantum Center of Tomsk State University (TSU) offers learning materials from early students to postgraduates through outreach programs and lectures [56].

Given the wide variety of approaches to industry development, both structural and educational, it is crucial and timely to ask what exactly is the state of the quantum industry now, to which the graduates of these programs may go to work. Engineering and technical roles, in particular, have been highlighted by prior studies [5,6,11], but to what extent is that reflected in the job market? In this article, we are investigating in a quantitative manner, using data from thousands of job posts in QT, the status and needs of the quantum industry. This work represents a step toward improving our understanding of how far QT is in development, how close it is to market, and what kind of workforce it needs. Furthermore, this work introduces an innovative classification scheme, making use of large language models (LLMs), in combination with human expert labelling, to work with a sizable dataset of over 3600 job posts.

2. Research questions

In this research, we attempt to shed light on the reality of the industry needs and what specifically must be done to address them, by using a quantitative method of investigating the QT job marketplace. Over the course of 2023 and 2024, we have gathered job posts relating to QT and in this article we use this large-scale job market data to understand the worldwide landscape of QT, through specific research questions:

RQ1: What are the characteristics of the QT Job marketplace worldwide?

RQ2: Are there regional differences between the QT job marketplace worldwide, particularly between the EU and the USA?

RQ3: What are the educational requirements of the QT workforce?

The backbone of this research has been the development of a robust algorithm to extract jobs from online and categorise them in a multi-step classification pipeline. The next section details this process.

3. Methodology

Historically, classification of qualitative data has been limited to human coders [57,58] often in the form of research assistants or through services such as Amazon's Mechanical Turk [59]. The process requires significant time and resources and moreover liable to inconsistencies stemming from individual biases and variability in interpretation of the codebook. Another drawback to human classification is its inherent ineptitude with scalability, making the classification of a large body of data intractable. Recent advancements in large language models (LLMs), particularly pre-trained models such as ChatGPT-4o-mini, represent a paradigm shift in the classification and analysis of qualitative data. These models mitigate many of the above mentioned limitations associated with human coders by leveraging computational efficiency, consistency, and scalability [60-62].

In the context of the investigation of the quantum technology job market, these capabilities are especially advantageous. LLMs offer an innovative methodology by transforming qualitative data—such as job postings and descriptions—into structured, analyzable formats. This transformation enables the application of data-centric approaches to derive insights that were previously elusive; by utilizing the vast training data encoded in a pre-trained LLM, combined with a human-in-the-loop methodology [63-64] these models can identify key skills, emerging roles, and other key pointers within the quantum job market. Another key advantage of using LLMs for classification is their ability to rapidly label data from large, dynamic datasets. This makes them particularly well-suited for continuously scraping and analyzing job postings from online job boards. By handling the constant influx of new data, LLMs enable real-time insights into the evolving trends of the quantum technology job market, a capability that traditional methods struggle to match.

3.1 Classification steps

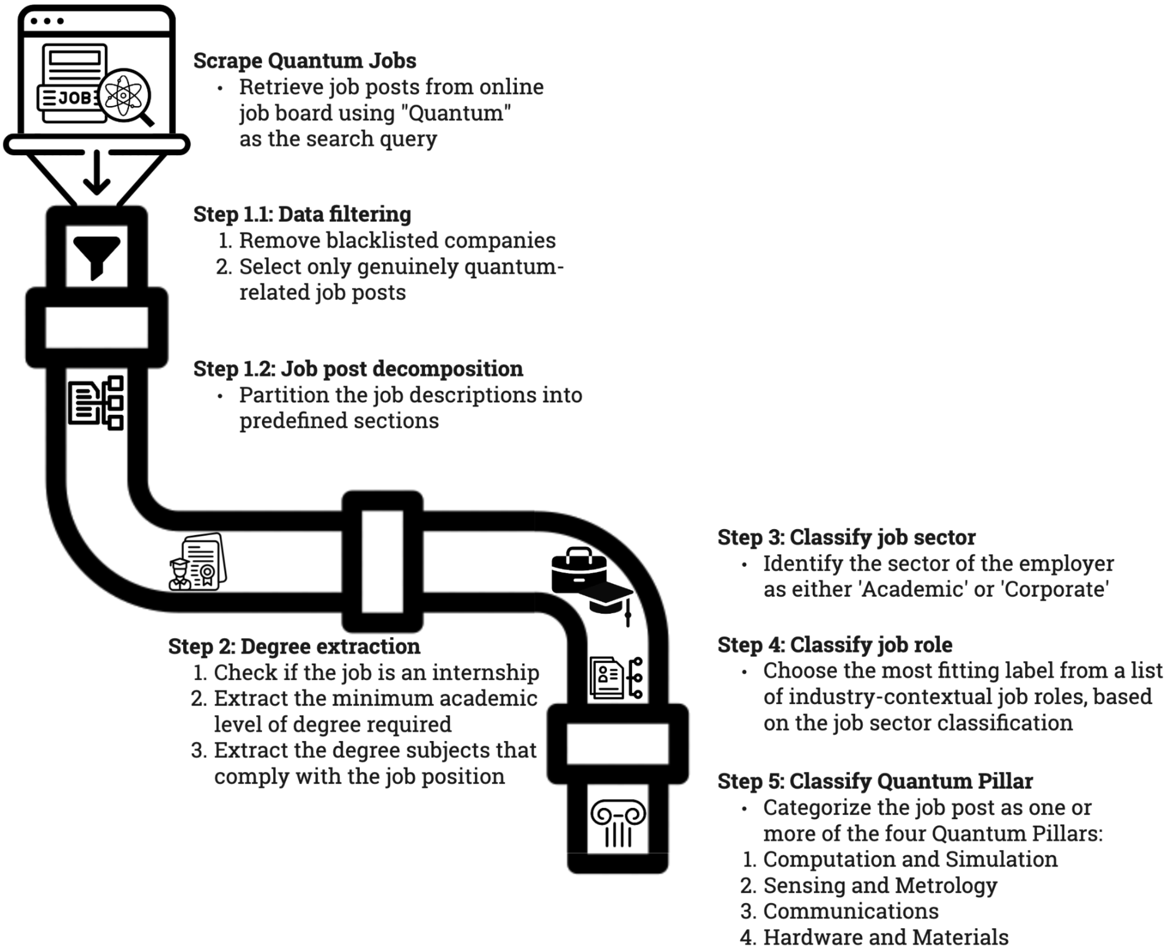

Figure 1. Data scraping and classification process. The figure illustrates the methodology used for data extraction and the steps conducted for classification across multiple categories.

Step 1: Scrape Quantum jobs

We used GPT-4o-mini [65] to classify quantum job postings from constructed prompts. The project relies on the data collection of job postings on an international labor market platform. The data was scraped weekly over the time period 03/2023 to 06/2024, using the search query “quantum” and setting the location to “Worldwide”. The scraped data was exported to an Excel file with the extraction date. After the data is saved in the project repository, an auxiliary scraping script written in Python [66] retrieves additional data to the job postings, such as job description and employer information. After some minor data cleaning, the data was then appended to the overall scraped job postings.

The data is now ready to enter the first classification step: data filtering and job post decomposition (see Figure 2). These compose cascading LLM-based classification steps, which are produced and validated by human experts. The human-in-the-loop aspect of the pipeline is crucial in order to ensure reliable, representative data, something that will be touched upon later.

The Data filtering step (1.1) starts out by removing blacklisted companies; companies that are known from experience of experts to not be associated with QT. It then finishes by selecting only genuinely quantum-related job posts, using the LLM to classify it as either quantum-related or not based on a human-generated prompt.
The next substep is 1.2, Job post decomposition, which partitions the job descriptions into predefined sections that can be used as a whole or selectively for the subsequent steps of the pipeline. This is useful, since it is then possible to input only sections relevant to the specific LLM-classification, which saves computational resources. The sections are defined from experience with job posts from an online job board, which usually consists of some of, if not all of the nine predefined sections: Organisation Information, Job Summary or Overview, Key Responsibilities and Duties, Required Skills, Preferred Skills, Required Qualifications, Preferred Qualifications, Required Previous Experience, Preferred Previous Experience.
After step 1, the now only quantum-related job posts in the dataset are also stored with their job description decomposition.

Step 2: Degree extraction

The purpose of step 2 is to extract information about the degree required for the job position. It achieves this through three different substeps; the first one, 2.1, starts by checking whether the position is an internship through pattern matching – if so, then 'Internship' is the classification label. The classification of the residual unlabelled job posts then continues into substep 2.2, which by pattern-matching classifies the minimum degree level from the preselected labels: "Bachelor", "Master", "PhD" and "None specified", totalling thus five possible classifications, including "Internship" from the previous step.
The last substep, 2.3, extracts the degree domains that comply with the job position: for example, a job position for a quantum hardware engineer could have required that the degree must be in a relevant field, such as electronic engineering and quantum physics. These required relevant degrees are then via the appropriate section from the previous decomposition (step 1.2) fed into a pattern-matching process that matches the subject into a corresponding domain, e.g. mechanical engineering would be labeled as 'engineering' and quantum physics as 'physics'. The process is a multi-label classification, meaning one job post can have a list of different domains associated with it. Columns of the classifications are appended to the data, so that the job posts have the minimum level of degree and degree domains required specified after step 2.

Step 3: Classify job sector

In step 3, the job sector of the job is classified as either 'Academic' or 'Corporate' based on information of the employer; that is, if the employer is a public, research institution, such as a university, or a research and technology organisation (RTO), the job will be classified as such. If the employer is from the private sector, it will, on the other hand, be labeled as "Corporate". The classification process starts by identifying the obvious instances using pattern matching, searching for words such as "national lab" or "university". Afterwards, classification by the LLM is performed on the remaining job posts, resulting in all of the job posts being labeled as either "Academic" or "Corporate".

Step 4: Classify job role

In step 4, the job role of the job post is identified through three substeps. Firstly, in substep 4.1, pattern-matching techniques are applied to the job title to identify clear instances where the job role is a PhD position. Next, using the degree level identified in step 2, the process determines which job roles are internships. In substep 4.2, the LLM is employed to classify job roles based on two distinct lists of job roles and their associated descriptions: one for 'Academic' roles and another for 'Corporate' roles. For example, if a job post is labeled as 'Academic' in the previous step, it is mapped to the most suitable role within this category. The classification process is further refined in substep 4.3, where certain roles are re-evaluated to ensure high confidence in classifications. This is accomplished using a refined prompt to specifically address roles that are prone to misclassification, such as distinguishing between 'Postdoc' and 'Professor,' or 'Product Manager' and 'Project Manager.' By leveraging sector-specific labels, the potential range of choices available to the language model is reduced, thereby enhancing classification accuracy.

Step 5: Classify Quantum pillar

Finally, the job posts enter step 5, the last classification step of the pipeline. This step checks the responsibilities of each of the job posts and checks whether they fit into one or more of the four Quantum Pillars; Computation and Simulation, Sensing and Metrology, Communications, and Hardware and Materials. It is a multi-label classification, meaning that each job post can belong to several labels in terms of which pillars the job responsibilities cover. The classification is carried out by letting the LLM extract which areas of the QT field the responsibilities of the job are associated with. Pattern-matching is then performed on the extractions, labeling the job posts with pillars that they fit into. The patterns used in the pattern-matching are generated through an iterative process of identifying which keywords are associated with which classes, running the sub-step, and refinding the patterns until the result is satisfactory.

As described above, each step is performed in a successive manner, making the pipeline cumulative and semi-cascading, whereby all subsequent steps depend on the initial two filtering and decomposition steps, but not necessarily on all preceding steps. Only selected steps incorporate outputs from earlier stages as additional inputs, such as step 4.
The result of steps 1-5 is a detailed corpus of information on the quantum job marketplace.

3.2 Classification validation

As mentioned in the previous section, a rigorous validation process is essential for any LLM-based classification to ensure the accuracy and consistency of the output data. The validation process of the pipeline of this paper has been carried out by a team of experts in the QT job market and data scientists, who have iteratively honed each of the prompts of the steps in order to reach a satisfactory classification accuracy. The validation framework utilized in this study is inspired by the works of Shah [67] and Pangakis et al., [68] and has been customized to meet the specific objectives and resource constraints of our project.

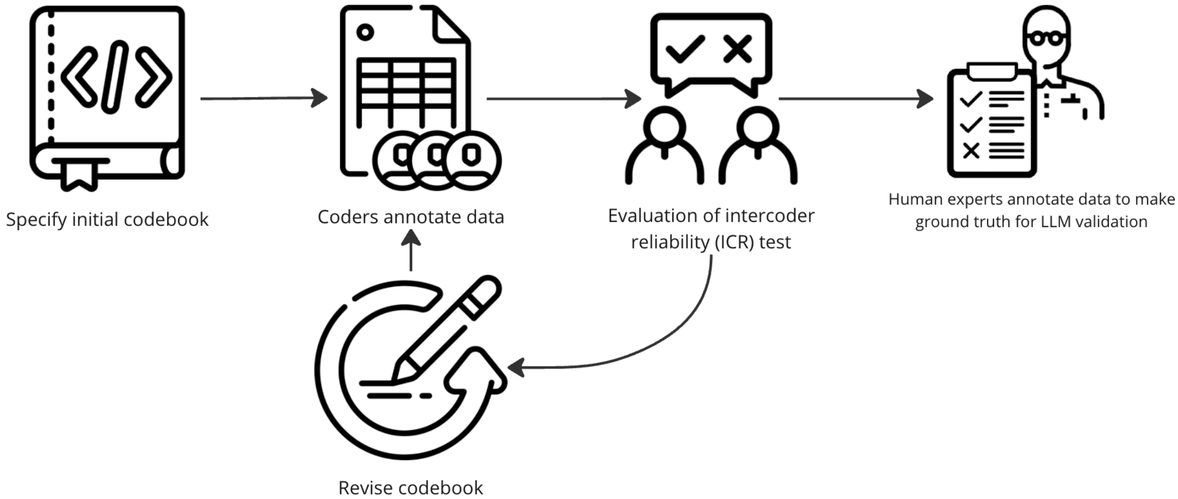

Figure 2. Initial phase of the validation framework. The figure illustrates the different steps involved in composing a codebook that the prompt used for classification is based on. The process is iterative and continues until the codebook has passed an intercoder reliability test.

The validation process of a classification step begins by formulating an initial codebook like any traditional coding task [69-70]. Human coders then annotate the data based on the instructions of the codebook; in our framework, three non-expert coders each had to label a subset of the data (25 job posts) whereafter the labelled data was compared against each other in an intercoder reliability (ICR) test [71]. The purpose of performing the ICR test is to ensure that the codebook is interpreted as intended and to catch any potential edge cases that were not accounted for in the initial codebook specification. Discordant labels formed the basis for revising the codebook, such as using more concise wording or expanding the codebook to encompass previously unforeseen cases. Once the codebook had been revised, the coders would once again label the data so a new ICR test could be conducted. This iterative flow would continue until there was at least 90% agreement between the coders. Once the codebook has passed the test, a human expert (i.e. a person well-acquainted with the QT job market) uses it to annotate 200 job posts in order to create ground truth that can be used in the assessment of the LLM-classification performance. This represents over 5% of the database and is in line with recommendations for LLM-classification validation from prior studies [68]. The next phase of the validation process involves converting the codebook into a prompt for the LLM. Although LLMs are trained on and adept at handling natural language, adjustments are made to ensure the output adheres to a format that the codebase can process correctly.

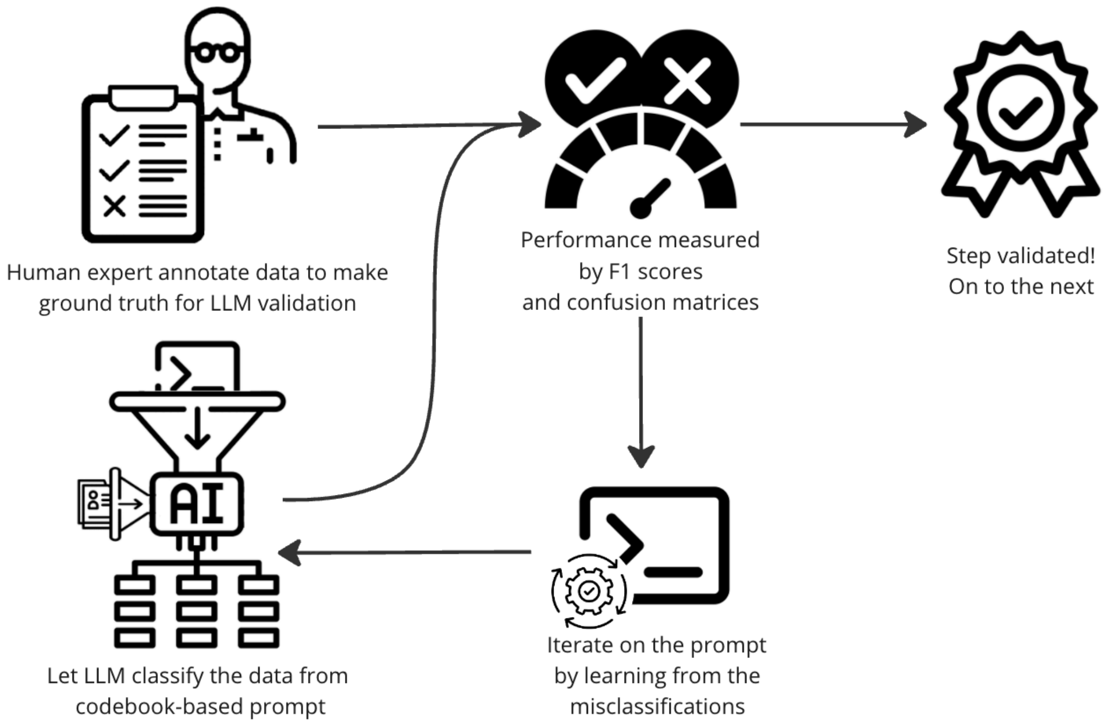

Figure 3. Second phase of the validation framework. The figure shows the process of comparing the ground truth in the form of annotations by a human expert with the classifications of the LLM. If the classification performance is unsatisfactory, the prompt is iterated upon and the LLM classifies the data anew. This is repeated until the performance is adequate.

Once the first version of the prompt for classification has been made, the same 200 job posts, where the true classifications have been defined, are classified by the LLM using the prompt. The classifications made by the LLM are then compared to the ground truth and the performance is evaluated using the weighted average of the F1-scores for the labels along with the associated confusion matrix. The weighted average of the F1-scores was selected as the performance metric for the classification task, as it offers a more robust assessment for datasets with imbalanced label distributions [72]. Since there is no conventional threshold for F1-scores—unlike p-values, which typically indicates significance if below 0.05 [73] — the scores were assessed on an ad hoc basis, using the general rule of thumb that a score of 0.7 or higher is regarded as good [74]. Following this guideline, the prompt was iteratively refined based on insights from misclassifications; the confusion matrix concisely highlighted any potential biases in the classification, thereby aiding in accurately adjusting the prompt. The process involved letting the LLM reclassify the data using the newly refined prompts, and subsequently generating the new F1-score and confusion matrix. This cycle was repeated until the score was deemed satisfactory. Consequently, the lowest weighted average F1-score achieved across all steps was 89%; below is an example of the classification performance for step 4 of the pipeline, on the job posts labeled 'Corporate' in the previous step.

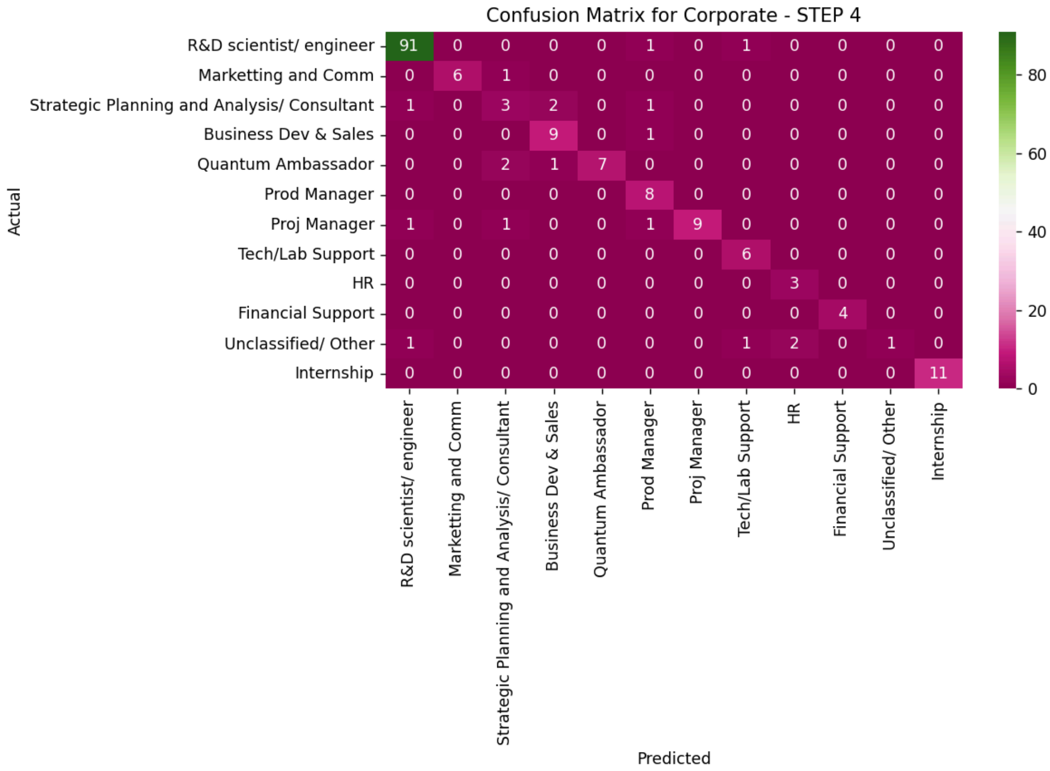

Figure 4. The confusion matrix provides an overview of the LLM's classification performance across different labels. Notably, the label 'R&D Scientist/Engineer' shows a high proportion of correctly classified job posts, likely due to it being well-defined and easy to delineate. Other roles, such as “Strategic Planning and Analysis / Consultant” may be more difficult to classify accurately, indicated by the off-diagonal components. Overall though, the LLM-classification performs quite well, as seen by the distinctly outlined diagonal of the matrix and quantified by the F1-score.

The majority of the steps of the pipeline was validated using the LLM-model gpt-3.5-turbo-0125 from OpenAI, while the remaining was done using gpt-4o-mini-2024-07-18, also from OpenAI [65]. The models were chosen by balancing cost and performance – the common denominator between the two models is, that they both are the affordable version of their correspondent flagship models. Due to the longevity of the development of the pipeline, gpt-4o-mini was chosen for the later steps, since this model has become available at this point in the process and that it “cheaper, more capable, multimodal, and just as fast [than gpt-3.5-turbo]” [75].

3.3 Methodological limitations

One clear limitation of this research is the data source used, exclusively representing jobs from one large online job board. However, this website, which remains anonymous in order to prevent any possibility of identifying personal information using the anonymised dataset available with this article, represents one of the largest available worldwide, particularly for technology related jobs. Therefore it seems reasonable to proceed with the dataset for this research, bearing in mind that although it is not comprehensive, it is likely to be reasonably representative of the state of the QT job market, at least in the corporate sector. There is limited information available about how the academic sector uses online job boards, however, and therefore whilst academic jobs are included in our dataset, we consider the academic and corporate roles separately in classification step 4.

Another potential limitation to consider is the relatively small subset of data employed in the ICR assessment, which may have influenced the overall reliability of the codebook's quality. While the limited size of the subset could be perceived as a drawback, it actually facilitated quicker iterative loops during the ICR process. This approach enabled more frequent assessments, allowing the team to systematically identify and discuss discrepancies between the annotations of different coders. Through these iterative cycles, valuable insights were gained into areas of inconsistency, which were then used to refine and improve the codebook. Consequently, although the smaller subset may have affected initial reliability metrics, it ultimately contributed to a more robust and thoughtfully developed coding framework.

4. Results

Over the time period 03/2023 to 06/2024, a total of 3641 jobs were extracted from an online job board. In this section, we present the aggregate descriptive information available from classification steps 1-5, namely the regional distribution of the job posts (subsection 4.1), the degree level requirements (subsection 4.2), the degree subject requirements (subsection 4.3), the job sector (subsection 4.4), the job subjects, QT pillars (subsection 4.5), and the job roles (subsection 4.6). Note that while 3641 comprises the total dataset of individual jobs, the total count shown on each plot differs from this number for several reasons, such as co-counted jobs (e.g in subsection 4.3) and the exclusion of jobs posted by recruitment companies (Fig. 6 and 7).

4.1 Regional distribution of QT jobs

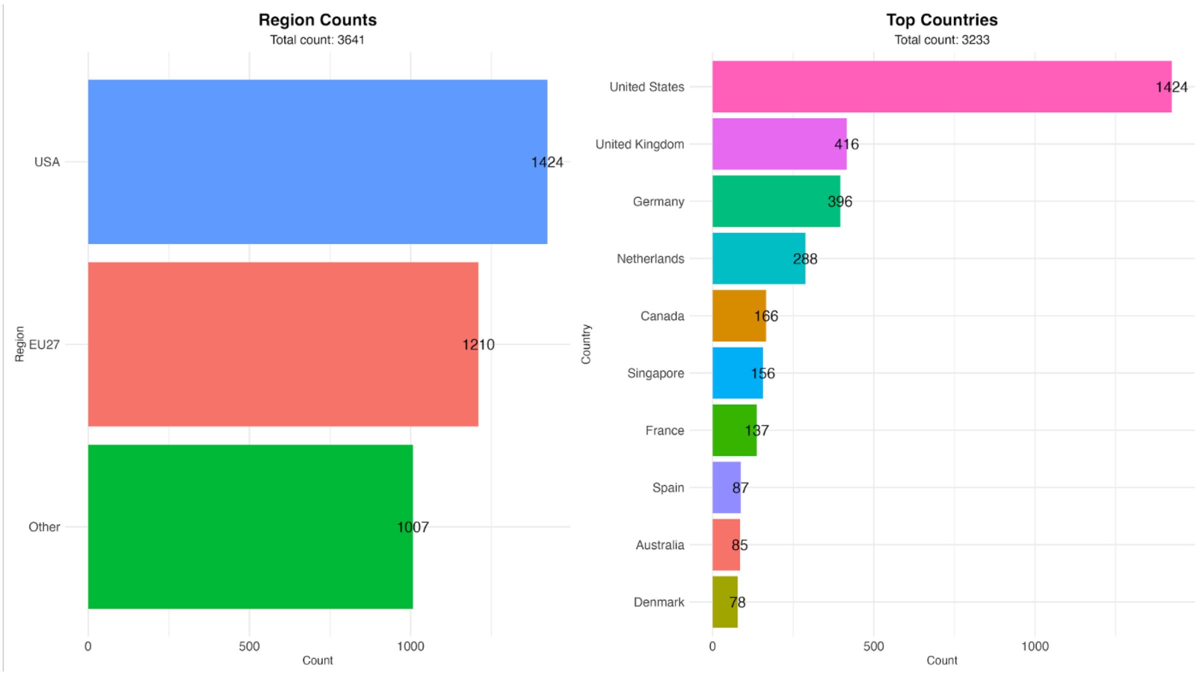

Figure 5. Number of countries posting quantum jobs worldwide. The figure shows the distribution of quantum jobs globally with the high presence of the United States (right figure) highlighting its dominant role in the quantum global market.

The USA has the highest count of quantum job postings (1424), while the EU27 has fewer but still a comparable number (1210). The dominance of the USA suggests that policy initiatives such as the National Quantum Initiative Act have been effective at fostering a conducive environment for job creation in this sector. The EU, meanwhile, benefits from both a region-wide program, the Quantum Flagship, and country-specific funding.The UK, where the national quantum technology program [44] has been in place since 2013, has been an early adopter in QT and this may have contributed to the overall large number of jobs there compared to the size of the nation (the UK has a smaller population [416 jobs, 69 million population] than Germany [396 jobs, 84 million population]). The Netherlands also has a strong quantum ecosystem in comparison to its size (298 jobs, 18 million population), perhaps owing to the efforts of the Quantum Delta NL [76] which has been a significant boon to the Dutch quantum ecosystem.

Regarding how different sized companies are distributed worldwide (Fig. 6): overall, the greatest number of job positions are found in large companies, with over 10,000 employees. We can glean further information from comparing this distribution between the EU27, USA, and other countries (Fig 7.). Note that in these plots, job posts advertised by recruitment companies are filtered out, as they do not accurately represent the company demographics. This reduces the total count from 3641 to 3037.

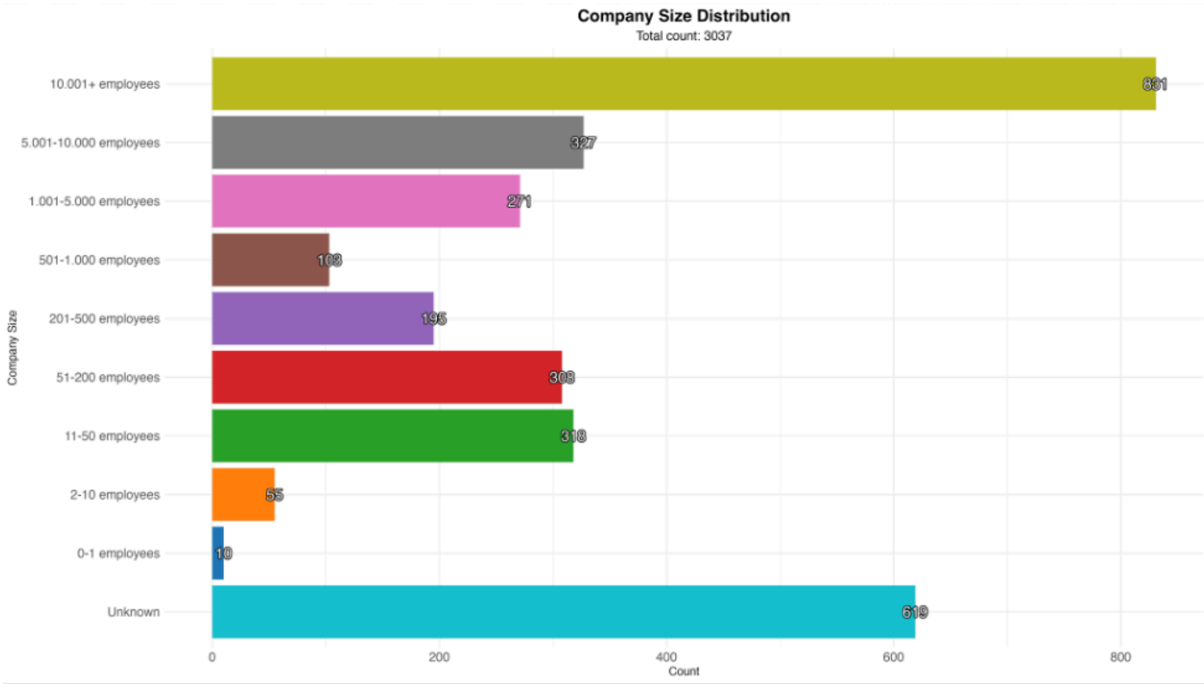

Figure 6. Company size distribution. The figure shows large companies posting the most jobs over the duration of the dataset accumulation.

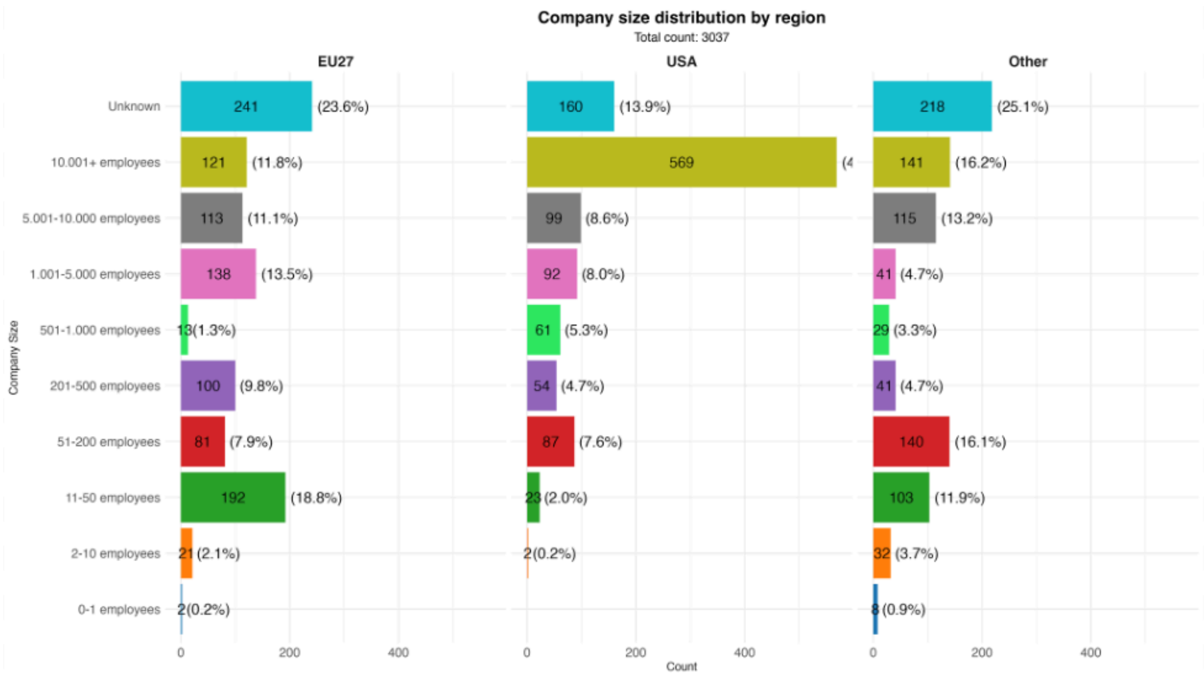

Figure 7. Company size distribution by region. The figure shows the presence of larger companies in the US, whereas in the EU, smaller companies are leading towards the hiring of quantum job roles.

We note that the worldwide distribution is largely similar, with one notable exception: The USA hosts a significant preponderance of larger companies (those with 10,000+ employees). These include major technology giants such as IBM, Google, Microsoft, and

Nvidia, which are highly active in hiring and building capacity, therefore increasing the count of job posts in the USA for large companies. The United States benefits from significantly higher levels of private and public investment in quantum technologies [77]. Large-scale government initiatives like the National Quantum Initiative Act have attracted substantial private sector funding. Venture capital and corporate R&D funding in the USA have also grown faster than in Europe, fostering an environment conducive both to the growth of QT startups and hiring by established companies. On the other hand, the EU27 has a stronger presence of small companies (11-50 employees and 2-10 employees), perhaps owing to the academic strength of the EU27 with a lead in the number of universities, leading to more small spin-off companies formed from research centers.

Another area which demonstrates the strength of the corporate sector in the USA is the comparison between academic and corporate job posts in the dataset (Fig. 7). Corporate job roles indicate a greater prevalence in the USA (77.5%) compared to the EU (70.7%).

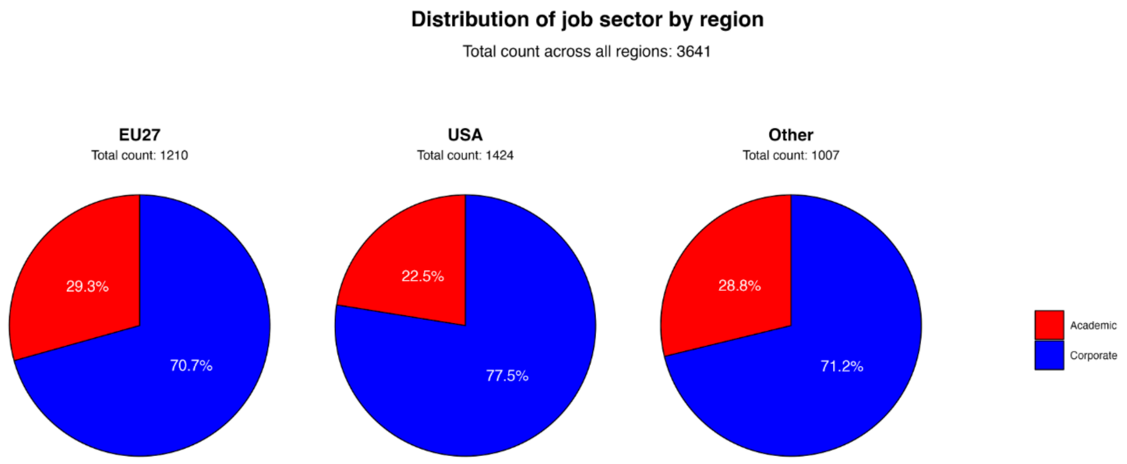

Figure 8. Distribution of job sectors compared by region. The dataset is primarily made up of corporate jobs. Academic jobs are more present in EU27 compared to the USA.

4.2 Degree level Requirements

In Fig 8., we show the indicated degree level requirements for the jobs posted worldwide. The overall high demand for PhD candidates (1233 jobs, 34%) may stem from the specialised nature of quantum technologies, which often require advanced research and analytical skills. Companies may prioritize candidates who have conducted extensive research or possess specialized knowledge. It is also notable that when combined together, Bachelor and Master graduates make up 1486 (40.1%) of the total job positions available, indicating they may take less-technical roles, or that companies may offer on-the-job training to bypass the PhD requirement. This may also stem from the increasing number of university programs offering education in QT [7], therefore there are more graduates able to take up these roles, and companies are more aware of this route to hiring. Still, the number of jobs requiring a PhD is large in comparison to other industries, as we consider in section 5.

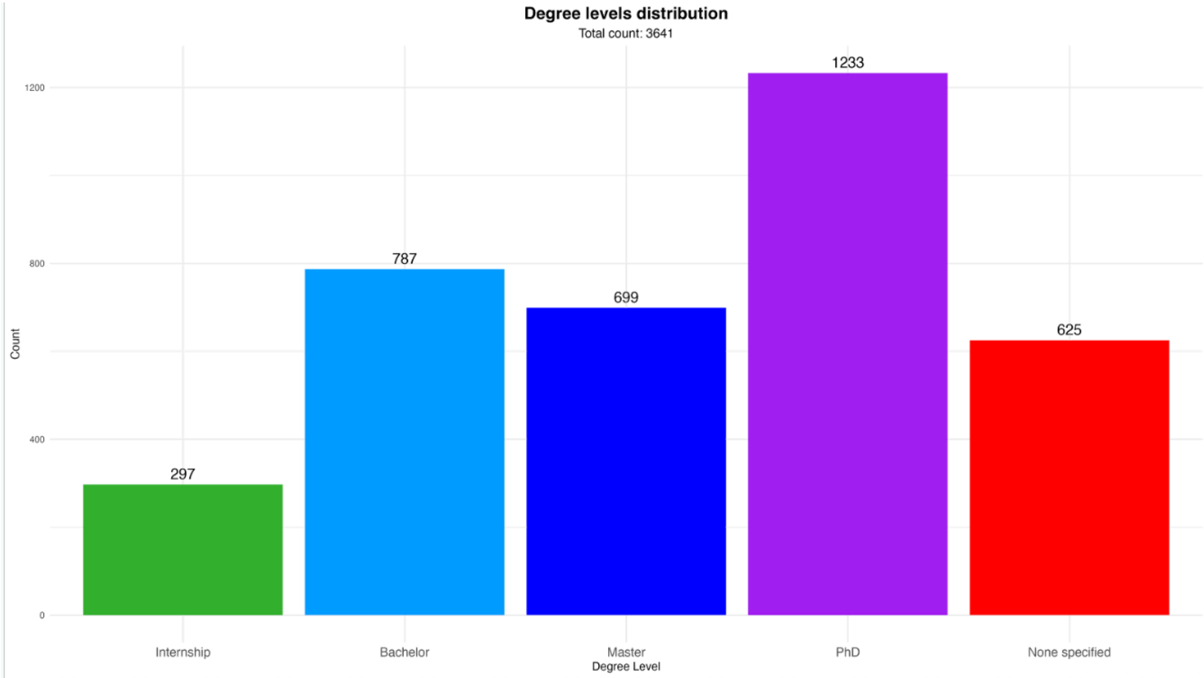

Figure 9. Degree levels requirements of QT jobs. The figure shows that while the PhD requirement is still the dominant route to the quantum industry, different degree paths are also available, with a strong presence of Bachelor and Master graduates accepted. Note that 297 job posts represent internships, with no degree requirements.

As far as the regional distribution goes (Fig. 9), we note that the USA has most jobs requiring PhD positions (496), and bachelor graduates (426), with a significantly smaller number of roles for master's graduates (169) as compared to the EU27. This may indicate that the value of a Master's is higher in Europe, potentially relating to the significantly higher number of Master's programs in the EU [7]. Employers could thus be more aware of Master's programs as a viable route to hiring.

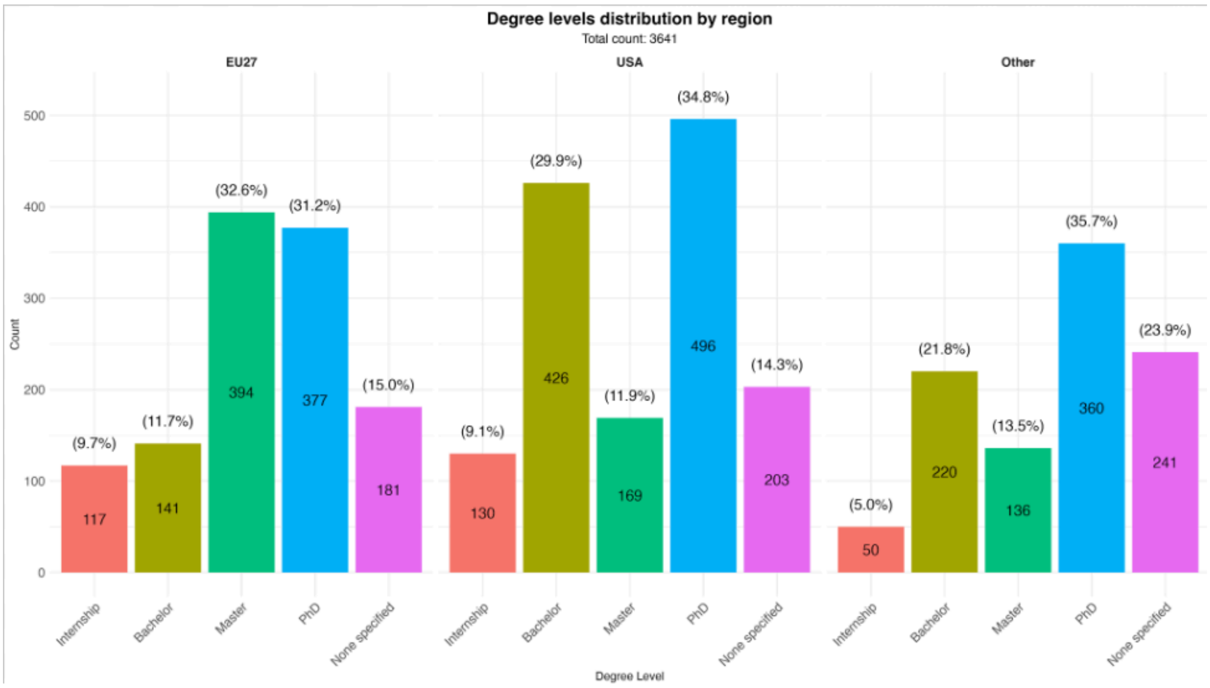

Figure 10. Degree levels requirements distribution by region. The USA hires more Bachelor and PhD graduates, while the EU supports more Master's graduates.

When comparing among different size companies (Fig 10.), the most notable difference is the presence of PhD requirements for the largest companies of 1000+ employees. These are likely the tech giants mentioned also in subsection 4.1, and require PhD graduates for their research and development roles. Furthermore, as the largest firms, they are likely to offer the most competitive salary and attract the strongest candidates, who are those with the highest level qualifications. Smaller companies offer a larger fraction of jobs to candidates with a Bachelor or Master, perhaps suggesting they are open to providing on-the-job training for more technical positions. Companies of all sizes offer a reasonable fraction of their roles as internships, around 10%, which is valuable for providing training on the job for future positions.

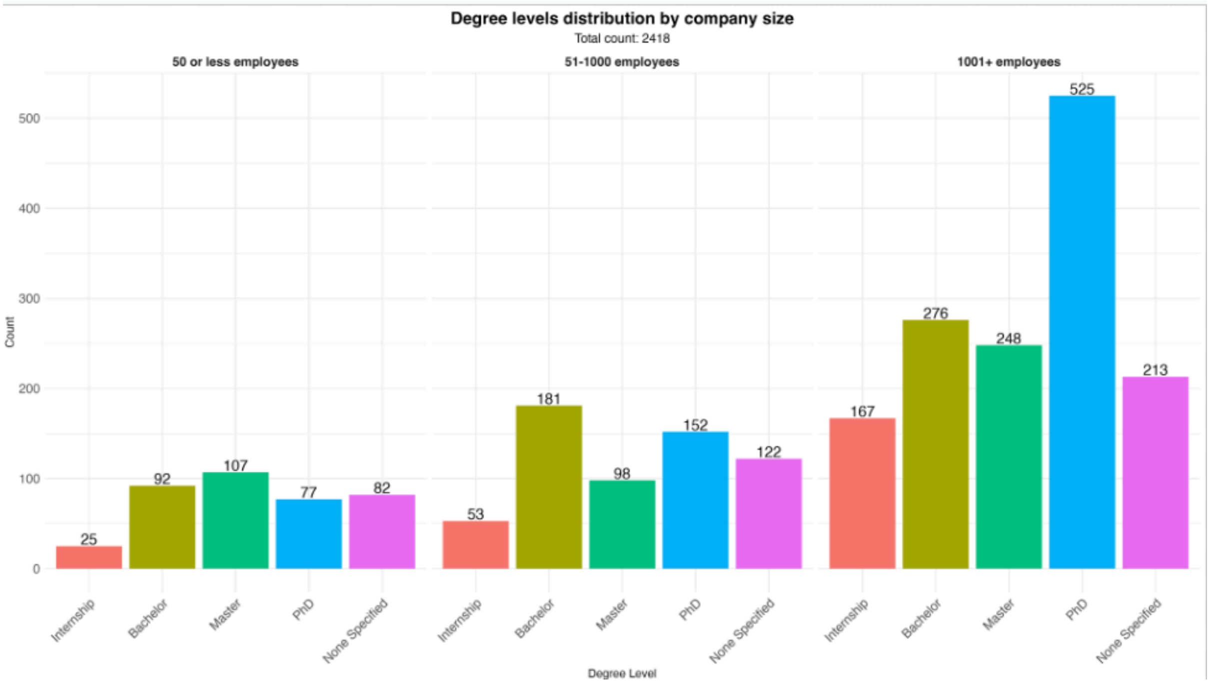

Figure 11. Degree level distribution by company size. Larger companies have a greater fraction of PhD requiring roles, while there is a more moderate requirement for smaller and medium sized companies.

4.3 Degree subject requirements

With regard to the degree subject requirements (Fig 11.), there is a high prevalence of physics across all regions (49%), indicating a high need for physicists in the quantum industry. This may stem from the fact that at least up until recent years, Physics degrees have provided the most quantum educational content out of all degree programs. Software and electronics/electronic engineering make up the next largest fractions, as it may be the case that more and more quantum course options are available in these degrees [17].

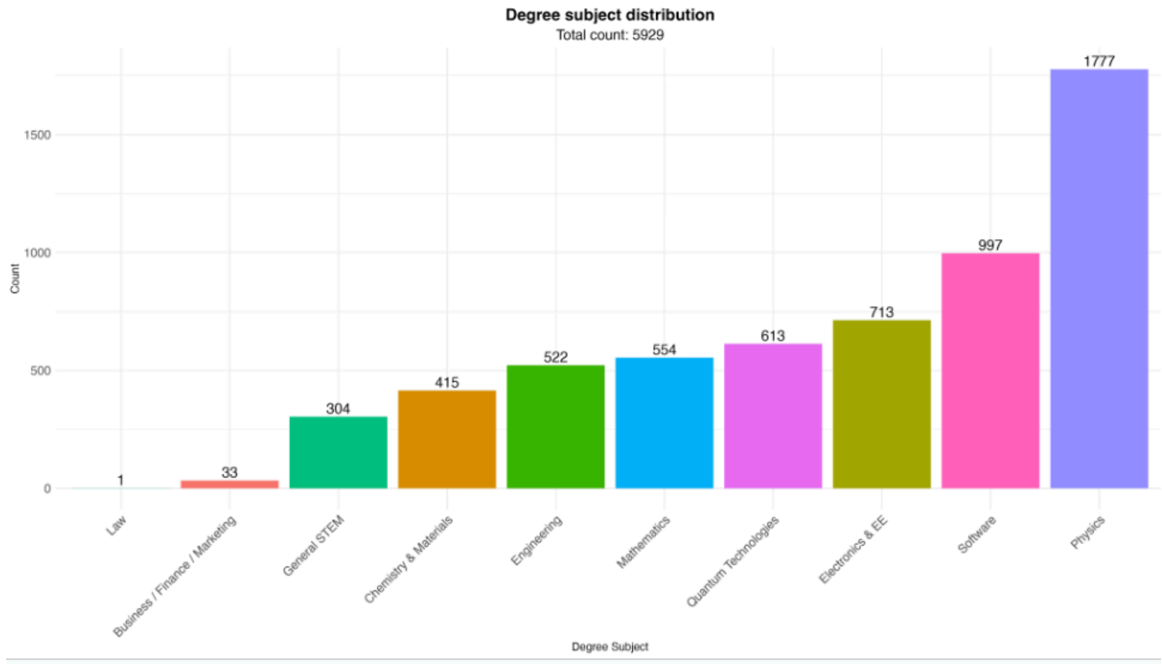

Figure 12. Degree subject requirements of QT jobs worldwide: Physics 49%, Software 27%, Electronics 20% QT 17%, Maths 15%, Engineering 14%, Chemistry & Materials 11%, General STEM 8%, business /finance/marketing 1% / law 0.03%.

When looking at the comparison between regions (Fig 12.), we note that the distribution is largely similar between countries, with the USA having the most jobs (as the USA has the most jobs overall). One notable difference is with respect to the "Quantum Technologies" degree demand, which is higher in Europe. As noted previously, this may be due to the high number of quantum master's in the region (41). The United States also shows a significant difference to the EU27 with respect to hiring electronics/electronic engineering graduates

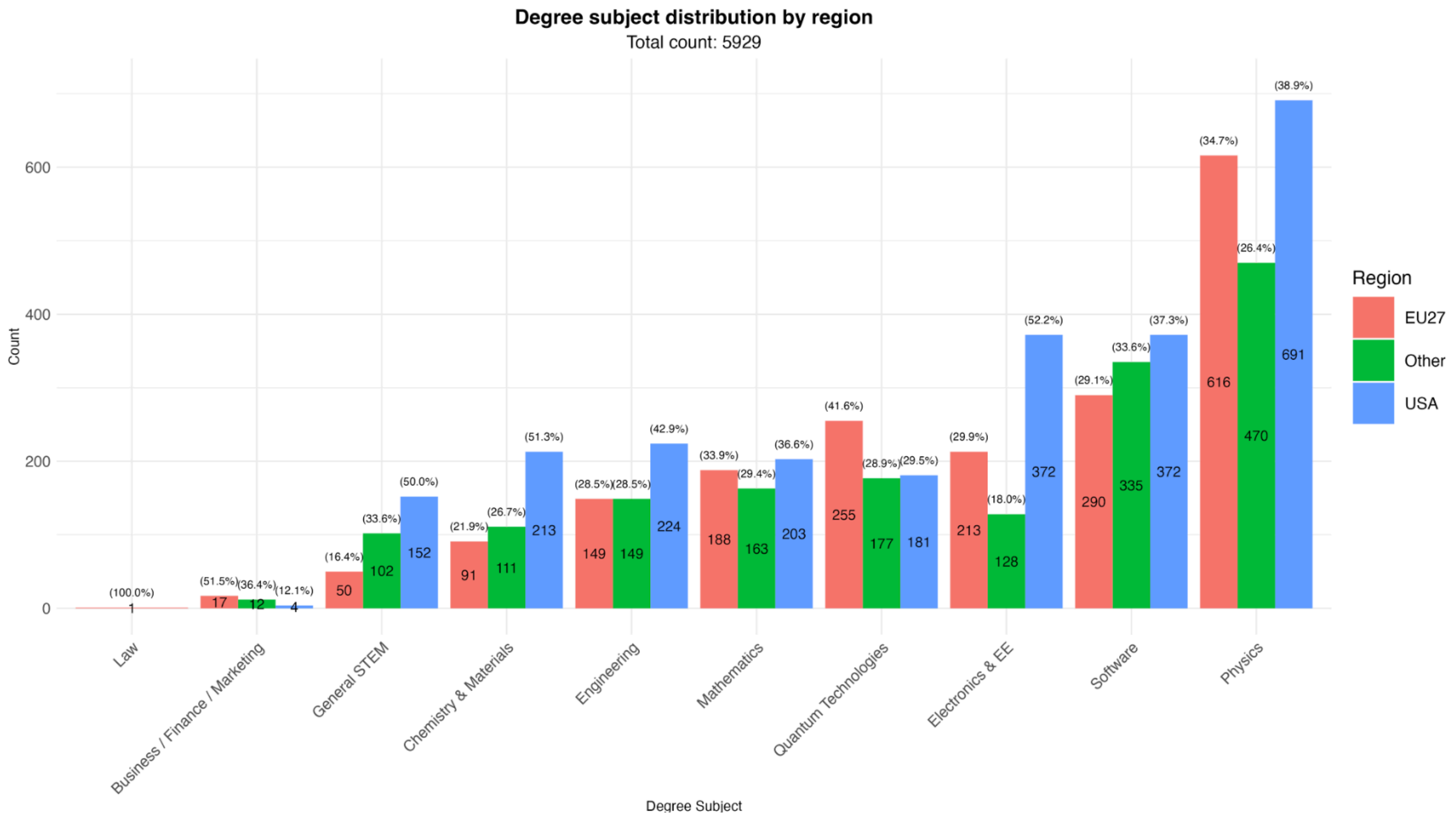

Figure 11. Degree subject requirements of QT jobs worldwide, compared between the EU27, USA, and other nations.

(372 jobs compared to 213), which could suggest a greater readiness in the US quantum industry for applications of quantum technologies, where graduates of electronics and software degrees may have a prominent role.

4.5 Job subjects: Quantum Technology Pillars

With regard to the subject area of the QT jobs, in classification step 5 we considered four classes, namely Computing & Simulation, Communication, Sensing, and Hardware. Each job can take one or more of the classes, and therefore we are able to distinguish between, for example, Quantum computing (software) and quantum computing (hardware) based on the classification in step 5. Quantum Computing (hardware) is the most prevalent combination, followed by Quantum computing (software), hardware (non-specified application). Quantum communication has more roles (585) than Quantum sensing (317).

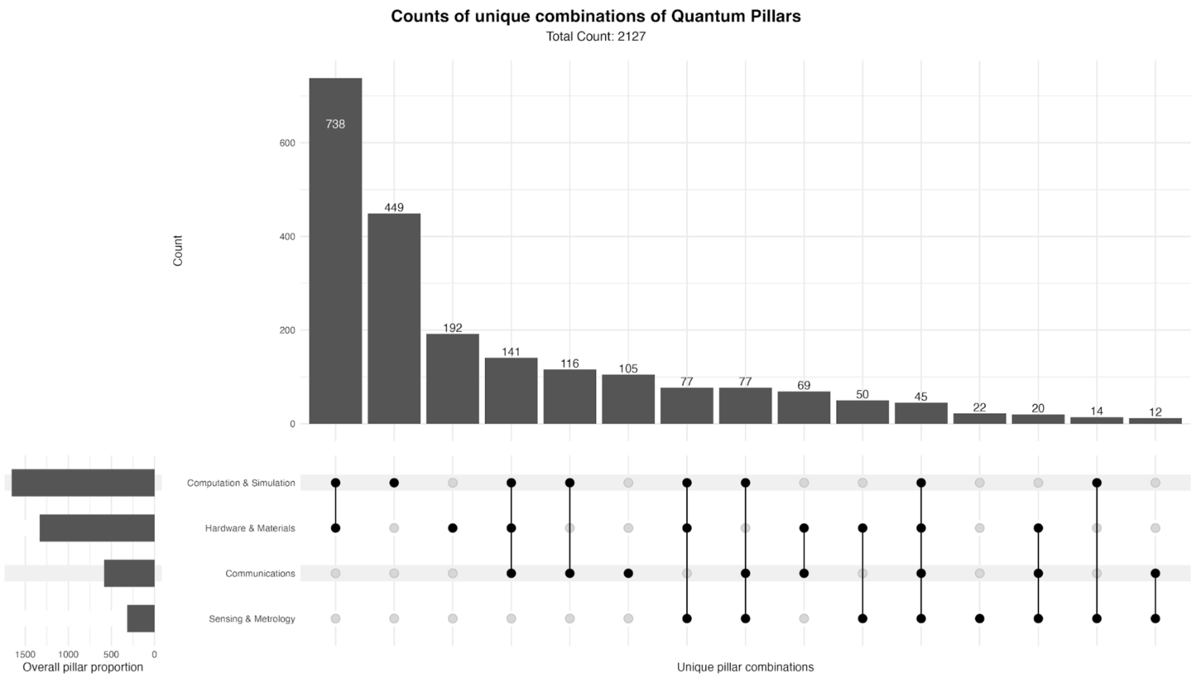

Figure 11. Unique combinations of Quantum Pillars. Computation & Simulation and Hardware & Materials can be considered to represent Quantum Computing (Hardware), while Computation & Simulation alone can be representative of Quantum Computing (Software).

It is not surprising that Computing has the most job positions, as the market for quantum computing is estimated significantly larger than sensing and communication [78]. The magnitude of the difference is very significant, however, which can also be observed in Fig. 12. Here we observe that the EU27 has a greater fraction of job roles in Hardware, and a similar fraction in Computation,while the USA shows a substantial lead in Sensing & Metrology and Communication. This may be related to the size of the companies, as noted previously the USA hosts more very large companies. These employers, with the capacity to diversify in different fields, may be the source of the sensing and communication jobs, discussed in section 5.2.

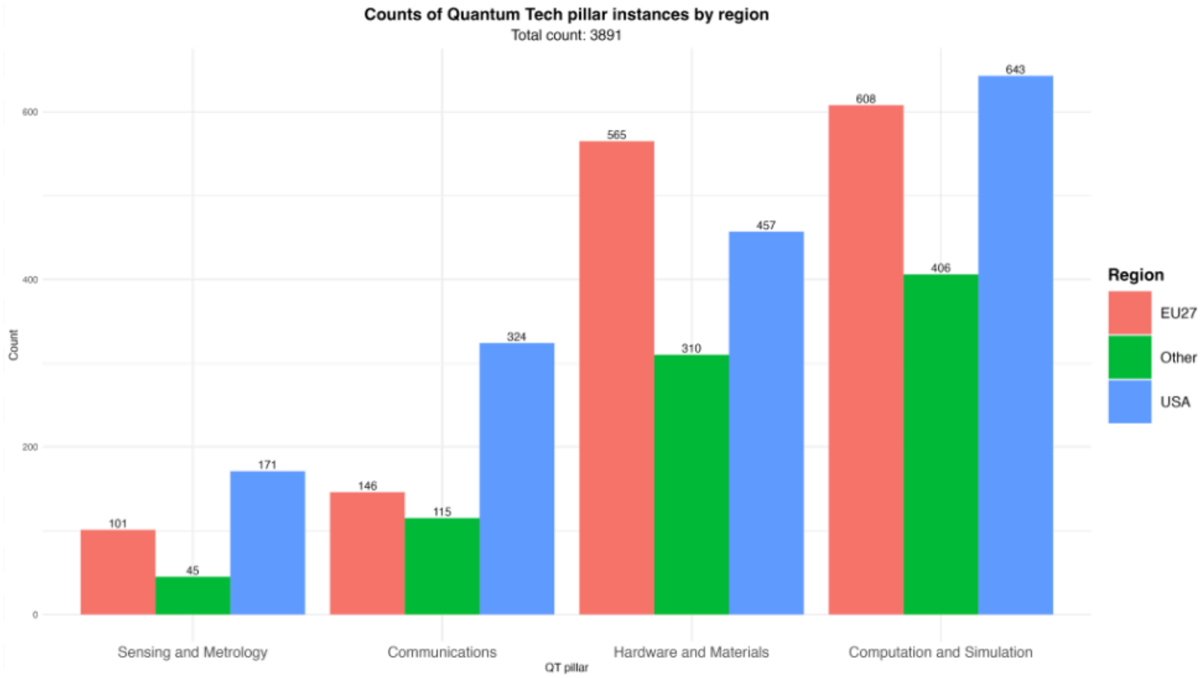

Figure 13: QT Pillars compared between EU, USA, and Other regions. Note that this plot counts jobs matching to multiple of the pillars more than once - hence the total count of 3891 is above the total number of jobs in the database.

4.6 Job roles

Within companies hiring for quantum roles, it is interesting to examine the roles being addressed. The largest class, by a substantial margin, are in technical research and development. R&D scientists or engineers make up 1839 (68.72%) of all corporate roles. By comparison, the other job roles indicated are substantially smaller in magnitude, such that internships (218 jobs) make up more job posts than any one other category. This is noteworthy as internships can offer a kind of on-the-job training for interns who can then go on to work in professional roles. The role *Strategic Planning and Analysis/ Consultant* (138 jobs) encompasses high-level planning, analysis, and strategy development - either internally or for other companies. This still requires some technical knowledge, and likely a higher degree is preferred. Business development, project managers, and technicians require less QT knowledge, but these still make up only a small fraction of the available jobs. Finally we note that the truly non-technical roles, such as marketing and communication (21 jobs, 0.07%), HR (21 jobs, 0.07%), and financial support (11 jobs, 0.03%), are almost negligible in the job market. This truly points towards QT as an infant industry, as we would expect these numbers to be much greater for more established technologies, discussed in section 5.1.

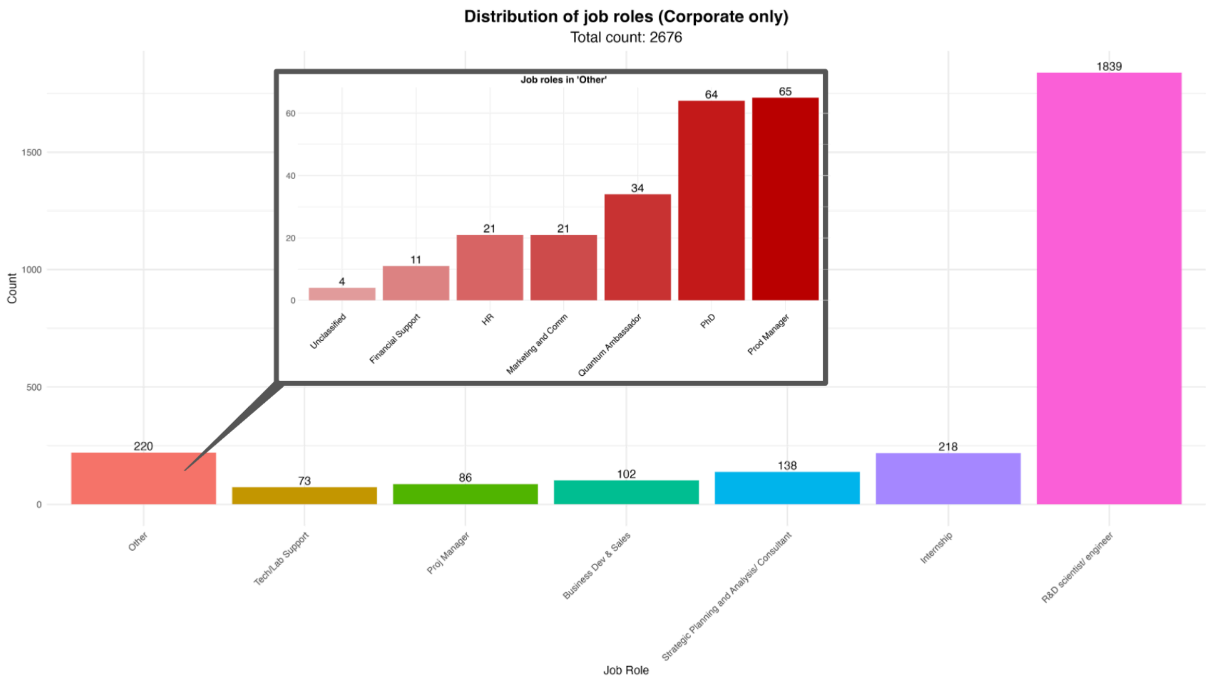

Figure 14. Corporate job roles indicate a high dominance of R&D scientist/engineer needed while a more moderate distribution across different job roles is observed.

5. Discussion

Here we consider some of the major implications of these results. Perhaps the most significant is what the trends can tell us about QT as a worldwide field, in terms of its level of technology and market readiness.

5.1 QT may still be an immature industry

Several of our results hint at QT being as-yet still nascent in terms of market readiness. When looking at Fig. 5, the distribution of company sizes, we see a significant presence of very large (10,000+ employee) firms and mid-large (5001-10,000) companies, indicating that these are likely to represent the early adopters of QT who can afford to invest in the technology at this nascent stage of application. Some of the largest companies, by number of jobs posted, include Google, IBM, and Nvidia, which are also some of the largest companies in the world. By comparison, there are relatively few mid-size and small companies in QT, unlike more established fields such as IT services and telecommunications, where the split between small, medium, and large firms is more uniform [79].

Fig. 8. demonstrates that there is still a high demand for PhD graduates in the quantum industry, representing over one third of all job posts. This is very high compared to other industries with a greater degree of maturity, such as software development, IT infrastructure, and telecommunications, which have reached a level of commoditization where practical skills outweigh theoretical knowledge [79]. These industries have far more jobs which are either non-technical, or at a lower level of specialisation to where fewer PhDs are needed.

The same trend is observed in the job roles in the quantum industry, where we identified that the significant majority of corporate roles are highly technical. Therefore, companies likely prioritize candidates who have conducted extensive research or possess specialized knowledge. When taken together, Bachelor and Master graduates make up 40% of the total job positions available, which is still not insubstantial, and it is likely that they occupy less technical roles, or that companies may offer on-the-job training to bypass the PhD requirement. As the number of educational opportunities increases, such as master programs and specialist QT minors, the fraction of graduates able to take up roles in the quantum industry, without the time commitment of a PhD, will likely increase [7].

5.2 Quantum computing is the most dominant area, but is it the most ready?

It is noteworthy to compare the subject area, in terms of the QT pillars, among the different sized companies (Fig. 16). There is a clear trend that a greater fraction of small companies are working in quantum computing, both in hardware and in software. When comparing quantum computing among small (<50 employees), medium (50-1000 employees) and large (10,001+ employees) companies, we note that it makes up 87%, 80%, and 74% of job roles respectively. This is in line with previous research noting that new startups, in particular, are more likely to favour quantum computing over the other pillars [81]. One explanation for this may be that smaller companies are more likely to be spin-outs from academic research labs, with facilities able to develop quantum hardware. Furthermore, smaller companies are more likely to focus on a single pillar, and quantum computing is perceived as having the greatest potential market value [77]. On the other hand, larger companies may be able to afford to be more diversified in their quantum efforts and therefore, be more likely candidates to include sensing and communication in their product development.

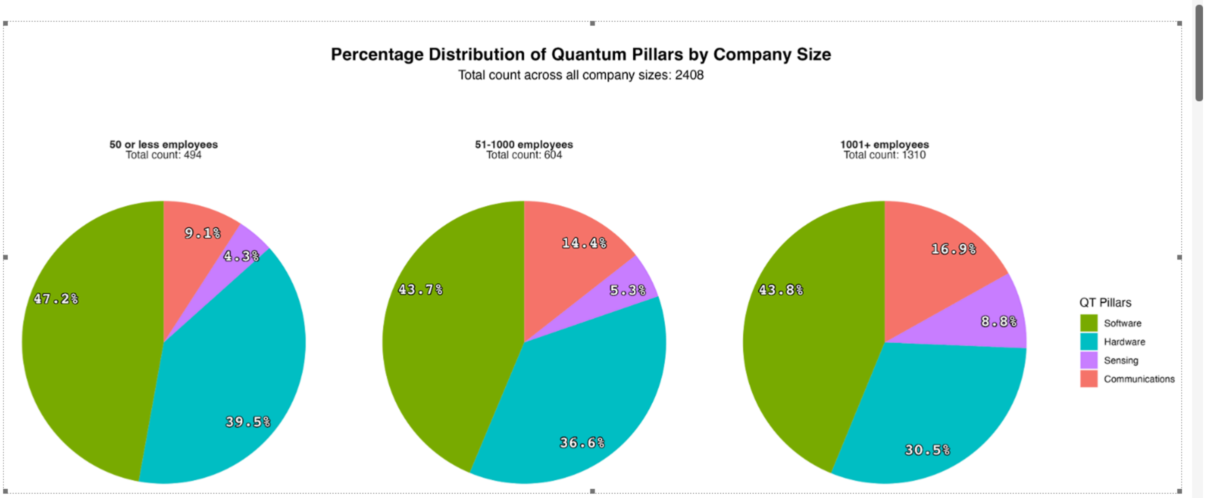

Figure 16. Quantum pillars across by company size. Quantum computing (hardware) and quantum computing (software) are among the most expected/needed across all company sizes.

While there is still much discussion about the technology readiness of quantum technologies, and quantum computing in particular [2], it is likely that sensing and communication are in fact closer to the market than computing is. So, while the majority of job roles in the quantum market are addressing computing, with the idea that it may be a more disruptive technology [82], sensing and communication may actually be lower-risk areas to invest in.

5.3 The USA leads the market

We have already noted that the largest tech giants are primarily USA-based companies, such as Google, Microsoft, Nvidia, and IBM. When comparing among the top 30 companies posting jobs in the dataset (Fig. 17), 16 (53%) of them are USA companies. Over half of the jobs posted are based in a single country. Another very telling statistic are the locations of jobs compared to the companies hosting them (Fig. 18). This provides information about how European, American, and other companies are expanding internationally. 79 EU-based jobs are in branches of USA companies (~7.7% of EU jobs), whilst only 15 USA-based jobs are in branches of EU companies (~1.3% of USA jobs),a difference of almost 600%. It is clear that the quantum industry of the USA is actively

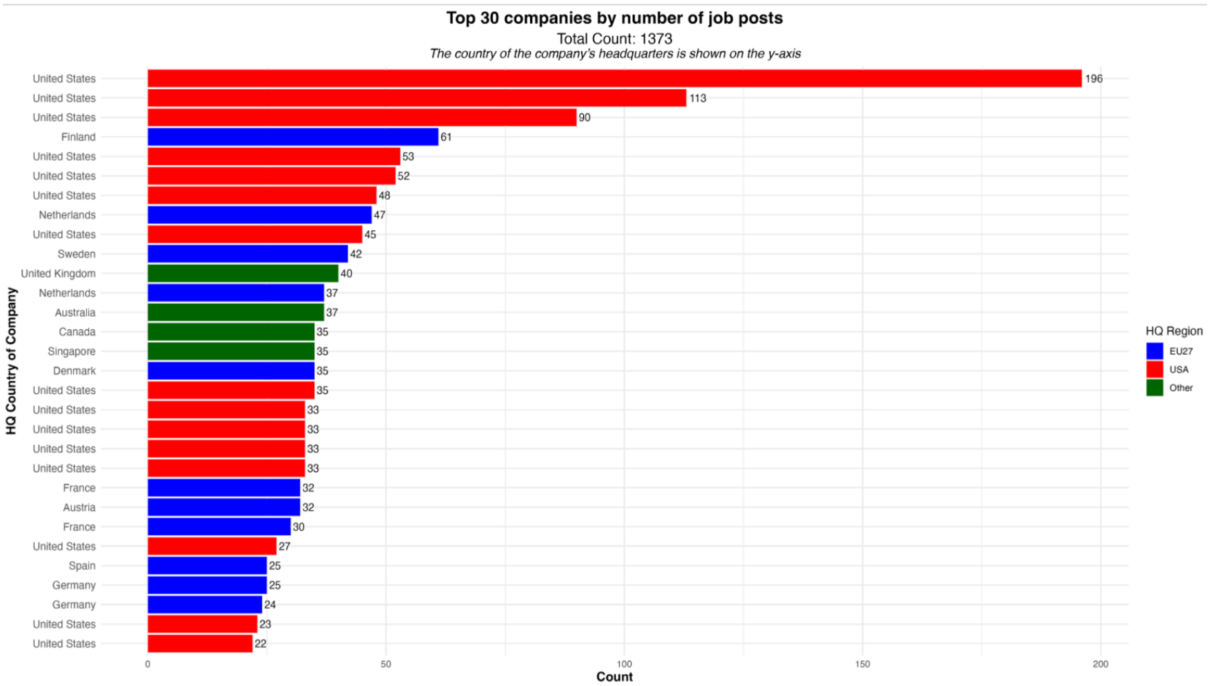

Figure 15. Companies leading the hiring of quantum professionals. The figure shows the presence of large firms in the USA.

establishing a presence in the EU, either to tap into the EU talent pool of graduates, where the EU is academically excelling [7], or to expand global operations. The EU quantum ecosystem has a smaller reciprocal influence in the USA, with fewer EU companies expanding their presence there. One implication of this result is that a net flow of talent from the EU to USA is present, as EU jobs are most likely to be taken by EU graduates, supporting USA companies. Given the already significant disparity between the market size in the USA and the EU, with the USA far ahead in market value, observed in Fig 17, and by previous sources [77], it is likely that this gap will continue to increase, as USA companies are able to further their international expansion.

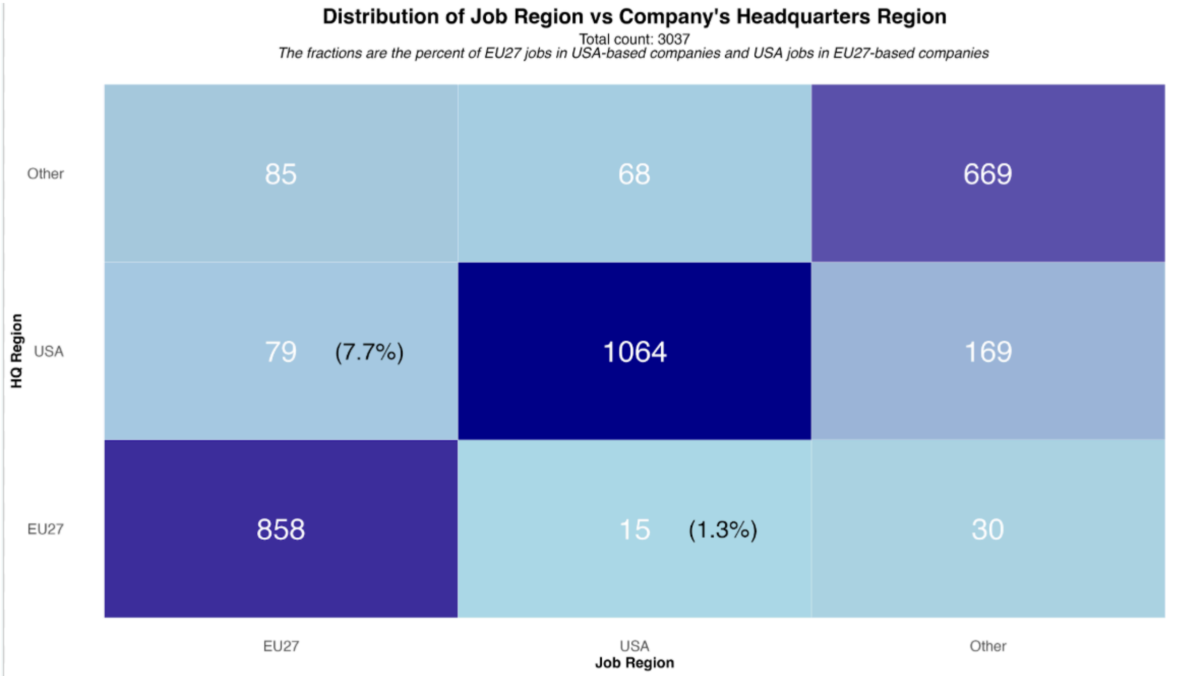

Figure 16. Matrix showing the distribution of job region vs company's headquarters region. All regions have the most jobs located in their headquarters nation. However, 7.7% of the jobs posted in the EU have headquarters in the USA, and only 1.3% of USA job posts are in EU companies.

6. Conclusion and outlook

In this work, we have examined the state of the QT job marketplace through job posts worldwide. Information extracted has covered job requirements, topic areas, locations, and company sizes. However, a crucial missing element is the specific skills involved in these jobs. What exactly are the day-to-day content of them? This research has shed light on the educational level for which quantum jobs require, but what exactly should be the content of bachelor, master, and PhD programs in order to most straightforwardly address the needs of the industry? As of now, this remains unclear. However, the competence framework may provide a means to address it. The job posts collected for this research contain information about skills, tasks, and responsibilities. Therefore, with advances in GPT-based classification, it may be possible to extract and cluster these skills. A first pilot of classifying the job market data using the competence framework is currently underway, and has already provided feedback for the latest version of the framework (3.0). In future work, we intend to comprehensively map the job posts and the regional job markets of the EU, USA, and worldwide, to the competence framework, identify the key requirements for a variety of roles, and perhaps take steps towards a truly industry-driven education landscape.

The quantum job marketplace reveals many signs of quantum technology's nascency as an industry still in early stages of development. The high demand for PhD graduates, low number of startups and mid-sized companies, and a market dominated by large US companies implies that there is still a way to go and much to be done for QT to reach a stage of maturity that enables it to be more present in our daily lives. Education plays an essential role in providing more trained graduates to fill the at-present rather technical roles, most companies in the QT industry need. This requires not only effective teaching methods at the university level, but also widespread efforts towards inspiration and outreach, so that members of the public and high school students may take a step towards studying for STEM or QT degrees. These graduates form the backbone of the quantum industry, and greater attention must be paid on this need for talent if the quantum industry is to mature to market readiness.

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