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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 3641 job postings worldwide. The classification pipeline leverages large language models (LLMs) whilst incorporating a "human-in-the-loop" validation process to ensure reliability. 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. However, there is some sign that there may be change to come, indicated by a strong presence of Bachelor and Master's graduates in the workforce.

Keywords

Job marketplace - Quantum technology - data science - GPT - industry - workforce - education - skills

Abbreviations

CFQT: Competence Framework in Quantum Technologies

DigiQ: Digitally Enhanced Quantum Technology Master

EU: European Union

HQ: Headquarters

ICR: Intercoder Reliability

LLMs: Language Large Models

QT: Quantum Technology

QTEdu: Quantum Technology Education

QTs: Quantum Technologies

R&D: Research and Development

RTO: Research and Technology Organisation

STEM: Science, Technology, Engineering and Mathematics

UK: United Kingdom

USA: United States of America

VC: Venture Capital

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 many different backgrounds, as QT becomes increasingly diversified [5].

The required characteristics of the workforce have been investigated in 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].

Shedding light on the most important skills for the quantum industry, from an industrial perspective, Fox et al. [11], conducted interviews with 21 companies, and reported that 90% of them 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” or soft business skills is growing across suppliers and end users of QT [15]. 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, 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 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 range of companies, identified the need for training programs to be formed based on different projected job roles, from engineers or technicians requiring technical skills to marketing and sales roles with a greater holistic understanding of QT and the market [6].

Hands-on experience is undoubtedly a great asset for entering the quantum industry, as reported by companies [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], to 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, 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 growing demand for engineering (95%) but a high proportion of experimentation and research, with roles such as “experimental physicist” (86%) and “theorists” (56%) still 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 (content domains of the framework) 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 throughout 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 will likely 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.

There is a wide variety of different approaches to industry development worldwide. Given this variance, it is crucial and timely to ask what exactly is the current state of the quantum industry, in which the graduates of the rapidly expanding education programs will likely find work in the future. Engineering and technical roles, in particular, have been highlighted by prior studies [5,6,11], as being important for the development of QT in the coming years. But to what extent is that reflected in the job market? In this article, we are investigating in a quantitative manner, the status and needs of the quantum industry, using data from thousands of job posts in QT. This work represents a step toward improving our understanding of how far in development QT is, how close it is to commercialising , and what kind of workforce it would need to boost it forward. Furthermore, this work introduces an innovative classification scheme, making use of large language models (LLMs) and combining them with human expert labelling, to generate a sizable dataset of over 3600 job posts, shedding light on the quantum labour market worldwide.

2. Research questions

In this research, we attempt to elucidate the reality of the industry needs and identify the actions required to address them using quantitative methodology. 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 platforms 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 [30,31] often in the form of research assistants or through services such as Amazon's Mechanical Turk [32]. The process requires significant time and resources and it is, moreover, liable to inconsistencies stemming from individual biases and variability in interpretation of the codebook. Another drawback to human classification is its inherent incompatibility with scalability, making the classification of a large body of data almost impossible. Recent advancements in large language models (LLMs), particularly pre-trained models such as ChatGPT-4o-mini [33], 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 their computational efficiency, consistency, and scalability [34-36].

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 [37-38] 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 retrieving 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. For details around the human validation process, see Appendix 1.

3.1 Classification steps

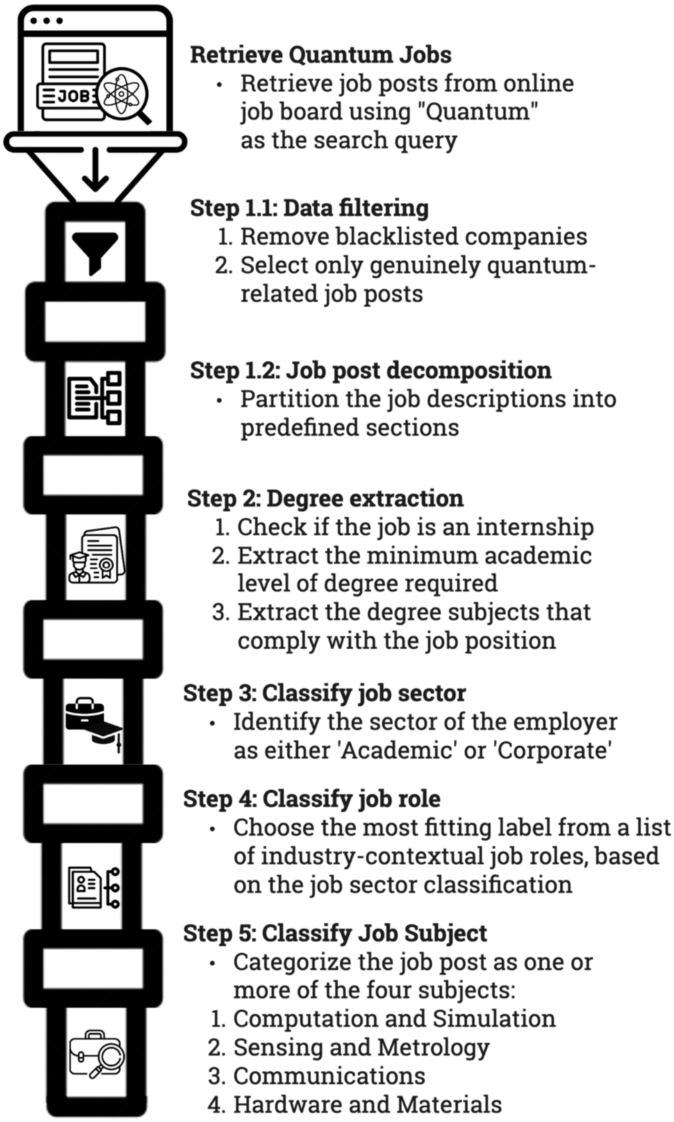

Figure 1. Quantum job classification process. The figure illustrates the methodology used for data extraction and the steps conducted for classification across multiple categories. The process begins by extracting quantum jobs from an online database (step 1) and identifying the degree requirements for each one (step 2). After that, three classifications follow (steps 3-5) with the categories being: job sector, job role and job subjects. Each step of the process was validated by human experts, see Appendix 1.

Step 1: Retrieve Quantum jobs

We used gpt-4o-mini-2024-07-18 [33] to classify quantum job postings from constructed prompts. This specific gpt model was used for all the steps described below, except from step 1.2, where gpt-4o-2024-08-06 was utilized instead and the validations of steps 1-3 that were initially performed with gpt-3.5-turbo-0125. The project relies on the data of job postings on an international labor market platform. The data was collected weekly over the time period 03/2023 to 06/2024, using the search query “quantum” and setting the location to “Worldwide”. The data was exported to an Excel file with the extraction date. After the data was saved in the project repository, an auxiliary script written in Python [39] retrieved additional data to the job postings, such as job description and employer information. The data is now ready to enter the first classification step: filtering and job post decomposition (see Appendix 1). 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 proceeds to select only genuinely quantum-related job posts, using the LLM to classify each one as either quantum-related or not, based on a human-generated prompt. Duplicates are handled by removing multiple instances of rows that have the same Job ID (the ID column), since each job posting is paired with a unique job ID, provided by the job posting site.
The next substep is 1.2, job post decomposition, which partitions the job descriptions into predefined sections that may be used as a whole or selectively for the subsequent steps of the pipeline. This is useful, since it offers the possibility of inputting to subsequent steps only sections relevant to the specific LLM-classification, which saves computational resources. The decomposition results in the following nine 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. It should be noted that job descriptions are pulled from a single online platform only. This was decided by investigating the four most prevalent online platforms and identifying which jobs were repeated across different platforms. One single platform was demonstrably more comprehensive than the others, and therefore it was decided to use this single source, which may represent around 75% of all QT jobs available to view. See Appendix 2 for additional information.

Step 2: Degree extraction
The purpose of step 2 is to extract information about the degree required for the job position. This is achieved in three different substeps; the first one, 2.1, checks whether the position is an internship through pattern matching – if so, then ‘Internship’ is the classification label. The residual unlabelled job posts then continue into substep 2.2, which by pattern-matching assigns the minimum degree level, choosing among 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 subjects that are mentioned in 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. The degrees mentioned are identified to a set of subjects by pattern matching. One job post can be associated with multiple degree domains.

Step 3: Classify job sector
Step 3 is concerned with the job sector of the job samples, and the possible categories they could fit into, are ‘Academic’ or ‘Corporate’. The decision is based on information regarding 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 “Academic”, while f the employer is a private entity, the job will be labeled as “Corporate”. The classification process starts by identifying the obvious instances using pattern matching, for

example searching for keywords such as “national lab” or “university”. Afterwards, classification by the LLM is performed on the remaining job posts, until all of them have been characterized with one of the two labels.

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. In substep 4.2, the LLM is employed to classify job roles based on job roles which are clustered from the whole dataset, 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 domain

Finally, the job posts enter step 5, the last classification step of the pipeline. In this step the LLM checks the responsibilities of each position described in the job posts and determines whether they fit into one or more of the four Quantum domains; 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 Quantum domains. The classification is carried out by letting the LLM extract areas of the QT field the responsibilities of the job are associated with. Pattern-matching is then performed on the extractions, resulting in the assignment of pillar-relating labels for each post. The patterns are generated through an iterative process of identifying which keywords are associated with which domains, running the sub-step, and refining 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. In this research, we used 3641 job posts and all steps were thoroughly validated by experts in QT and data scientists to ensure accuracy of classification. This involved manual classification of a subset of job posts (10%) and comparing human annotated results to those from the classification, as a form of inter coder reliability (ICR). A detailed overview of the validation process can be found in Appendix 1.

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 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 classified by QT domains (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. 3 and 4).

4.1 Regional distribution of QT jobs

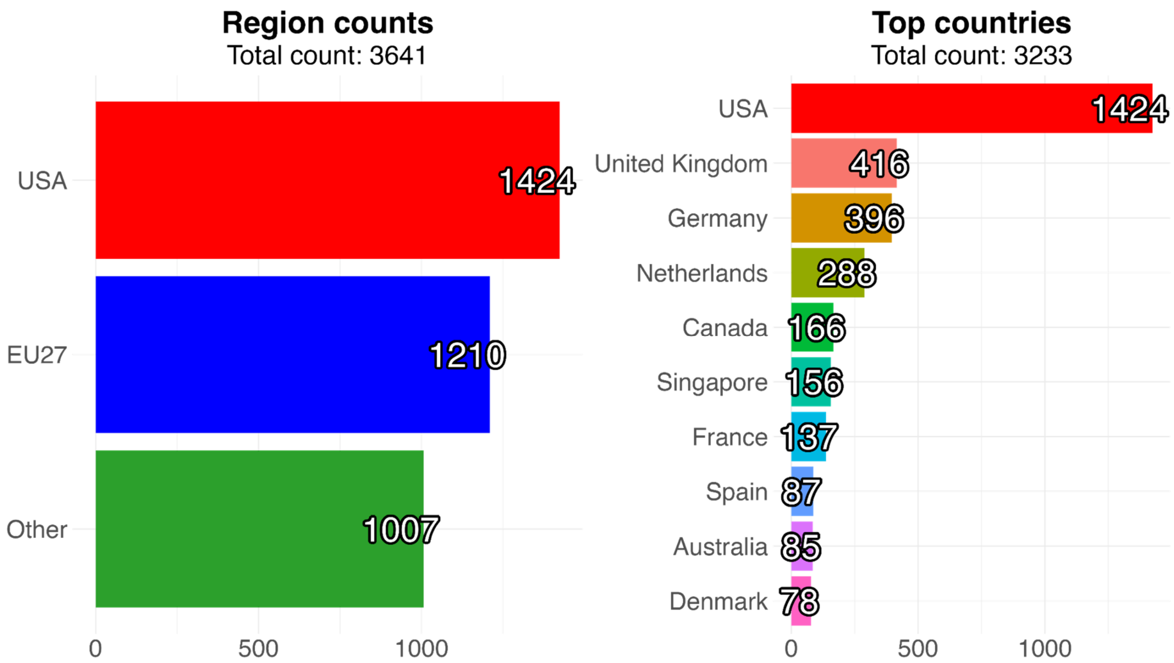

Figure 2. Number of countries posting quantum jobs worldwide. The figures show the distribution of quantum jobs globally with the left presenting the number of jobs found in the USA, in EU27 collectively and in all other countries, in order to directly compare between EU and USA. On the right figure, the distribution of QT jobs per country is presented, with the United States standing out, highlighting their 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 [40] 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 [41], and country-specific funding.The UK, where the national quantum technology program [42] 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 have a strong quantum ecosystem in comparison to the country's size (298 jobs, 18 million population), perhaps owing to the efforts of the Quantum Delta NL [43] which has been a significant boon to the Dutch quantum ecosystem.

Regarding how different sized companies are distributed worldwide, it is evident in Fig. 3 that overall, the majority of job positions are offered by large companies, with over 10,000 employees. We can glean further information from comparing this type of distribution between the EU27, USA, and other countries (Fig. 4). 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.

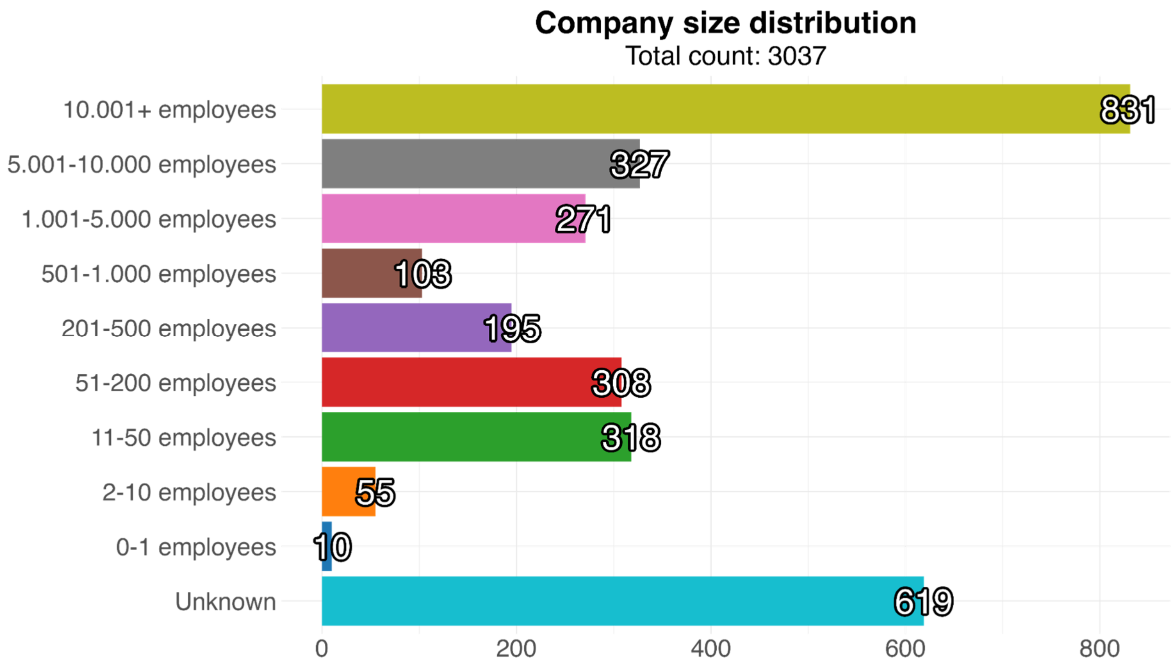

Figure 3. Company size distribution. The figure presents the number of job posts found in each company-size category, ranging from the smallest companies with 0-1 employees to the largest, employing more than 10000 people. The distribution shows large companies posting the most jobs over the duration of the dataset accumulation.

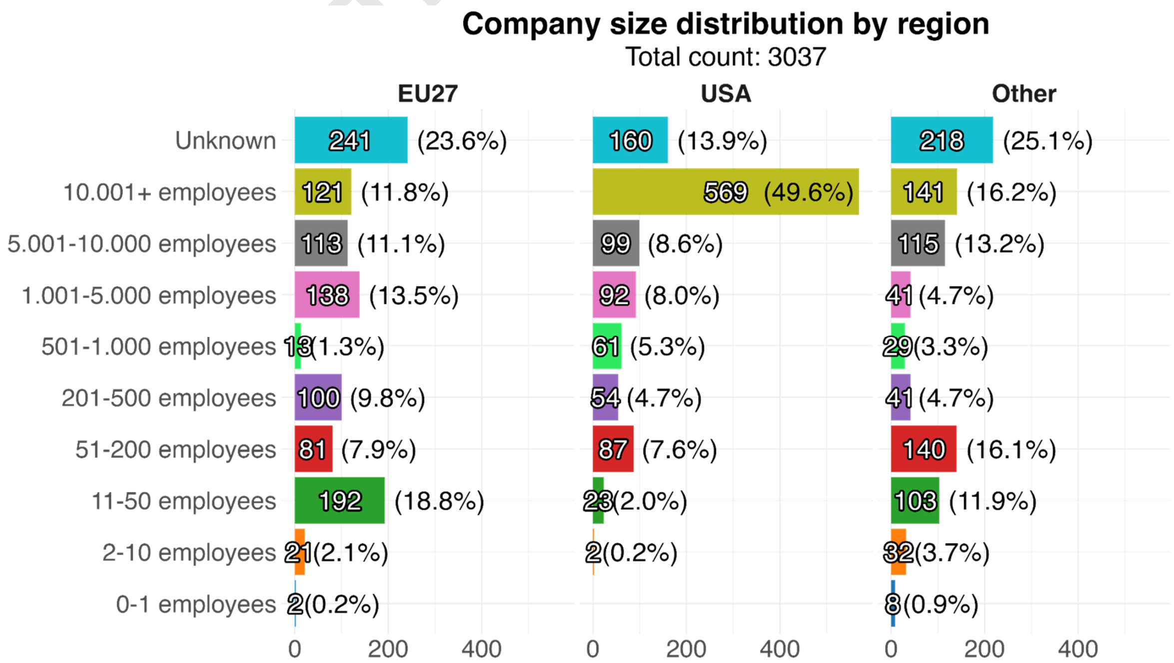

Figure 4. Company size distribution by region. The figure divides the findings of Figure 3 regionally, forming three distinct categories of EU27(left), USA (center) and Other (right).The overall results indicate the presence of larger companies in the US, whereas in the EU, smaller companies are leading 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 [44]. Large-scale government initiatives like the National Quantum Initiative Act [40] 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 the intensification of 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 Union which leads in the number of universities and thus resulting in the formation of a number of smaller spin-off companies 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. 5). Corporate job roles indicate a greater prevalence in the USA (77.5%) compared to the EU (70.7%).

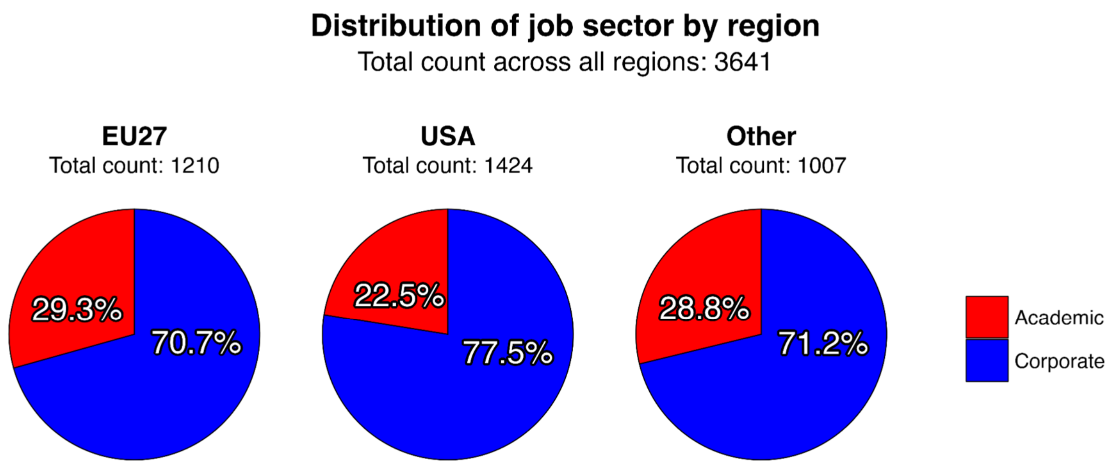

Figure 5. Distribution of job sectors by region.This figure shows how academic and corporate jobs are found, percentage-wise, in each of the three regions: EU27(left), USA (middle) and Other (right). The plots indicate that the dataset is primarily made up of corporate jobs and that furthermore academic jobs are more present in EU27 compared to the USA.

4.2 Degree level Requirements

In Fig 6, 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], leading to more available graduates for these roles. Still, the number of jobs requiring a PhD is large in comparison to other industries, as we consider in section 5.

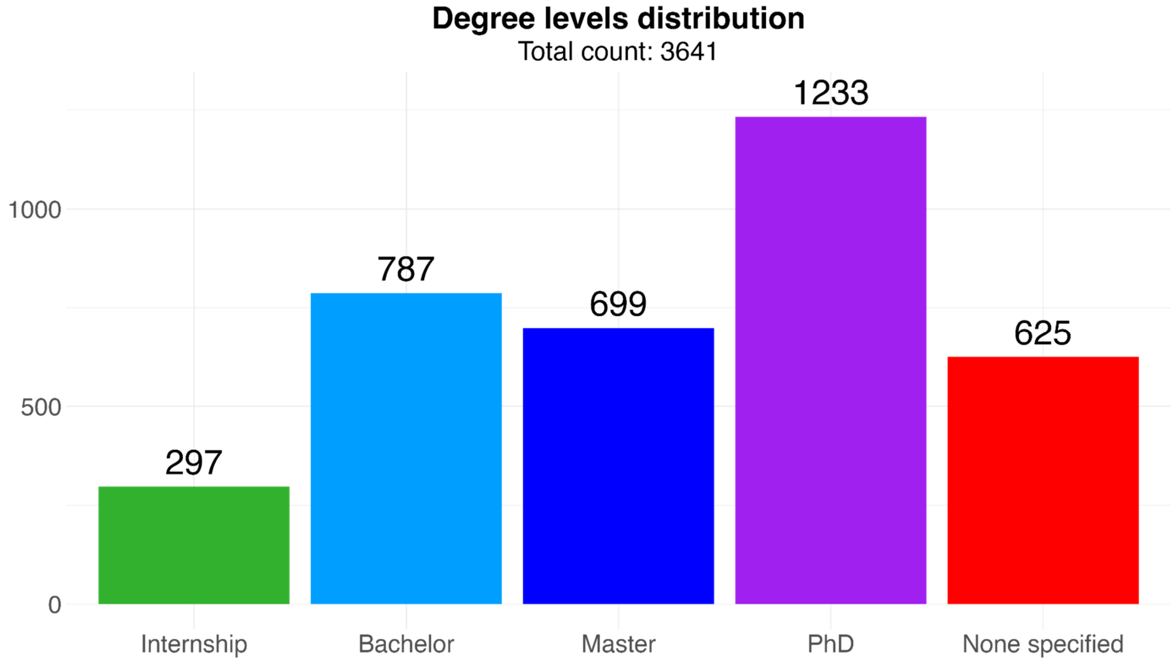

Figure 6. Degree levels requirements of QT jobs. The figure presents the distribution of quantum jobs based on the level of degree they require. The categories are: “Internship”,”Bachelor”, “Master”, “PhD”, and “None specified”. The resulting distribution shows that while the PhD requirement is still 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. 7), we note that the USA has most jobs requiring a PhD (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. Furthermore, the educational content of degrees with the same award level is not necessarily the same between countries, and this may influence the hiring practices of local companies.

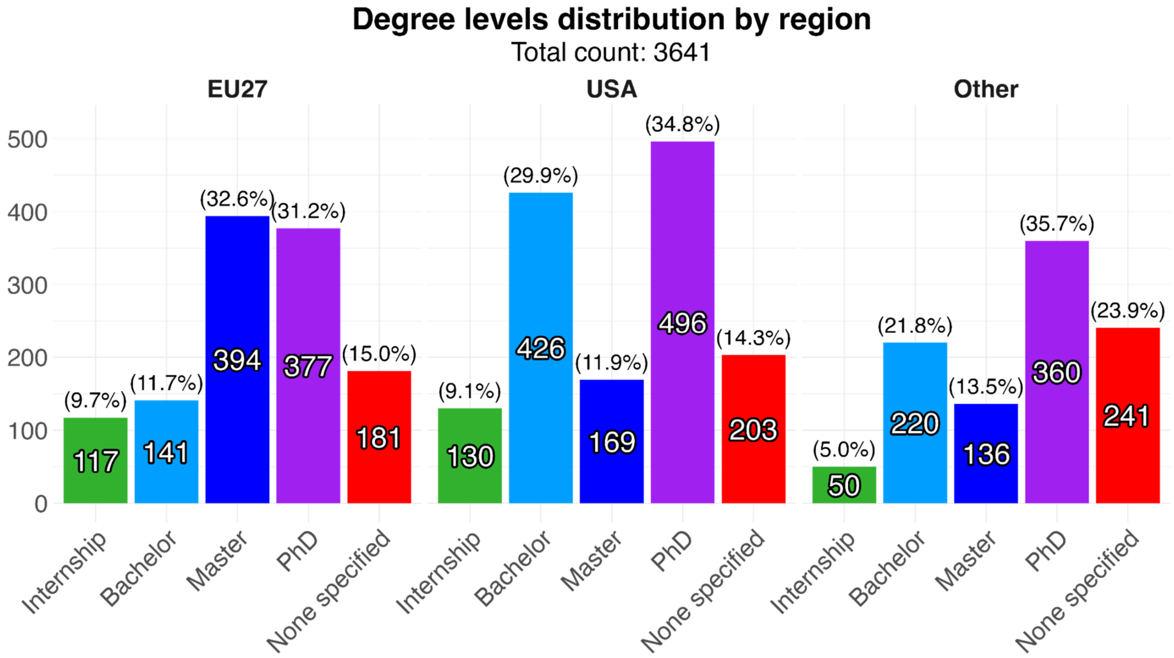

Figure 7. Degree levels requirements distribution by region. This figure divides Figure 6 regionally with the three subfigures representing EU27(left), USA (middle) and Other (right). The results show that the USA hires more Bachelor and PhD graduates, while the EU tends to aim more for Master's graduates.

When comparing among different-sized companies (Fig. 8), what stands out the most, is the overwhelming preference of PhD holders as job candidates for the companies of 1000+ employees. These are likely the tech giants mentioned in subsection 4.1, who 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 subsequently those with the highest level of 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, around 10%, as internships potentially aiming at training recent graduates for their needs, in order to take up future job positions in the company.

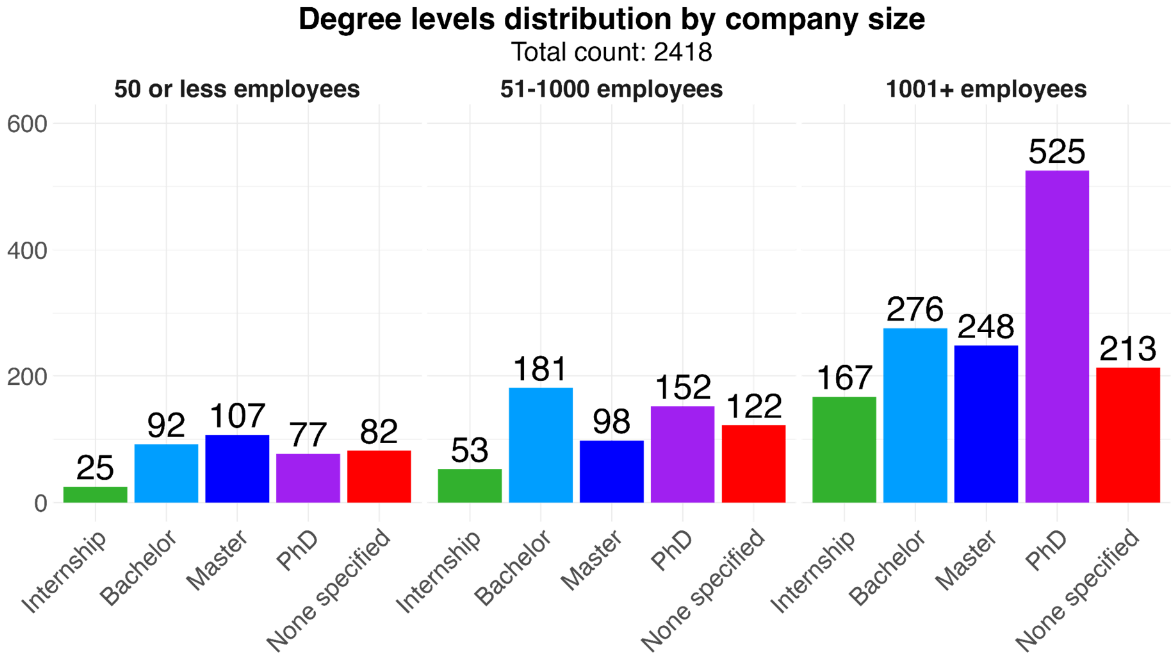

Figure 8. Degree level distribution by company size.This figure divides Figure 6 based on the size of the hiring company: 0-50 employees (left), 51-1000 employees (middle) and 1001+ employees (right). The results show that the USA hires more Bachelor and PhD graduates, while the EU tends to aim more for Master's graduates.

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. 9), 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]. In addition, all of these "hard STEM" degrees offer the same crucial skills such as numeracy and analytical thinking, and these are sought after by all employers in the quantum sector, even aside from the specific quantum knowledge the graduates have.

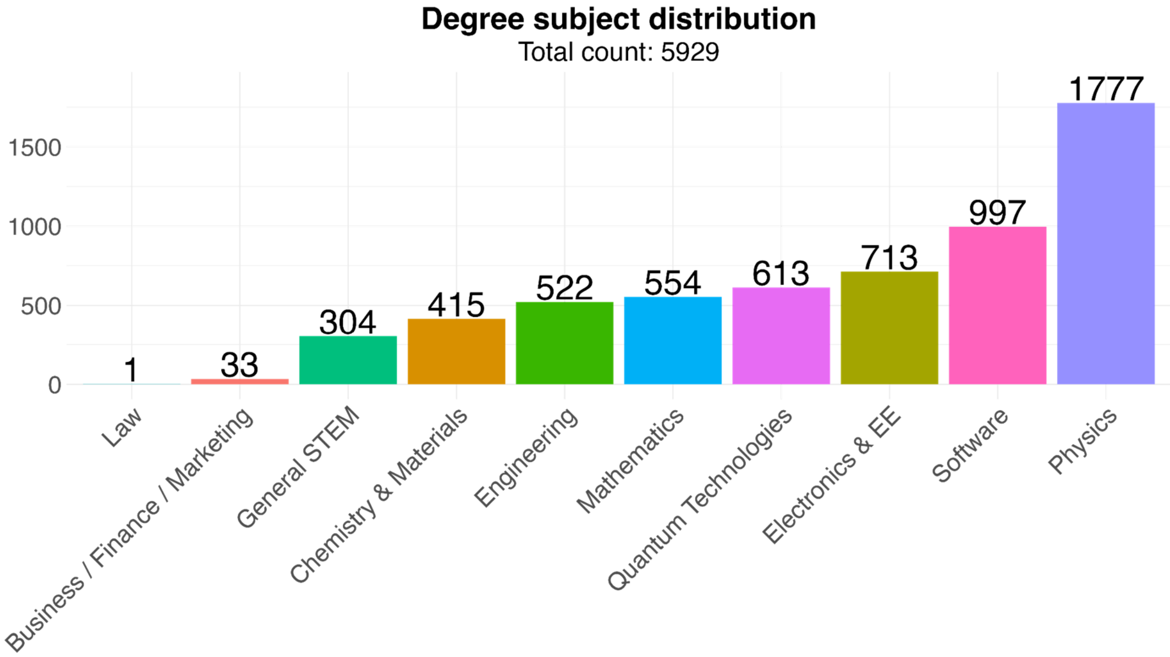

Figure 9. Degree subject requirements of QT jobs worldwide. The figure visualises the frequency of each degree subject found in the different job posts: Physics 49%, Software 27%, Electronics 20% QT 17%, Maths 15%, Engineering 14%, Chemistry & Materials 11%, General STEM 8%, Business /Finance/Marketing 1% / Law 0.03%.

When looking at the comparison between regions regarding the degree subject distribution (Fig. 10), we note that the trends are largely similar between countries, but with a few notable differences. The first is with respect to the “Quantum Technologies” degree demand, which is higher in Europe. As identified previously, this may be due to the high number of specific quantum masters in the region [7]. The United States also show a significant difference to the EU27 regarding hiring electronics/electronic engineering graduates (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 more prominent role.

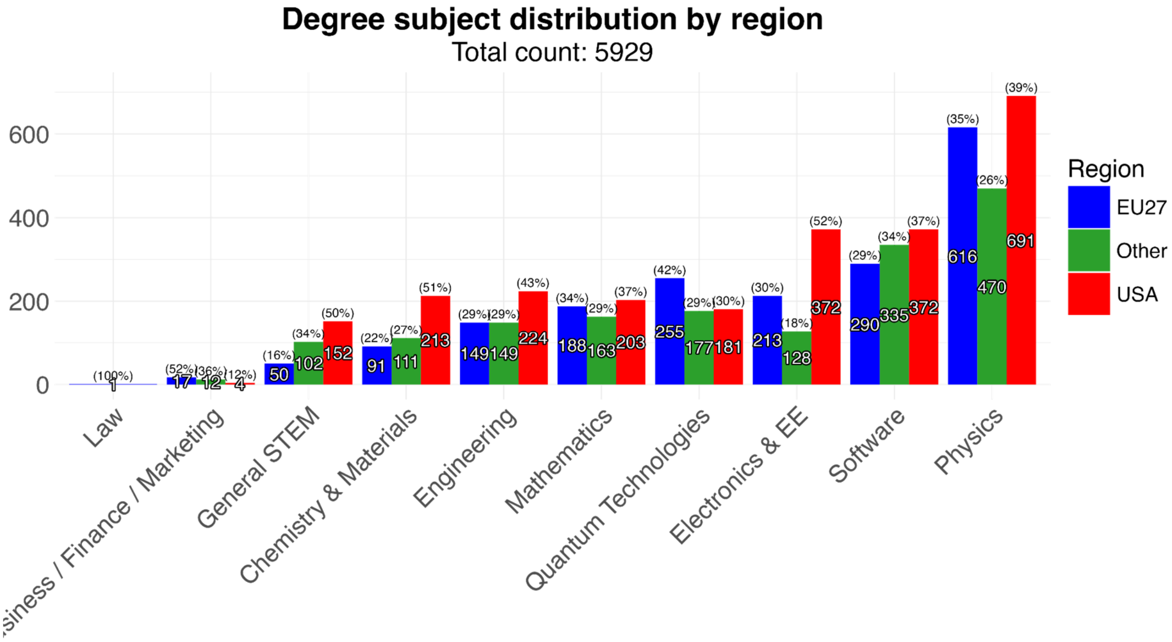

Figure 10. Degree subject requirements of QT jobs worldwide by region.This figure divides Figure 9 regionally with the three colors representing EU27(blue), USA (red) and Other (green). Physics is the most common degree subject required for quantum jobs for all three regional categories.

4.5 Job subjects

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. These cover the so-called QT "pillars" as used in the European Quantum Flagship, Quantum computing, simulation, sensing, and communication. In addition, the hardware class is used to distinguish between jobs related to hardware or software for each of the QT pillars. Each job can take one or more of the classes. For example, Quantum computing (software) and quantum computing (hardware) based on the classification in step 5. Quantum Computing (hardware) is the most prevalent combination, representing jobs relating to computation and involving work with hardware. These are followed by Quantum computing (software), and hardware (applications in multiple quantum domains). Quantum communication has more roles (585) than Quantum sensing (317).

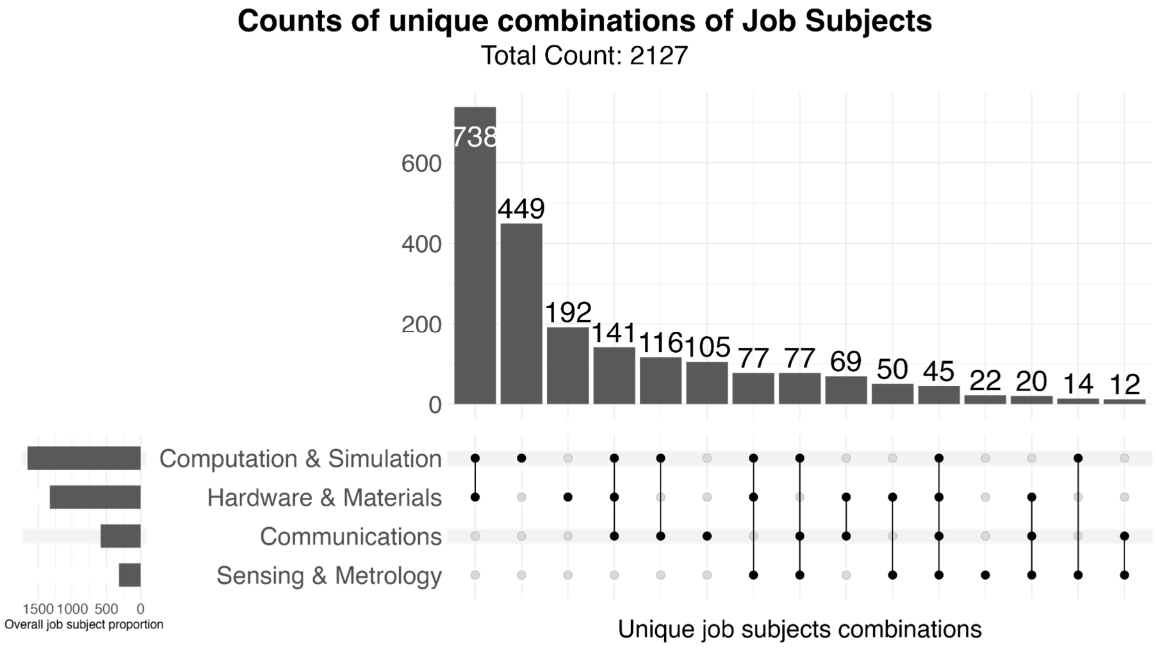

Figure 11. Unique combinations of Quantum domains. Computation & Simulation together with Hardware & Materials can be considered to represent Quantum Computing (Hardware), while Computation & Simulation alone can be representative of Quantum Computing (Software). Quantum Computing seems to be the most represented domain.

It is not surprising that Computing has the most job positions, as the market for quantum computing is estimated at being significantly larger than sensing and communication [45]. The magnitude of the difference is sizeable, however, which can also be observed in Fig.12. Here we see 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 the USA hosts more very large companies, as noted previously. 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.

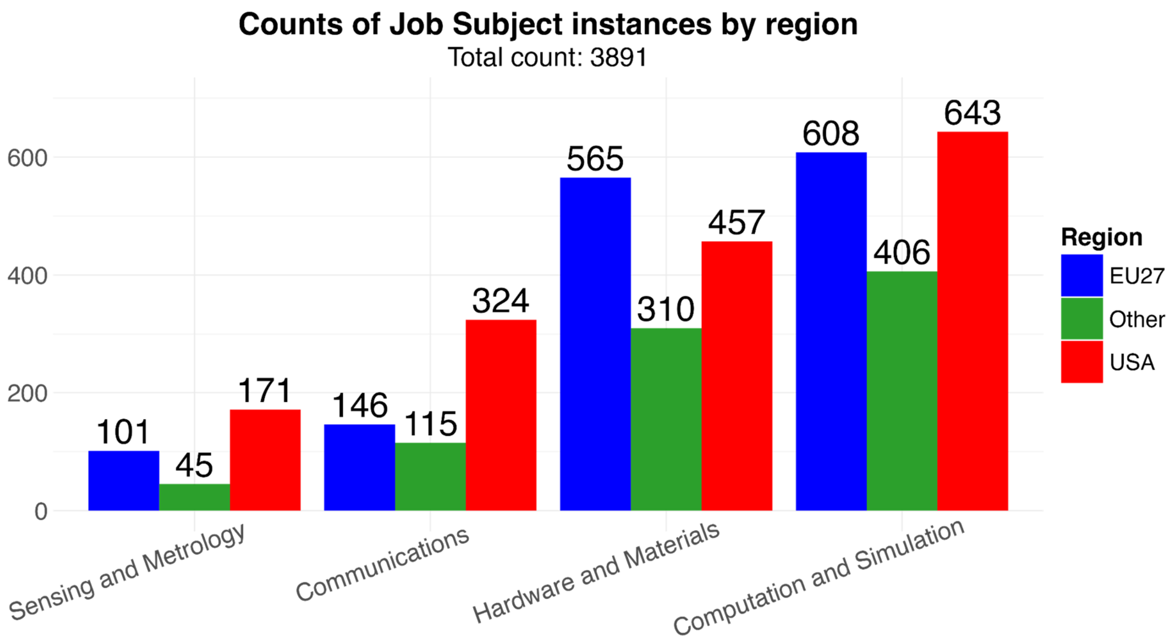

Figure 12: QT domains (Sensing and Metrology, Communications, Hardware and Materials, and Computation and Simulation) compared between EU, USA, and Other regions. Note that this plot counts jobs matching to multiple of the domains more than once - hence the total count of 3891 is above the total number of jobs in the database.

4.6 Job roles

The last category of interest is that of the specific roles found in these job postings. 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) makes up the second-highest number of job posts.This is noteworthy as internships can offer a kind of on-the-job training for graduates 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 strategic development - either internally or as an external service 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 such positions make up only a small fraction of the available jobs currently. 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 QT job market, in the early stages that this paper covers. 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. The definitions we used for each job role in our analysis, can be found in the supporting material.

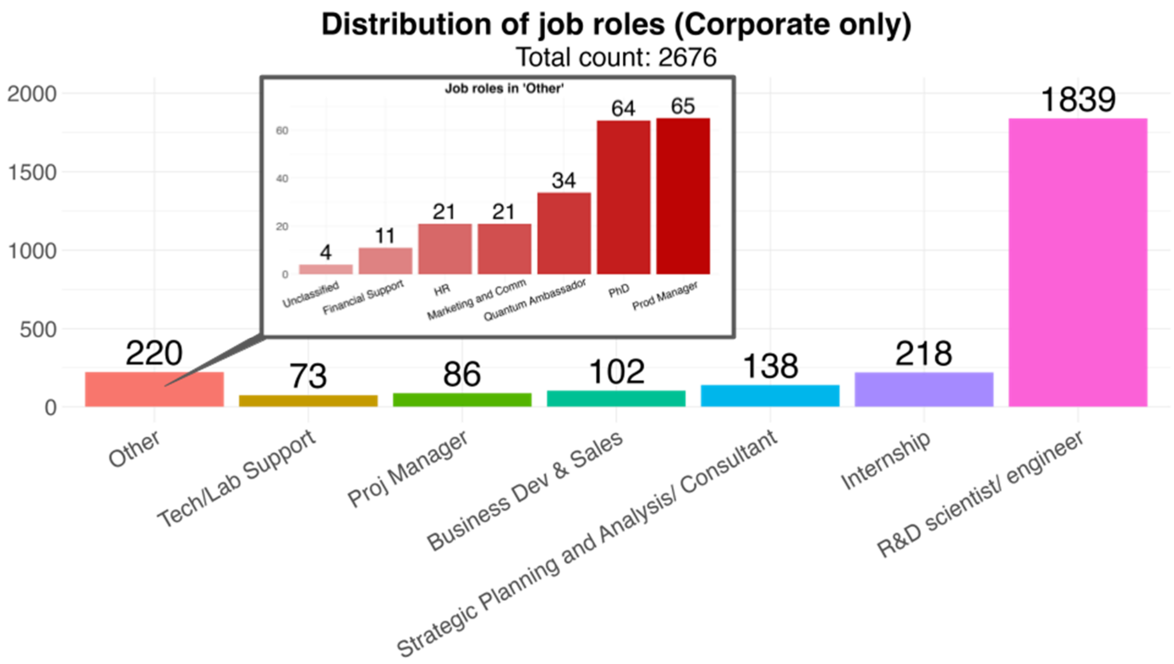

Figure 13. Distribution of job roles that fall under the “Corporate” label. The plot indicates a high dominance of the R&D scientist/engineer while a more moderate distribution, across the rest of the job roles identified, is observed.

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. 3, the distribution of company sizes, we see a significant presence of very large (10,000+ employee) firms and mid-large (5001-10,000) companies, which likely represent the early adopters of QT who can afford to invest in the technology at this early 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 distribution of small, medium, and large firms is more uniform [46].

Fig. 6 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 [47]. These industries have far more jobs which are either non-technical, or at a lower level of specialisation and hence fewer PhDs are needed. The same trend is observed in the job roles of 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. This further highlights the need for specialized master's programs, since companies are possibly looking for experts in the field, while such graduates are a recent phenomenon, as the majority of Master's programs have only been developed within the last 5 years. 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 or the lack of specialized knowledge of physics and engineering graduates. As the number of educational opportunities increases, 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 domains, among the different- sized companies (Fig. 14). It is clear to see 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 domains[48]. 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, due to limited resources, are more likely to focus on a single domains, and quantum computing is perceived as having the greatest potential market value [44]. 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.

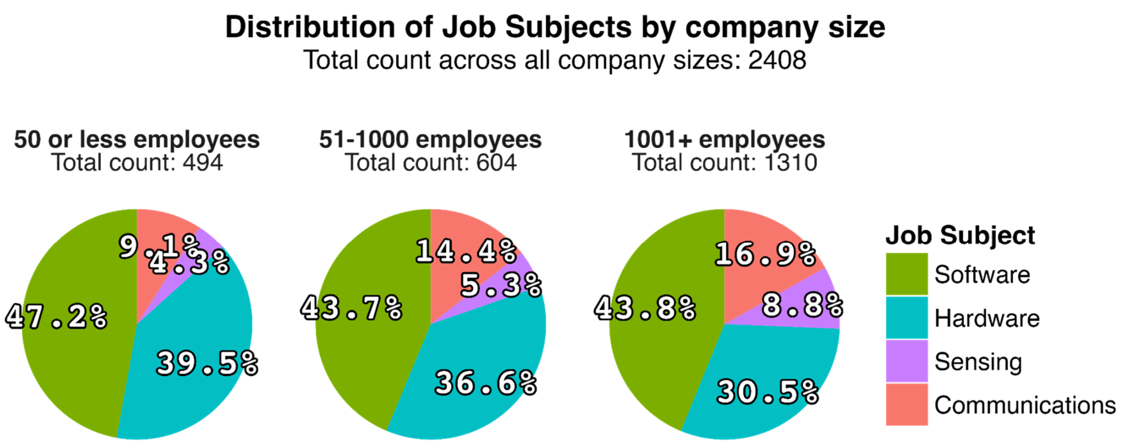

Figure 14. Quantum domains across company sizes. The figure presents the distribution of the four quantum domains across companies with different size: 0-50 employees (left), 51-1000 employees (center) and 1001+ employees (right). Quantum computing (hardware) and quantum computing (software) are among 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 [49], sensing and communication may actually be lower-risk areas to invest in. Our findings around the prevalence of jobs relating to computing also agree with the state of the quantum market, in which computing takes the bulk of total QT revenue among the pillars [59] and computing companies receive the largest share of VC funding in the quantum tech space [60].

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. 16), 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. 15). 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%.

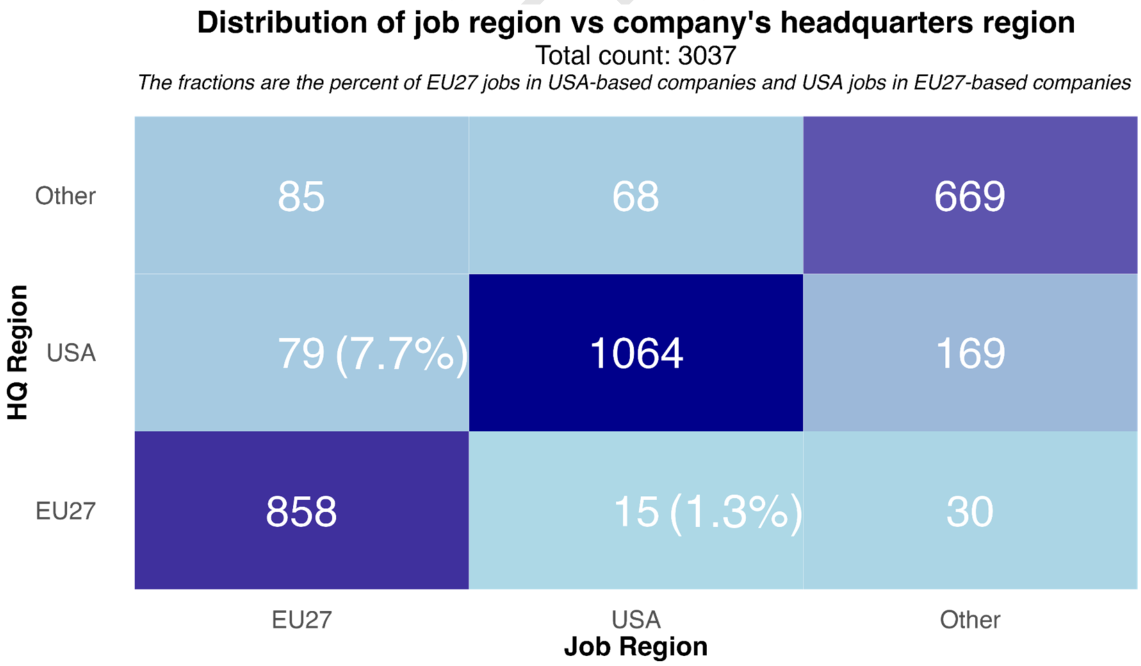

Figure 15. Matrix showing the distribution of job region vs the hiring company's headquarters region. All regions have the most jobs located in their headquarters nation. However, 7.7% of the jobs posted in the EU have headquarters in the USA, while only 1.3% of USA job posts are in EU companies.

It is clear that the quantum industry of the USA is actively 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 there is a net flow of talent from the EU to USA. 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. 16 and by previous sources [44], it is likely that this gap will continue to increase, as USA companies are able to further their international expansion.

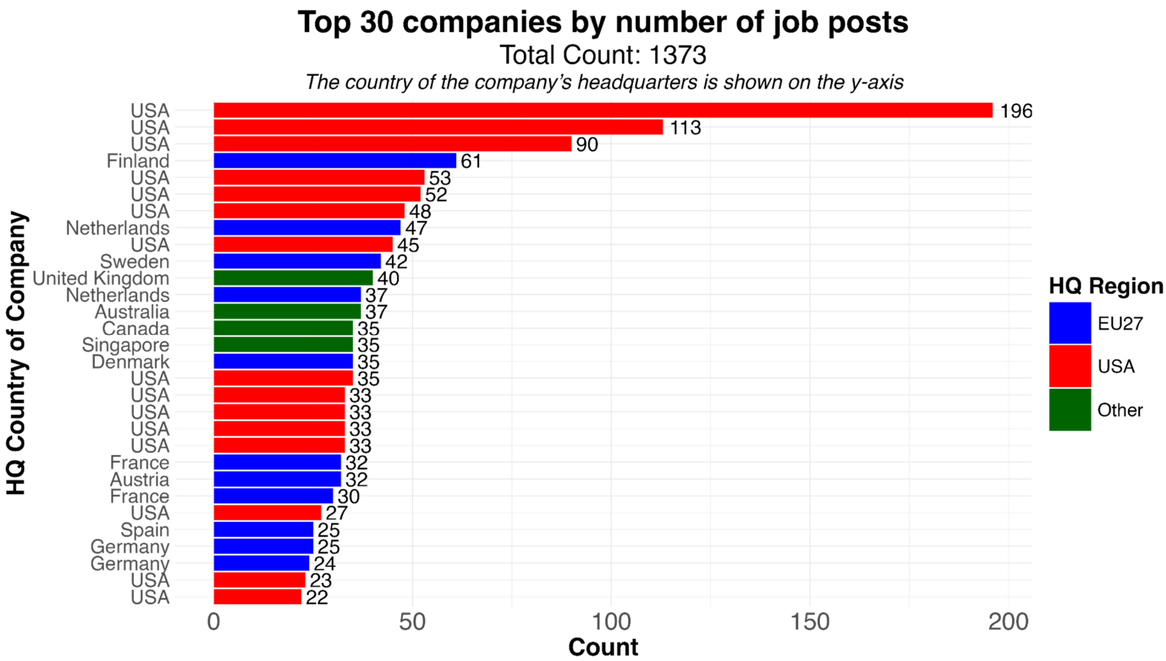

Figure 16. Headquarters (HQ) location of the thirty companies with the highest number of job positions. Note that these companies may have branches in other countries but only the HQ location is shown. It is clear from this figure that there exists a strong presence of large firms in the USA.

6. Limitations

Whilst the dataset involved in this research is large, we still acknowledge several limitations on perfect accuracy for job classification. One clear limitation of this research is the data source used, exclusively representing jobs from a single large online job board. However, this website, anonymised to protect personal information, 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 (see Appendix 1), 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.

7. 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 is their day-to-day content? This research has shed light on the educational levels that 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 (CFQT) 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 USA 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.

Declarations

The authors declare no conflict of interest

Availability of data and materials

Data generated as part of this research is property of the European Quantum Readiness Center. Interest parties may contact the authors to request access.

Competing Interests

The authors declare no competing interests.

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Author's contributions

JS conceptualised and supervised the work. SG managed the scientific team and research planning, and led the writing of the manuscript. BM, ZS, EK contributed to the scientific interpretation of the findings. BM wrote parts of the manuscript. OS led the data science including all development and data analysis. AT supervised the data analysis. All authors reviewed and commented on the manuscript.

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Appendix 1: Validation of classification

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 [50] and Pangakis et al., [51] and has been customized to meet the specific objectives and resource constraints of our project.

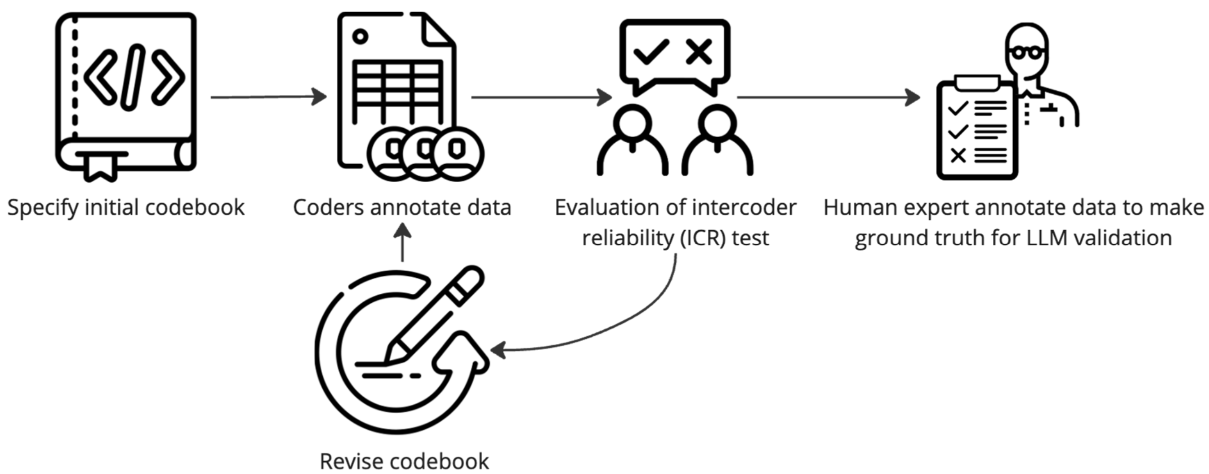

Figure 17. Initial phase of the validation framework. The figure illustrates the different steps involved in composing a codebook which acts as the basis for the classification prompt used. The process is iterative and continues until the codebook has passed an intercoder reliability test.

The validation process of a classification step begins by formulating an initial codebook like any traditional coding task [52-53]. 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 [54]. 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 [51]. 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.

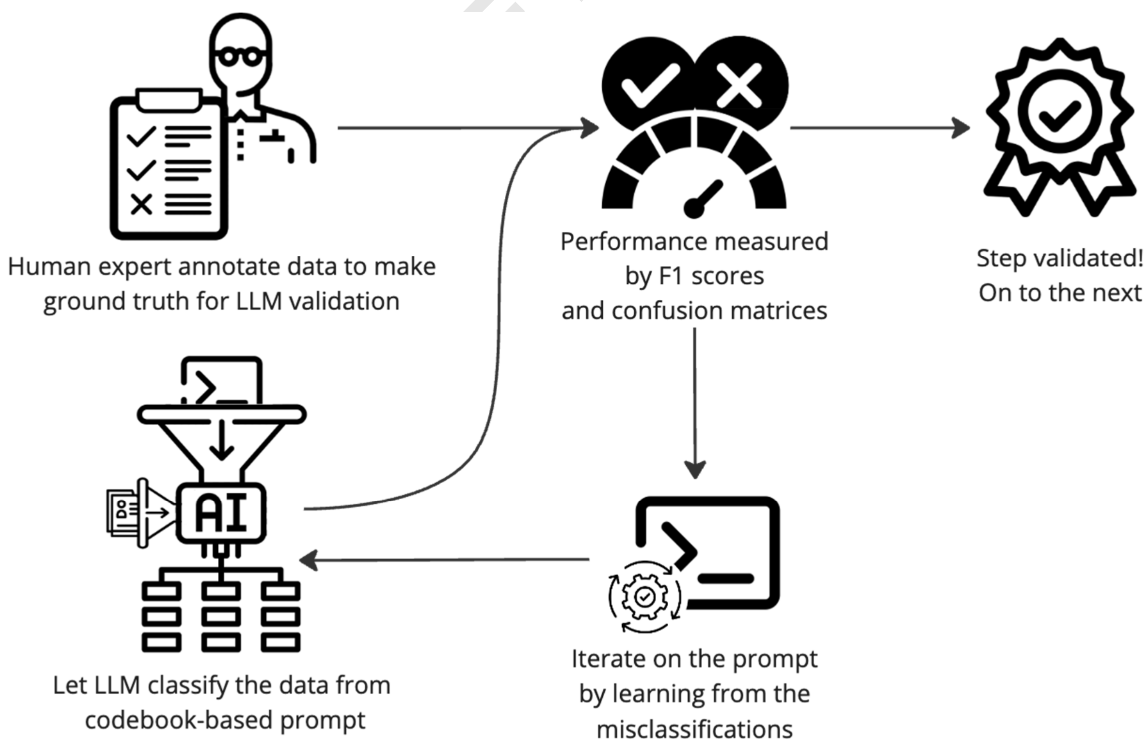

Figure 18. Second phase of the validation framework. The figure shows the process of comparing the ground truth in the form of annotations by a human expert with the classifications of the LLM. If the classification performance is unsatisfactory, the prompt is iterated upon and the LLM classifies the 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 [55]. Since there is no conventional threshold for F1-scores—unlike p-values, which typically indicates significance if below 0.05 [56] — 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 [57]. 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.

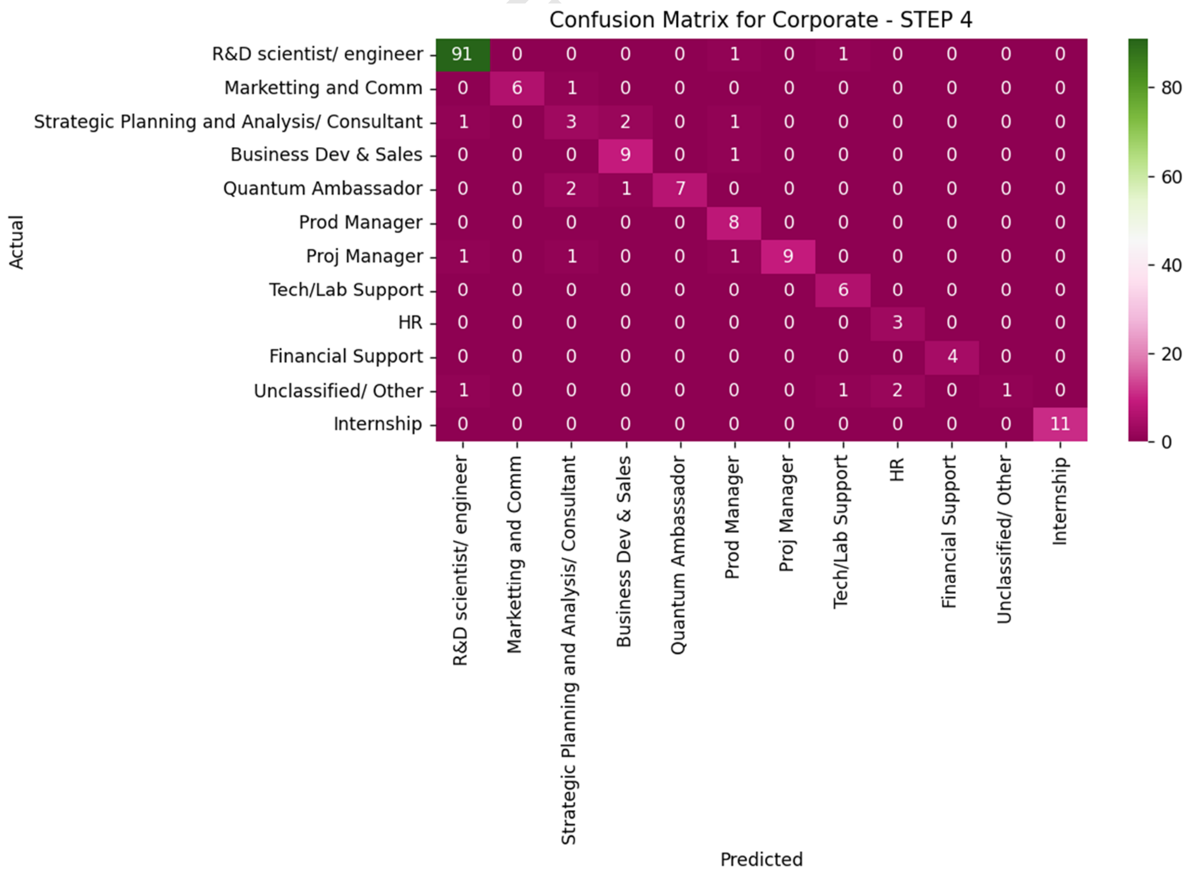

Figure 19. Performance matrix for step 4 of the classification. The confusion matrix provides an overview of the LLM's classification performance across different labels. Notably, the label 'R&D Scientist/Engineer' shows a high proportion of correctly classified job posts, likely due to it being well-defined 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 were 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 [33]. 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 had become available at this point in the process and it was “cheaper, more capable, multimodal, and just as fast as gpt-3.5-turbo” [58].

Appendix 2: Quantum Job platforms

We have chosen to retrieve all job posts from one platform only, consistently, since that made the process of decomposition easier. In order to decide which one to use, we investigated the four most prevalent online platforms for quantum jobs and identified which jobs were repeated across different platforms. As seen in Figure 20, it is clear that one single platform (P2) was demonstrably more comprehensive than the others and so it was chosen as our main job board, representing around 75% of all QT jobs available to view. Practically, this means that P2 was used as the data source for this work, which we acknowledge is not a complete source, but it balances proportionally high representation with the development requirement to retrieve jobs.

	Also found on			
Posted on	**P1**	**P2**	**P3**	**P4**
P1	20	18	13	3
P2	6	20	5	3
P3	2	17	20	10
P4	4	17	14	20

Figure 20. Comparison of four different anonymised job platforms. Twenty unique job posts were selected in each platform and then we checked whether or not they had also been posted in each of the other three platforms. The results indicate a clear prevalence of platform P2.

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