Because of the universities' third mission, academics are facing a new phenomenon of linking their work more closely to economic needs and to becoming important engines for development and economic growth. Therefore, some academic scientists commit to spin-off and start-up creation, some chose less entrepreneurial paths like licensing or patenting and some tend to remain in their traditional occupational choices as full-time scientists (Bercovitz & Feldman, 2008). It was therefore recognized that only some faculty members driven by entrepreneurial intention or/and aspiration for entrepreneurial reward, are actively interested in commercialisation.

D'Este and Perkmann (2011) found four motivations for researchers to engage in AE activities: commercial exploitation of science; gaining new insights and receiving feedback on research through engagement with industry; access to private funding; and access to external resources such as industry-provided equipment, materials and data. Thus, academics involved in AE may not be motivated primarily by an entrepreneurial vision to maximise profits. Fini, Grimaldi and Sobrero (2009) argue that the most important incentive for AE is the enhancement of academic status, but, Guerrero and Urbano (2014) suggest that there are other relevant motivational factors, namely, attitude towards entrepreneurship and perceived behavioral control (ease or difficulty of becoming an entrepreneur), that acts as knowledge filters from the individual perspective of the KSTE. Similarly, Lam (2011) emphasized the importance of the scientist's intrinsic motivation for AE, as some might become "barriers inhibiting the conversion of knowledge produced in R&D laboratories of incumbent firms and in universities into commercialised knowledge" (Ghio, Guerini, Lehmann, & Rossi-Lamastra, 2015, pp. 9–10).

Clarysse, Tartari and Salter (2011) argue that the key predictors of academic scientists' entrepreneurial engagement are the individual-level attributes and prior experience. Other studies highlighted the importance of demographic factors, like age (ambiguous effect on collaboration with business partners), gender (male academics are significantly more likely to engage with industry) and seniority (positively related to collaboration) (Perkmann et al., 2013). Hence, deeper understanding of these individual characteristics determines different AE approaches. Würmseher (2017) assumes that some scientists prefer to become entrepreneurs and refers it to "the inventor entrepreneur model", while some prefer to let go of their inventions to others interested in their commercialisation ("the surrogate entrepreneur model"). There is also an intermediate model, which the author calls "founding angel model", where inventors cooperate with other co-founders who provide finance, new venture experience, networking or technological knowledge (Festel, Breitenmoser, Würmseher, & Kratzer, 2015). According to Shane (2004), "the inventor entrepreneur model" is the most common in practice, which in fact assumes that the inventor becomes an entrepreneur (O'Shea, Chugh, & Allen, 2008; Kenney & Patton, 2009). Based on Jensen and Thursby (2001), an academic entrepreneur is someone engaged in formal commercialisation activities that often lead to patent creation, license sales or the derivation of new venture. However, Meyer (2003) and Bicknell, Francis-Smythe and Arthur (2010) assume that some faculty members participate in a wider range of engagements, such as collaboration with industry e.g. by consulting, and so recognize them as entrepreneurial academics that are often driven by the research related motivations described above, but who are not primarily motivated by an entrepreneurial vision to maximize profits.

All motivational factors are captured by entrepreneurial intentions that influence behaviour. Miranda, Chamorro-Mera and Rubio (2017), based on studies in Spanish universities and relying on the theories of planned behaviour, found entrepreneurial intentions as the key to understanding the first step in the AE process. As indicated by Bird (1988), entrepreneurial intentions are the most proximal predictors of the decision to become an entrepreneur, and as Krueger, Reilly and Carsrud (2000) add, even if someone may have potential, he or she will refrain from making the transition into entrepreneurship when he or she lacks the intentions. As antecedents of the AE construct, Miranda and others (2017) consider creativity, perceived utility (e.g. the income anticipated, the amount of work effort anticipated to achieve this income, the risk involved), self-confidence, previous business experience, entrepreneurship training and the perception of an enabling environment for entrepreneurship. Prodan and Drnovsek (2010) found that entrepreneurial self-efficacy, type of research, perceived role models, number of years spent at an academic institution and the number of patents generated are significantly related to the formation of academic entrepreneurial intentions.

For knowledge or technology-based AE, the opportunity for any kind of AE activities is usually recognized in knowledge or technology that potentially can be developed into highly innovative products or services. D'Este, Mahdi, Neely and Rentocchini (2012) suggest that the creation of such opportunity is driven by scientific excellence. Hence, according to Wood (2009, p. 930), university research can lead to new innovations defined as "any invention, new technology, idea, product, or process that has been discovered through university research that has the potential to be put to commercial use", and in his subsequent paper (Wood, 2011), argues that the AE process just starts with university derived innovations and scientific discoveries. Therefore, university-origin innovation as entrepreneurial opportunity is assumed as the first step in the presented process model of academic entrepreneurship, and, referring to Acs et al. (2009), the use of university-produced innovation is a mechanism for knowledge spillover with regards to KSTE, in which, as described above, some academics motivations act as knowledge filters (Figure 2.1).

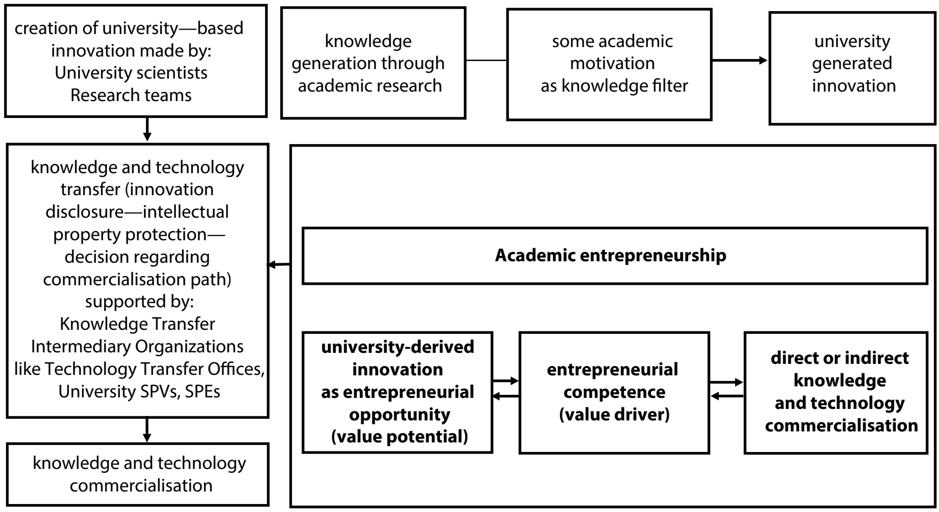

Figure 2.1. The process model of academic entrepreneurship during which knowledge spills over from universities in order to be commercialised
Source: Own work.

2.4. The entrepreneurial competences as value drivers

Relying on the theory of entrepreneurship, the entrepreneur discovers an opportunity that is leveraged by the entrepreneurial resources and reconfigured to develop entrepreneurial competences (Mishra & Zachary, 2015). Rasmussen and others (2015) described three competences required to succeed in new academic venture creation. First—identification and development of an opportunity (opportunity development competency). Second—the need for championing individuals that provide business, managerial expertise and energy to the entrepreneurial process (championing competency). Third—the need to access the resources for commercial exploitation of the opportunity (resource acquisition competency). Other prior studies have focused on scientists commitment to AE and their entrepreneurs' attributes such as risk-taking, opportunity recognition, the ability to identify market potential of their research output, creativity, perseverance, expertise knowledge, team building skills, ability to organize financial resources and technical facilities, ability of customer needs analysis, networks building and self-confidence of the members of the scientific team (Clarysse et al., 2011; Morris, Webb, Fu, & Singhal, 2013; Soetanto & Jack, 2016; Wang, Soetanto, Cai, & Munir, 2021).

At this point, however, it should be noted that a vast number of literature studies emphasize that the entrepreneurial opportunity recognition is not only attributed

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Patent 227096. (2017). Sposób wytwarzania nanożelaza oraz zastosowanie nanożelaza wytworzonego tym sposobem do pochłaniania tlenu w opakowaniach oraz w pochłaniaczach tlenu.
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4. ACADEMIC ENTREPRENEURIAL ATTITUDES IN THE ASSESSMENT OF ECONOMIC FACULTIES STUDENTS

https://doi.org/10.18559/978-83-8211-143-9/4

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Abstract

The aim of the research is to analyse selected attitudes related to entrepreneurship and to present their significance assessment according to students of economic faculties. The empirical basis is built upon the results of the research conducted in March 2021 on a group of 270 students of the Poznań University of Economics and Business. As part of the questionnaire and using the 5-point Likert scale, the respondents assessed various features, skills and abilities that, according to the respondents, are key in the context of an entrepreneurial attitude. In addition to the general statistical analysis of the response, a factor analysis was also carried out that aims to reduce the number of variables to a few, the most important ones that highly describe the analysed problem. Based on the research conducted, it can be concluded that from the students' perspective, the entrepreneurial attitude profile consists of a combination of personality types such as precursor, creator, rival, individualist, risk-taker. The research was limited because it was based on one academic centre (Poznań University of Economics and Business). Extending the research to other areas of higher education (e.g. law, medicine, psychology, computer science, mechanics) would allow the conclusion to be drawn on a wider scale and provide more insight into the nature of the phenomenon. The value of this study lies in the fact that it presents a coherent framework to explain the diverse characteristics of entrepreneurial attitudes in the business school environment.

Keywords: entrepreneurial attitudes, economic activity, entrepreneurship, economic education.

Introduction

The time of university is full of milestones and challenges for young people. It is often associated with living away from home, taking their first paid job, planning a budget on their own, determining a professional career and choosing an educational

Suggested citation:
Narojczyk, S., & Marcinkowski, B. (2022). Academic entrepreneurial attitudes in the assessment of economic faculties students. In H. Nowak-Mizgalska & A. Szulczewska-Remi (Eds.), *Academic entrepreneurship in theory and practice* (pp. 59–72). Poznań: Poznań University of Economics and Business Press. https://doi.org/10.18559/978-83-8211-143-9/4

path. At this time, students develop entrepreneurial attitudes that will determine their future and success in the demanding and dynamically changing market.

Entrepreneurial attitudes are an important aspect that is the subject of interest of many different scientific areas such as economics, sociology, anthropology, psychology, political science and organization theory, etc. The growing emphasis on the development of a knowledge-based economy makes the creation and development of appropriate attitudes a key problem from the point of view of future entrepreneurs, academic circles and the business world.

The aim of the research is to analyse selected attitudes related to entrepreneurship and to present their significance assessment according to students of economics. The empirical basis is constructed upon the results of research conducted in March 2021 on a group of 270 students of Poznań University of Economics. The research had the form of a diagnostic survey using the CAWI (Computer-Assisted Web Interview) method. The results were analysed using descriptive statistics and factor analysis.

Due to the fact that there are many definitions of the entrepreneurial attitude and they are interpreted in different ways, and this issue is analysed in the light of different scientific disciplines, the theoretical part of the study outlines its essence from the perspective of the conducted research. In the empirical part, the most important results from the point of view of the aim of this publication are presented.

4.1. The essence of academic entrepreneurship—theoretical approach

A detailed discussion of the theoretical underpinnings of the entrepreneurial attitudes is provided in the chapter titled "Advancements in conceptualisation and studies on Academic Entrepreneurship phenomenon". However, it should be emphasized that from the point of view of the empirical research presented in this chapter, some clarification of the theoretical background was necessary.

Entrepreneurship is a commonly used term; however, it is difficult to identify a single definition in the literature that captures its essence fully. Moreover, one can feel that it should be seen as a multidimensional concept that plays an important role in the socio-economic processes (Czyżewska & Kozioł, 2020, p. 47). According to Drucker (1992, p. 8), the science of entrepreneurship is a means to an end, and the object of this science is mainly determined by the purpose by which such activities are carried out, i.e. by practice.

Entrepreneurship can be considered from different perspectives, such as economic phenomenon or social phenomenon, but also in the context of business activities (Glinka & Gudkova, 2011). On the other hand, the definitions of entrepreneurship themselves centre around four of its dimensions (Wach, 2015, pp. 26–28):

1) market—as a search for the effects of entrepreneurship, where it is reduced to a function of the micro, small and medium enterprise sector;
2) personality—research focuses on the characteristics of human action, and most often concerns the entrepreneur or, less often, the team of employees;
3) managerial actions—the research focuses on the analysis of the entrepreneurial process;
4) individual entrepreneur—where the role of the entrepreneur is analysed.

Due to the subject matter of this chapter, the authors focused on entrepreneurship considered in the context of personality. Entrepreneurship (as a personality element) as discerned within the management sciences is an important conceptual category related to the sub-discipline of management of human resources (human capital) (Matejun, 2016, p. 132).

An analysis of the concept of entrepreneurship should begin with a rather narrow definition presented by Rachwał (2004). This author perceives entrepreneurship as a set of human personality traits, such as creativity, enthusiasm for work, divided attention, initiative, self-discipline, self-confidence and a tendency to take risks.

In contrast, a broader definition is presented by Bojewska (2002), according to which entrepreneurship includes knowledge, skills and attitudes necessary for the effectiveness and efficiency of these activities that are related to the undertaking and implementation of projects that enable the achievement of specific values in conditions of uncertainty and risk.

An interesting approach was presented by Noworol (2006, p. 41), who assumed that entrepreneurship is the human activity of creating economic well-being through the creation of additional values, including jobs, based on the risk of capital, time and personnel, on the basis of own commitment and energy to achieve self-interest, contributing to the construction of wealth of the whole society.

Worth mentioning, the European Union sees entrepreneurship as a key competence within the European education system (European Union, 2006). According to the "Entrepreneurship Roadmap 2020: Fostering Entrepreneurial Mindsets in Europe", entrepreneurship is considered a competence that can be learned and should be promoted at all levels of education. Consequently, the European Union—for the purposes of its education policy—defines entrepreneurial competence as the ability of an individual to turn ideas into action (European Union, 2007). This competence includes creativity, innovation and risk-taking, as well as the ability to plan and manage projects in order to achieve objectives.

Entrepreneurship should also be explored in the course of academic studies, in particular in the field of economics or management. The appropriate development of career choice represents an attempt by pupils/students to take the initiative to participate in social competition (Misiak-Kwit & Zhang, 2022, p. 119). Starting a business can be a good alternative for young people facing employment pressures, but also an expression of their creativity, which can be a key factor in creating the right entrepreneurial mindset (Hirschmann, Hartley, & Roth, 2020, p. 116). Shaping an entrepreneurial mindset is supposed to help young people who benefit from entrepreneurial learning to develop their business knowledge and basic skills and attitudes (including creativity, initiative, perseverance, teamwork, understanding of risk, and sense of responsibility), and on the other hand, it supports putting ideas into action and notably improves employment opportunities (Urbaniec, 2016, p. 77). Therefore, creating students' awareness of different types and forms of behaviour considered entrepreneurial together with the development of soft skills such as e.g. leadership, risk taking and risk tolerance or teamwork management should be the goal of the academic entrepreneurial attitude that young people acquire during their studies (Jando, 2018, pp. 195–197).

Continuing the educational theme, it should be emphasized that entrepreneurship significantly exceeds the space of decisions and actions related to the professional functioning of the individual. According to Liao, Liu and Li (2022, p. 3), strictly academic entrepreneurship is an innovative combination of two elements: resources and risk. Shane (2003) adds that this is related to the fact that:

- project results are not guaranteed (risk element),
- organisational effort is required as a new way of exploiting opportunities is created (resource element),
- the venture must be innovative, i.e. it cannot duplicate what is already available on the market (innovative background).

As a result, entrepreneurship should be treated as a cardinal trait necessary for flexible, prolific and creative functioning in almost any sphere of human activity, regardless of the type of profession (Nowak, 2011, pp. 45–62; Nowak & Wściubiak, 2020, pp. 160–172; Strojny, 2010, p. 178). If entrepreneurship is accepted as a cardinal trait, then it should be considered a component of the canon of competencies necessary for positive transgression from education to work (Klimkowska, 2019, pp. 252–253). Therefore, one can expect its possession (or at least theoretical knowledge) by students of economic studies, i.e. young people standing on the threshold of entering the labour market or starting their own business.

4.2. Methodology of research

The aim of the research is to analyse selected attitudes related to entrepreneurship and to present their significance assessment according to students of economics. The research problem has taken the form of a research question: what combinations

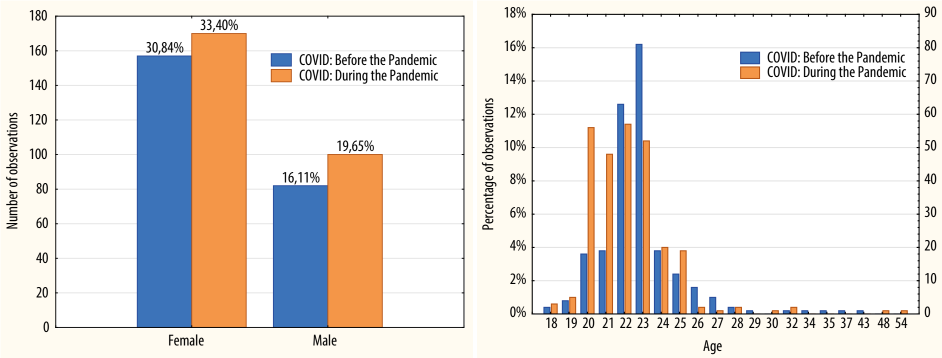

Figure 5.2. Structure of respondents by gender and age
Source: Own elaboration based on empirical results.

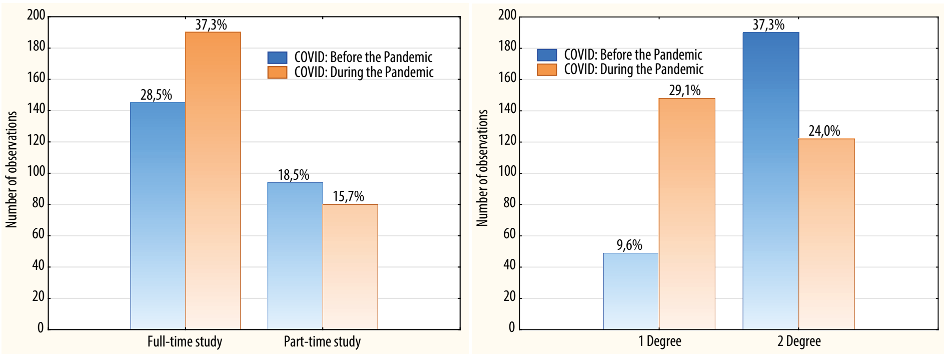

Figure 5.3. Structure of respondents by mode and degree of study
Source: own elaboration based on empirical results.

were second degree students (37.3%), while during the pandemic, these were first degree students (29.1%).

When examining the current occupational situation of the respondents, it should be noted that both before and during the pandemic, the respondents were economically active (36.9% and 35.2%, respectively). However, one can see a significant increase in the proportion of non-workers (by as much as 79%) due to the pandemic. The forms of employment based on a contract of mandate or a contract of employment were clearly dominant. In this case, no large differences were observed between the survey stages. Detailed data with the distribution of responses are shown in Figure 5.4.

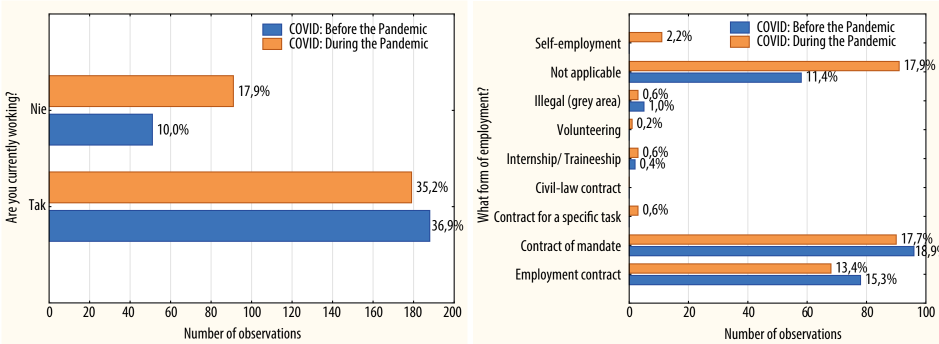

Figure 5.4. Respondents' current work situation
Source: Own elaboration based on empirical results.

5.4. Findings

During their studies, young people often encounter the job market for the first time, where there are many offers aimed specifically at students. Some industries and professions are almost entirely based on the employment of students. The Polish labour market offers many opportunities for young people, and finding a job, even a casual one, is not particularly difficult in large academic centres. At the same time, purely economic emigration is widely present in Polish society, which, in the case of students, is mainly limited to short trips during the summer holidays (up to 4 months), so that the money earned can be used for living during the academic year. We can also observe an increased interest in running a business, which manifests itself, for example, in the growing popularity of business incubators. This shows that students want to be active and develop in this direction, and undoubtedly they are a significant group with a huge economic and entrepreneurial potential (NZS, 2017, pp. 4–5). In recent years, students' behaviour and plans have also been strongly influenced by the pandemic situation, which has caused huge changes not only in local labour markets, but also in the global market.

Based on the above reflections, the purpose of the study was defined as presenting the significance of the coronavirus pandemic in the context of starting a business, by business students. At each stage of the research (before and during the pandemic), respondents were asked to answer a series of questions about their situation and work experience, as well as their plans for starting a business. This allowed conclusions to be drawn about the impact of the pandemic on young people's business prospects.

First, respondents were asked to identify how they envision their professional future. It can be observed that before the pandemic, the predominant desire was to work in private enterprise (24.4%). Own business was desired by 16.1% of the respondents. Other career plans or lack thereof were marked by only less than 7% of the respondents. An interesting situation occurred during the second stage of the research, where the number of people planning to work in a private enterprise significantly decreased (by about 8 percentage points). The largest increase was noted among those planning to start their own business (by about 8 percentage points), but also increased the percentage of responses in other groups, i.e. among people planning to work in a public company, family business, abroad, as well as without any professional plans.

The desire to look for a more stable job, in the public sector or a family business, is understandable. Of particular interest, however, is the shift in optics from working for a private company, to running one's own business. Despite the fact that in theory those who run their own business bear the greatest risk, the pandemic situation has shown that private enterprises, flexibly adapting to changing economic conditions, as well as lack of demand and imposed legal restrictions, look primarily for opportunities to reduce operating costs, including personnel costs. Students noted that when running their own business, they often have more security than when working in a private enterprise—they have the opportunity to benefit from assistance of various nature. In addition, the pandemic has caused major changes in global markets, resulting, on the one hand, in the collapse of many companies or a change in their operating strategies, but, on the other hand, in the emergence of new gaps and lucrative sectors where there is a high demand for specialized products or services. Details of the respondents' career plans are shown in Figure 5.5.

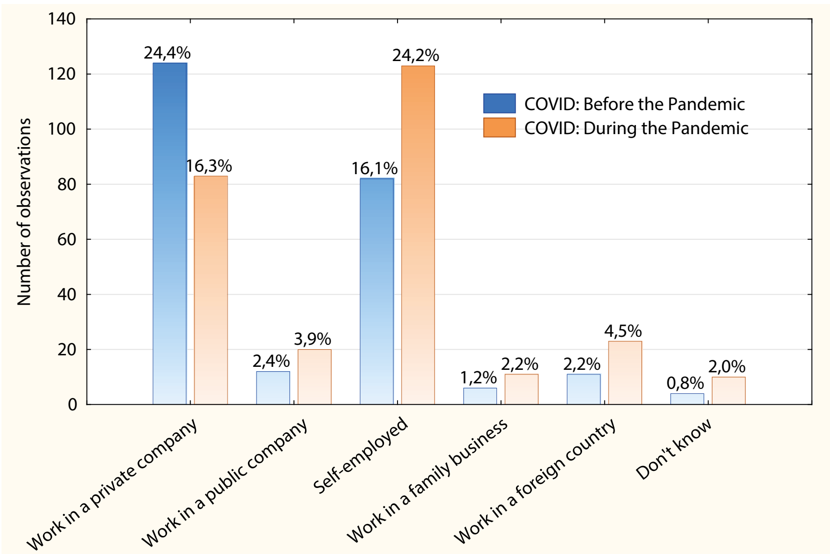

Figure 5.5. Distribution of responses regarding respondents' career plans
Source: Own elaboration based on empirical results.

Respondents were then asked to identify the profile of activities related to their future professional work. Both before and during the pandemic, services clearly dominated (28.9% and 27.5%, respectively). It is worth noting, however, that the pandemic resulted in a significant increase in the share of trade (by less than 7 percentage points), while the share of services and manufacturing decreased (by 1.4 and 1.1 percentage points, respectively). This probably has to do with the high flexibility of this type of activity, the relative ease of changing the sector of activity, and the fact that trade was relatively little affected by the regulatory tightening. Detailed data, including the structure of responses, are shown in Figure 5.6.

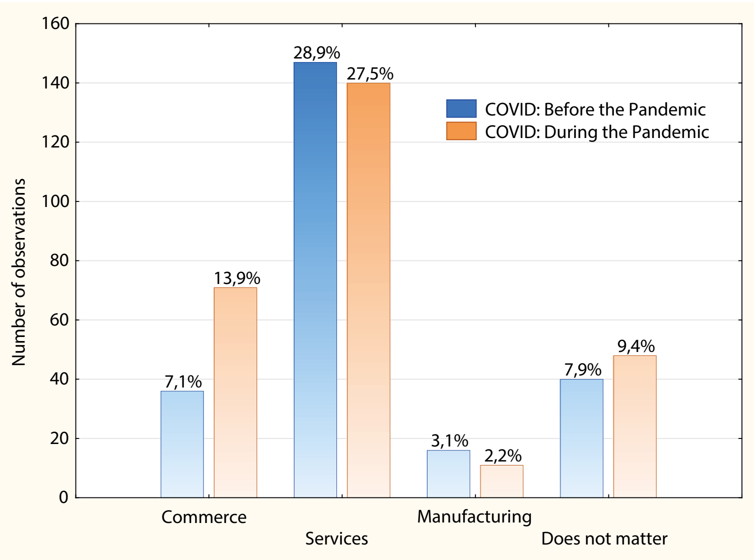

Figure 5.6. Distribution of responses regarding planned work-related activity profile

Source: Own elaboration based on empirical results.

The respondents were then given the opportunity to respond to a question about their plans for starting their own business. At this point it is also worth mentioning that out of more than 500 people participating in the survey, 30 already have experience in running a business. Both before and during the pandemic, responses indicating a desire to start their own business (definitely yes and rather yes) predominated. The pandemic significantly increased the proportion of "definitely yes" responses by 62% and "rather yes" by 23%, which is consistent with the results of previous questions. Detailed data are shown in Figure 5.7.

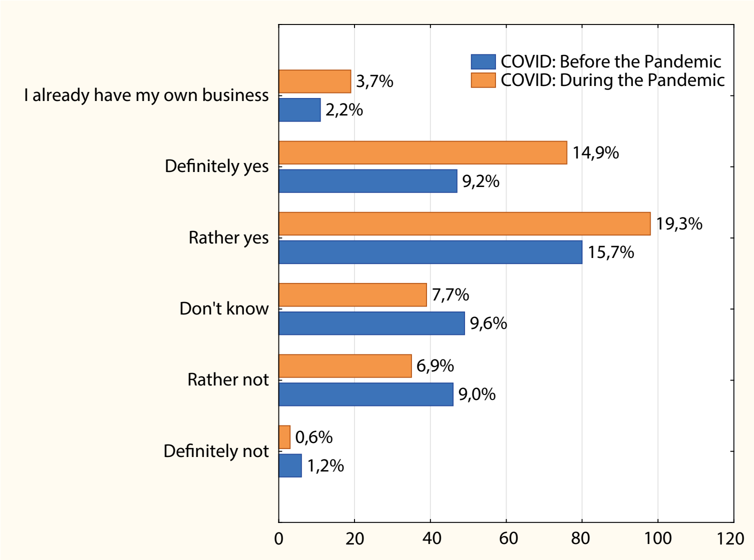

Figure 5.7. Distribution of responses regarding desire to start your own business

Source: Own elaboration based on empirical results.

The next question was designed to elaborate on the conclusions of the previous question—respondents could specify within what time frame they planned to start a business (if any). Both before and during the pandemic, the predominant intention was to open a business in more than two years, which was mainly due to the desire to complete the study first and acquire the necessary knowledge and experience. The differences in the shares of individual responses in this case were not due to the pandemic situation, but rather to the age of the respondents and the year and degree of study. Detailed data are shown in Figure 5.8.

Finally, respondents were asked to identify whether they already had an idea for their own business. Both before and during the pandemic, affirmative answers dominated (among those planning to start their own business). It is particularly interesting to note that in the surveys conducted during the pandemic, the percentage of "definitely yes" answers was 63% higher and "rather yes" 49% higher compared to the pre-pandemic stage. At the same time, it should be emphasized that the second stage of the research was dominated by younger people, in the earlier years of study, which only confirms that students take their future business seriously and its plans are well thought out. Detailed data on the structure of responses are shown in Figure 5.9.

extracted over 72 thousand job offers from one of the biggest online job advertisement services in Poland. We analysed only the technical offers[1], meaning the offer was included only if it classified the job offering as an IT job. The collected offers spanned from January to December 2019 and their geographical distribution, where the expected focus on large towns is clearly visible, is shown in Figure 7.1.

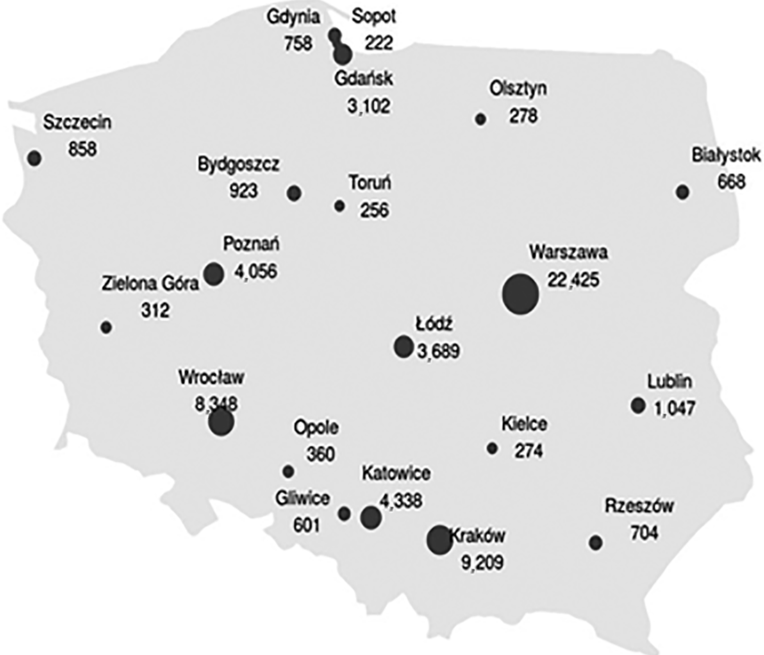

Figure 7.1. Distribution of all IT offers (duplicates removed) by city
Source: Own elaboration from authors' dataset.

We have cleaned the data to include only the offers written in Polish and English (we have used Python's "langdetect" library). The structure of extracted languages after the filtering procedure is shown in Figure 7.2. We have also excluded offers that were placed multiple times. All of the cleaning resulted in a preprocessed sample of 42,885 job offers.

Due to the size of the dataset, automatic keyword extraction and stemming and other similar natural language processing (NLP) techniques were applied as a part of our approach to the problem. The "soft skills" extraction for now was an issue, because of the complexity of Polish language, a lot of mixed-language words and potential translation errors when comparing Polish and English offers.

[1] From "IT—administration" and "IT—Software Development" categories, the only two directly connected with IT jobs.

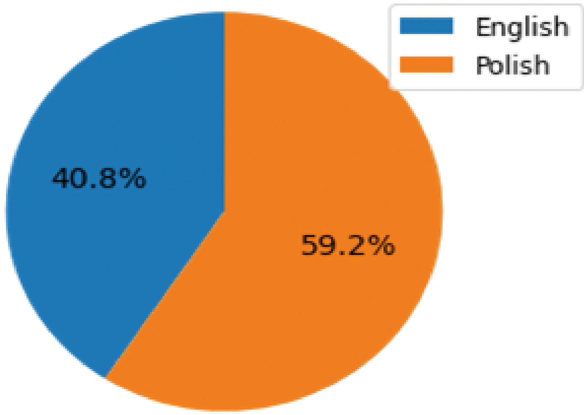

Figure 7.2. Distribution of languages in the prepared study
Source: Own elaboration from authors' dataset.

The technical skills, on the other hand, were mostly identified by a technology name: Python, SQL, Spark, Tensorflow etc., which are usually nouns, hence our approach for extracting technical skills was applicable for the offers in both languages. Due to that, and to compare the results with similar studies focused on the skillset identification, we decided to focus on technical skills. As an extension of our approach, however, extracting soft skills could be a valuable area of further work. An interesting approach for the English language has been explained in the work from 2017 (Papoutsoglou, Mittas, & Angelis, 2017). To extract the skills required by the data centred roles, the NLTK[2] and spaCy[3] Python libraries were used. Thus, the following approach was proposed:

- Part of Speech tagging was applied to extracting NNP (ang. propel nouns) as the skill names. Similarly, extracting ORG (original names) parts of speech by NLTK was tested, but it extracted significantly less names that were usable.
- Due to the fact that not all of the technical skills are single nouns, bi-gram detection was performed on the extracted nouns.
- The nouns and bi-grams representing technical skills were then compared with the Wikidata ontological database categories[4], which resulted in 24,580

[2] https://www.nltk.org/

[3] https://spacy.io/

[4] That included: programming language (Q9143), python library (Q29642950), free software (Q341), object-based language (Q899523), functional programming language (Q3839507), scripting language (Q187432), multi-paradigm programming language (Q12772052), imperative programming language (Q21562092), interpreted language (Q1993334), highlevel programming language

different technologies. **This is the main extension of this work over SOTA as it significantly increases the possibility of matching the extracted skill-set with its natural language descriptions without manual labelling work.**
- Some of the ambiguous phrases such as "nice" or "possess", which are rarely used terms in technologies, were parts of the "nice to have" and similar phrases. After careful examination, skills not matching the context were manually removed.

After the analysis of extracted skills, considering top 20 skills for all of the IT related jobs our results showcased, that:

- the most popular skill was SQL, connected with relational databases querying, and was included in 28% of all offers,
- Linux (15%) and Windows (13,5%) were commonly mentioned in posted offers,
- the most popular programming languages demanded besides SQL were: JavaScript (14%), Java (13,5%), HTML (11%), Python (9%) and C# (7,7%),
- knowledge of git versioning system was mentioned in 12% of all offers,
- analytical skills like "office" were present in 11% of the offers, and beyond this, "excel" was mentioned explicitly in 7% of the offers,
- Scrum (9%), Agile (11%) and Jira (9%) knowledge, corresponding to project management skills was also present in the job applications, and were used to identify the portion of jobs aligned with project manager roles among all of the IT offers,

(Q211496), statistical package (Q13199995), JVM language (Q56062429), procedural programming language (Q28922885), structured programming language (Q28920117), computing platform (Q241317), Web API (Q20202982), markup language (Q37045), academic discipline (Q11862829), numerical software (Q74086777), mathematical software (Q1639024), software library (Q188860), software framework (Q271680), computer science (Q21198), NoSQL database management system (Q82231), database management system (Q176165), document-oriented database (Q1235236), relational database management system (Q3932296), proprietary software (Q218616), open-source software (Q1130645), message-oriented middleware (Q1092177), programming paradigm (Q188267), artificial intelligence (Q11660), service oriented architecture (Q220644), communications protocol (Q132364), computer network protocol (Q15836568), continuous integration software (Q16947796), free and open-source software (Q506883), virtualization engine (Q7935198), web framework (Q1330336), virtual hosting (Q588365), agile software development (Q30232), computer science term (Q66747126), operating system (Q9135), software development methodology (Q1378470), protocol suite (Q67080166), Internet Standard (Q290378), distributed data store (Q339678), collaborative software (Q474157), application framework (Q756637), event-driven programming language (Q28920813), platform as a service (Q1153767), platform as a service (Q1153767), computer data processing (Q6661985), software design pattern (Q181156), architectural pattern (Q635346), search engine (Q19541), web server (Q11288), operating system shell (Q18109), certificating services provider (Q13460321), software (Q7397), modelling language (Q1941921), query language (Q845739) and generic top-level domain (Q29469).

- the most common coexisting pairs of skills were also analysed, but, mostly, the versioning systems and SQL were mentioned, along with their corresponding programming language. The only exceptions to this were the (Windows, Linux) pairing that was in 5,95% of all the offers and the (Agile, Scrum) pair. The meaning of this is twofold:
    - firstly, among the IT offers, only the knowledge of SQL and databases and the GIT versioning system can be considered basic and necessary knowledge,
    - there are no combinations of technical skills required that are strongly tied together.

This means that there is a wide array of independent skills necessary for the data analysis jobs.

7.3. Findings—data centred roles

Further on, only offers that contained the words "data" were included, creating a subsample of all IT offers. Additionally, for comparison with the standard programmer profile, developer job offers that contained the word "Python" were included and henceforward we will refer to them as the "Python developer" role. For each of these roles, the job offers were extracted based on the inclusion of the keyword name in the "data" subsample of offers. To characterize these roles in companies, an analysis of extracted skills was performed. The top skills for each of the roles are showcased in Figure 7.3.

To measure the stability of the job's profile, a classification experiment was performed. Its goal was to showcase how stable the skill profile is, based on a sample of skills extracted for a specific role. Relying on that, TFIDF vectorizer[5] was applied on the keywords extracted. After a few experiments, top 500 words were used to represent a single job offer in the data centred area. Further on, the SVM linear classifier with $C = 1$ parameter was used to train a machine learning model that can classify the job into: data scientist, data analyst, data engineer and Python developer categories. This was just a short experiment to showcase the potential accuracy and stability of data centred profiles—the low accuracy of the classifier would mean that potentially the identified positions do not differ much in terms of required skills and there are no distinctive technologies connected with a specific occupation. Fortunately, the classifier resulted in over 87,5% average accuracy and the results on a sample of job offers can be seen in Figure 7.4. Accordingly, there

[5] Term frequency—inverse document frequency statistic implemented in the scikit-learn Python library was used.

Data Scientist

	Skill	%
1	python	74.19
2	r	59.86
3	sql	46.59
4	machine_learning	37.28
5	spark	24.37
6	tensorflow	22.22
7	hadoop	21.86
8	big_data	17.20
9	data_science	16.85
10	hive	16.49
11	aws	14.34
12	java	14.34
13	linux	14.34
14	sas	13.98
15	git	13.26

Data Analyst

	Skill	%
1	sql	64.97
2	excel	46.12
3	python	25.50
4	r	22.17
5	power_bi	20.84
6	tableau	19.96
7	office	18.63
8	vba	17.52
9	sap	10.20
10	computer_science	9.76
11	sas	9.31
12	access	9.09
13	big_data	8.43
14	oracle	8.20
15	etl	5.76

Data Engineer

	Skill	%
1	sql	59.41
2	python	57.56
3	big_data	35.42
4	spark	35.42
5	java	35.06
6	hadoop	33.95
7	linux	30.63
8	etl	30.26
9	aws	22.14
10	agile	21.77
11	kafka	21.77
12	scala	19.19
13	oracle	18.08
14	nosql	17.71
15	hive	15.87

Python Developer

	Skill	%
1	python	88.31
2	linux	38.96
3	git	36.04
4	django	31.49
5	javascript	31.17
6	sql	29.55
7	postgresql	23.38
8	docker	21.75
9	rest	18.18
10	mysql	16.88
11	html	16.23
12	aws	14.61
13	flask	14.61
14	jenkins	12.66
15	css	12.66

Figure 7.3. Top skills extracted for data analyst, scientist, engineer and Python developer/programmer job postings

Source: Own elaboration from authors' dataset.