On Current Job Market Demands for Process Mining: a Descriptive Analysis of LinkedIn Vacancies

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Abstract. Process mining is growing to a billion-dollar market, focusing on dedicated techniques for improving existing business processes. With the increasing popularity and application of process mining, most scholars have focused on technical research while the organizational and people-related aspects remain under-investigated. To partly fill the gap, this paper explores current job market demands in process mining by means of an empirical and analytical study of vacancies on LinkedIn platform. Our dataset uncovers a wide variety of vacancies from 47 countries, including organizations of different sizes and 12 sectors. The vacancies are issued by end-user companies, vendors or consultancy firms and include a combination of technical or business orientation. Given this wide variety among process mining vacancies, future research can also benefit from better complying with companies' needs.

Keywords: process mining, vacancy, job advertisement, skills, human resource, descriptive analysis

1 Introduction

Process mining with an estimated market growth of $1 billion in 2022 [4], is considered a suitable technology to enable people, processes, services, channels, business models and operating technologies. The popularity of process mining applications is growing in both industry and academia [18]. Therefore, more calls for research on its application in organizations have been issued in recent years [8, 16, 17]. Concurrently, the number of software companies providing process mining capabilities and consultancy firms that offer such services is increasing. There are over 40 commercial process mining tools worldwide [19] among which Gartner monitors a few of them regularly. While process mining is getting more complex, the implementation is also getting more complicated across different domains [1]; Hence, organizations are allocating more resources and are hiring specialized employees, contracting consultants, or training existing analysts and managers to adopt this technology within the boundary of their improvement initiatives. Although process mining as an innovative IT tool can be a great enabler for organizations, getting the right people on board is a key success factor [13]. In this regard, it is crucial for organizations to be aware of the individual competencies and specialties they would require for succeeding in their process mining journeys.

Some organizations are assigning specific users to work with process mining tools. Given that a single business process can involve several departments, their corresponding managers and process participants are also involved [17]. Thus, process mining implementations can be highly challenging, and it makes human resources an essential factor that should be taken into consideration. At the same time, new technology and tools in process mining require new skills, roles, responsibilities and education of a new generation of experts with new competencies and a thorough understanding of computer science, data and IT [14]. In this regard, it is beneficial for organizations to be aware of the job market and the required skills and job positions by other organizations. Such information will help them plan for an appropriate job definition in process mining practices and know the variety of roles and skills in the market in order to plan for their best team composition. Process mining adoption in organizations and the reason for its failure/success are still under-researched, yet crucial [16]. Two factors that are required to successfully leverage the potential benefit of process mining are team composition and skills. Despite their importance and the high priority of this area, an open issue exists on the subject [8]. In this regard, we argue that gaining insight into what job demands process mining is currently sought by organizations will shed light on this gap. To the best of our knowledge, this area has not been specifically investigated yet. We argue that vacancies reflect the current needs of organizations and make a link between needs and demands.

Hence, our research question is:

– **RQ. What are the current job market demands for process mining?**

In this regard, we use vacancies as a proxy to reflect upon those demands for process mining practices in organizations.

To address this question, we developed the following objectives:

(O1) To report the geographical distribution of vacancies

(O2) To report the vacancies based on the size and sector of organizations

(O3) To refine the job titles in vacancies and report what 'job types' and 'job titles' are sought by different types of organizations and to what extent they are technical or business-oriented

In order to accomplish our objectives, we followed an empirical and analytical approach. We extracted all vacancies related to process mining from LinkedIn jobs in May 2022. In this regard, we considered process mining vacancies from all countries in the world without considering the original language used in the vacancy. The final dataset had 921 vacancies, after removing the duplicates and unrelated items regarding our inclusion and exclusion criteria. We performed a descriptive analysis to unfold the knowledge behind the dataset and address the research objectives.

The remainder of the article is structured as follows. In Section 2 the related studies are discussed. Section 3 presents the research design for this study. In Section 4, we explain and demonstrate the results of statistical analysis. In Section 5, we discuss our findings and their implications, our research limitations, and suggestions for future work. Finally, the paper is concluded in Section 6.

2 Literature Background

The popularity of process mining applications in the industry is growing in both industry and academia. Meanwhile, the integration of process mining with machine learning, simulation and other complementary trends, such as digital twins of an organization, is gaining significant attention in recent years [18]. In most cases, organizations adopt process mining to visualize, analyze and improve business processes that shape information systems [5]. Nevertheless, process mining has moved into wider areas in recent years and Gartner identified ten capabilities such as predictive and prescriptive analysis, customer interaction support, and task mining [4], just to name a few. Such capabilities provide the opportunity for the application of process mining in digital transformation journeys, RPA, hyperautomation, artificial intelligence usage or operational resilience.

Since the inception of process mining in the early 2000s, researchers have mainly focused on the development of technical - rather than organizational aspects [18]. While the focus of research has been on the technological aspect of process mining and the number of organizations that adopt process mining is increasing, more organizational and managerial research is required. In this regard, calls for research on the application of process mining has been issued in recent year. Studies have tried to emphasize the importance of considering this perspective and the existing gaps [8, 16, 16]. Based on a Delphi study on the existing challenges of process mining, four challenges were identified as directly-related to people competencies and data/process orientation of the organization culture [8]. Van der Aalst [20] was one of the first ones to discuss process mining from the perspective of applications in industrial practice.

In fact, the technical view of academics has come a long way, but people- and culture-related aspects present very prominent challenges [8]. People play a key role to put process mining into action, which implies that it is crucial to select the right staff to deliver these kinds of projects [13]. Moreover, even if the bases of models are built automatically using process mining insights, human domain knowledge is still crucial [11]. These statements represent the Importance of people playing role in process mining practices and their skills. Furthermore, the notion of Augmented Business Process Management Systems (ABPMSs) is going to introduce a new class of process-aware information systems [2]. In this regard, each level of the Augmented BPM pyramid requires specific capabilities and skills on the organizational side. Therefore, considering the competencies of people who are performing process mining in an organization directly affects their success and progress in this pyramid.

Different job positions are dealing with process mining in organizations such as process analysts, process participants, process stakeholders, and external partners [5]. In this regard, online job portals like LinkedIn and monster websites have been considered appropriate tools for understanding the demographics of BPM professionals, their skills and the job positions In BPM projects [6,7]. Notwithstanding the emphasis on organizational and managerial perspectives, to the best of our knowledge, there has been not a specific study on job positions and skillsets that are applicable in process mining practices in organizations.

3 Research Design

Our research consists of three main steps as depicted in Fig. 1. At first, we dealt with data collection and created a vacancies dataset. Then, we performed several data cleaning and preparation steps. We also derived more columns based on the existing columns in the dataset. Third, we applied descriptive statistics to derive insights from the cleaned dataset.

To achieve our research objectives, we applied the search terms of Table 1 to all LinkedIn jobs, which was the leading website that publishes vacancies [12], and downloaded them in an Excel worksheet. The search was conducted in May 2022. To analyze vacancies that were directly related to end-users and process mining in practice, we defined inclusion and exclusion criteria (Table 1). Furthermore, in order to take benefit from all vacancies around the world, we used an auto-translation library to translate non-English vacancies into English. In sum, 656 vacancies were in English, whereas the rest were in 12 different languages (e.g. German, Dutch, French, etc.). Subsequently, we describe the steps applied to this study.

3.1 Data Collection

To obtain the dataset, according to the inclusion criteria in Table 1, we developed a web crawler using the Selenium library of Python that could automatically go through all search queries related to process mining vacancies in different countries. Regarding the limitation of LinkedIn on showing job search results with a maximum of 1000 records, we had to include the search query for every country within our web crawler because searching for “process mining” in “worldwide” would return more than 3000 results. All vacancies were at the end extracted into an Excel worksheet. During the scraping, the language was automatically detected by GoogleTrans library and if it was a language rather than English, the job title and job description columns were automatically translated into English and saved in separated columns in the Excel file. Meanwhile, a field was also automatically generated for each record based on a list of process mining vendors in order to identify which organization is a vendor. After running the web crawler twice within a period of ten days in May 2022, we obtained a dataset containing 5,460 records to start the second phase of data preparation.

3.2 Data Preparation

Based on the exclusion criteria (Table 1), we manually identified not related records and labeled them as zero in the corresponding column to be excluded in our analysis.

This goal was fulfilled by job title and if needed, job description (i.e., which contained job responsibilities and required skills).

Meanwhile, there was an unintegration in the sector column as the sector name was not following a specific rule. We also found that some sectors were not correctly defined. Therefore, we used uniform NACE codes [3] to redefine the sector column. Meanwhile, the organization size was missing in some records. This issue was manually resolved by looking at the company profile on LinkedIn or the company website.

Our dataset initially revealed 838 different job titles among 921 records, and we

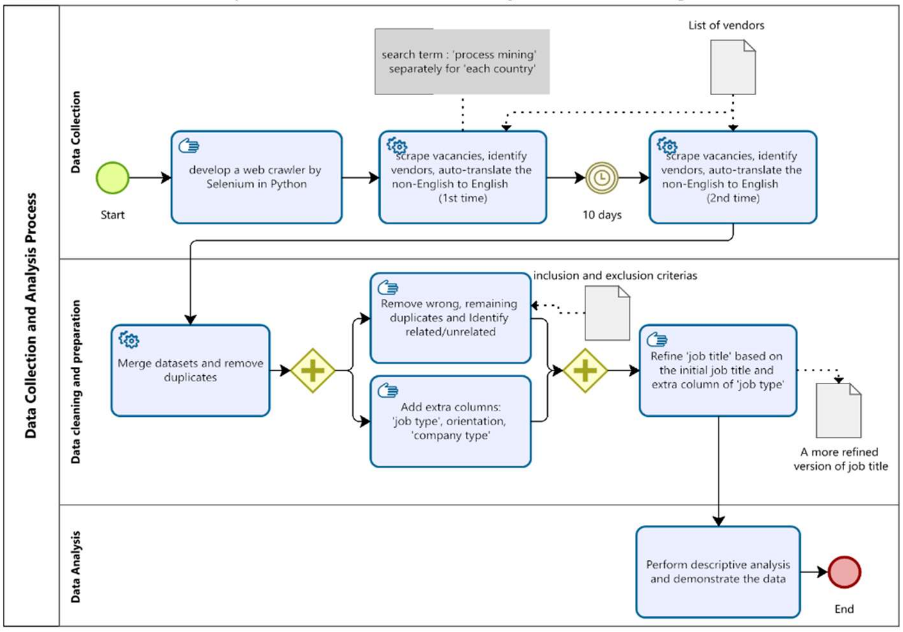

Fig. 1. Research Process

observed that job titles in vacancies contained multiple extra information (e.g., gender, city, etc.). After some basic cleanings and removing extra parts in the title (including the seniority), the number was reduced to 740 different job titles. This number was still too many to extract categorized information about job types and titles. In this regard, we added two new columns in the dataset as follows: 'Job Types' to reflect the job type/level of the prospect employee (e.g., manager, analyst, consultant, etc.) and 'Job section' as the subject of the vacancy like process, business, process mining, etc. The former was filled with deep consideration and attention to the initial job title and if required, the job description column. Nevertheless, since we received a lot of variety in job types, we made decisions upon merging some similar job levels with each other. For example, we considered merging expert, specialist, expertise and officer as specialists. The combination of job section and job type will create a new job title that is more clear and more homogenized than the initial job title.

3.3 Data Analysis

Our final dataset consisted of 921 vacancies in process mining worldwide. Based on the initial data columns that were available, extra columns were constructed specifically for this research. We applied descriptive analysis for demonstrating different aspects of the dataset, in order to address our objectives and the research question.

Table 1. Research Protocol

Search Term	'process mining' separately for 'each country' in the world in 'any languages' on LinkedIn Jobs page
Inclusion Criteria	All vacancies from end-users/consultancy firms that require either responsibilities or skills related to process mining implementation or both; without considering the percentage of their engagement.
	All vacancies from end-users that make benefit from process mining results but are not really involved in process mining implementation
	All vacancies from vendors that have direct contact with customers for implementation, technical support or consultancy purposes
Exclusion Criteria	Vacancies from end-users that do not clearly mention any skills or responsibilities related to process mining; although they might indicate that the company has process mining.
	Vacancies from end-users planning to implement process mining in the future but do not mention process mining as a requirement in the job description or skillset.
	Vacancies from end-users that have process mining skills only as an extra point or bonus but have not mentioned related responsibilities
	Vacancies from vendors that are not directly involved in process mining practices in organizations e.g. marketing, sales, inventory, algorithm development, software production, finance, training, procurement, account management, etc.
	Vacancies from research institutes/universities for researchers/students

4 Results

4.1 Geographical Distribution of Vacancies (O1)

In order to address O1, we now report on our findings regarding the distribution of vacancies in process mining. Fig. 2 presents the geographical distribution of vacancies throughout the world. According to the dataset, 47 countries were seeking for employees to participate in their process mining journeys. The map clearly shows that the majority of these vacancies were centralized in some regions across Central Europe and North America, while Germany and the United States possessed about 40% of all vacancies. Furthermore, our dataset shows that vacancies came from 438 different organizations and 12 different sectors. This variety supports us to argue that our dataset is a small yet appropriate sample of required job positions that could be generalized to vacancies for process mining practices across the world. Our data can thus be seen as a good representation of the vacancies at this particular moment in time.

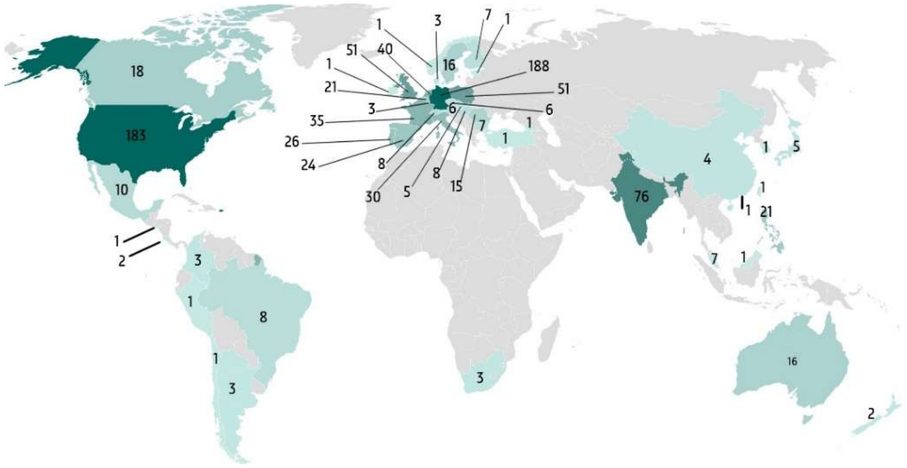

Fig. 2. Number of Vacancies per Country

4.2 Distribution of Vacancies Based on Company Type and Sector (O2)

To address O2, we identified three types of organizations that advertise for vacancies (Fig. 3), namely end users, vendors and consultancy firms. The first category contained 476 vacancies from organizations that hire employees either for their own process mining practices or for other organizations while playing the role of recruiters.

The second category contained 82 vacancies from organizations providing process mining software applications and services as vendors. Among them, we found software companies that are offering process mining features within their existing services but also software companies that are empowering their teams to enter this rapidly-growing market. The third group was 363 vacancies from consultancy firms giving consultancy services to end-users for helping them to leverage process mining.

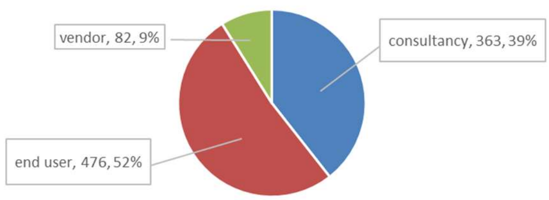

Fig. 3. Number of Vacancies by Organization Type

Table 2 presents the size of the organizations and their sector. 43.4% of the sampled vacancies were related to organizations working in the sector of 'Information and communications', and more than 50% (486) of them came from large organizations with more than 10,001 employees. Furthermore, the size of organizations working in the sector of 'Administrative and support service activities mostly contained organizations acting as recruiters. Therefore, it cannot present the size of the real employer and that size is not clear in those cases. Fig. 4 shows the technical/business orientation of job types. Within each blue box, job types and the corresponding frequencies within that orientation are presented. Fig. 5 demonstrate the job types regarding their frequency in either technical or business orientation or both.

Table 2. Vacancies by Sector and Size of the Organizations (based on NACE)

Sector (NACE)	1-10	11-50	51-200	201-500	501-1,000	1,001-5,000	5,001-10,000	10,001+	Total	%
Information and communication	8	7	33	24	14	88	30	196	400	43.4%
Manufacturing	2	2	1	2	1	20	23	133	184	20.0%
Professional, scientific and technical activities	4	2	7	1	4	40	3	72	133	14.4%
Administrative and support service activities	6	23	12	7	5	9	7	4	73	7.9%
Financial and insurance activities	4		1	2	3	8	5	43	66	7.2%
Human health and social work activities	1					1		18	20	2.2%
Wholesale and retail trade				2		3	1	10	16	1.7%
Transportation and storage			1		1	6	1	5	14	1.5%
Construction			1			5	1	3	10	1.1%
Public administration and defence								2	2	0.2%
Education					1	1			2	0.2%
Other professional, scientific & technical activities						1			1	0.1%
Total	**25**	**34**	**56**	**38**	**29**	**182**	**71**	**486**	**921**	

4.3 Job Types, Job Titles and Technical/Business Orientation (O3)

In order to address O3, we identified three types of job categories based on the orientation of the job: technical, business, and both. Such orientation was identified based on the 'job responsibilities' and 'required skill' in the 'job description'.
The distribution of these orientations and their relevant job types are presented in (Fig. 4). We identified 12 different job types. Fig. 5 demonstrates these types based on the orientation to which they are related. The number on the 'data labels' presents

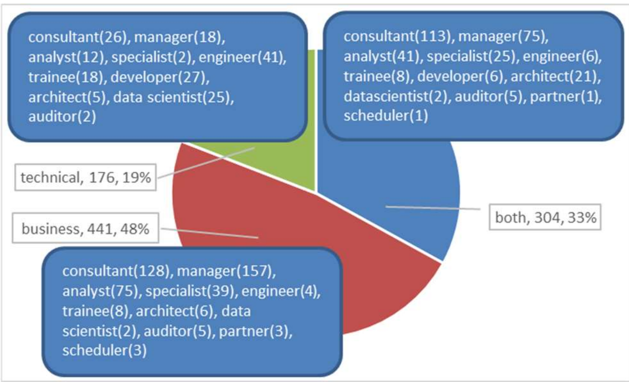

Fig. 4. Job Types and Technical/Business Orientation

the number of vacancies in each orientation for a given job title. After cleaning the job title as described in Section 3.2, the frequency of job titles was reduced to 252 items of which more than 50% have a frequency of below ten and 14% have a frequency of one. Because of the long list of output, we show only the first 20 results with a frequency of at least 10 (Table 3)

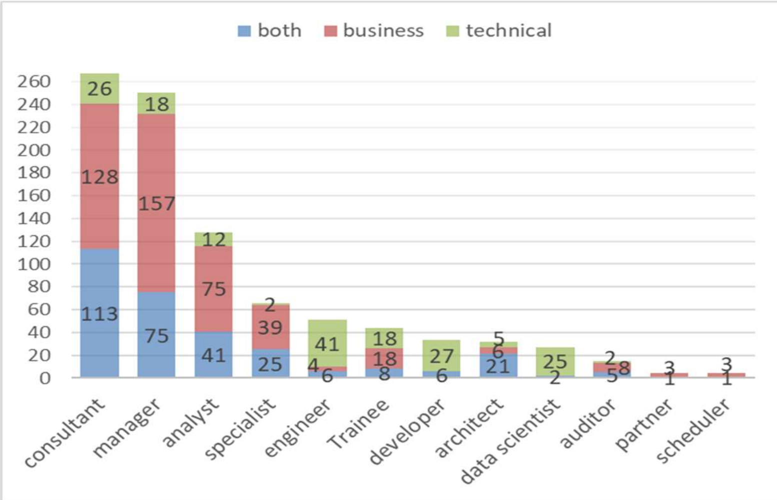

Fig. 5. Job Types and Technical/Business Orientation

Table 3. The Frequency and Orientation of the Job Titles

Row Labels	Business	Technical	Both	Total
process mining consultant	15	4	39	58
process manager	31		2	33
business analyst	25		7	32
process mining manager	7	2	19	28
data scientist		25	2	27
process analyst	22		3	25
data analyst	6	8	9	23
data engineer		21	1	22
business transformation consultant	9		8	17
process mining specialist	3		13	16
intelligent automation manager	6	1	9	16
customer value manager	15			15
process mining analyst	2	2	10	14
process consultant	12		1	13
RPA developer		12	1	13
process mining architect			12	12
process excellence manager	11			11
intelligent automation consultant	5	1	5	11
RPA consultant		3	7	10
process mining Trainee	1	5	4	10

5 Discussion

The results could address our objectives, answer the research question and present an understanding of job market demands and vacancies in process mining. In the following sub-sections, we discuss and present the implications of our study (Section 5.1) and acknowledge the limitations of this research and propose some avenues for future works (Section 5.2).

5.1 Implications

Our findings have some implications. First, end users can get a basic understanding of different vacancies and roles to consider in their process mining implementation. Second, the technical/business orientation is also an interesting outcome of our study. Given that process mining is connecting data science with process science, there are multiple job types and job titles that need a hybrid orientation. This shows that technical versus business orientations in process mining job titles have their own dedicated specifications and for some job types and job titles, the orientation differs. Indeed, process mining has caused new job definitions to be created in the field of BPM and Information Technology. Jobs such as process mining consultant, process mining analyst, process mining manager, etc. are some examples. Meanwhile, changes in job requirements of process analysts, process specialists, data analysts, etc. show the impact of this technology on the definition of such roles for process mining practices. Third, our result is helpful for job seekers to know what types of job opportunities exist in this market with technical, business or technical-business orientation.

Fourth, our study unveils the fact that there is no integrity in job titles in process mining projects. Therefore, almost all employers have their own language for defining job titles and job descriptions. Fifth, our study reveals the niche markets and newly growing demands while also unveiling the growing interest in software companies to adapt process mining techniques to their existing software applications and services. This finding provides insight for vendors and intermediaries to focus on expanding the market to other countries and also other sectors so as to empower the application of process mining in other areas. Simultaneously, our findings provide insight into improving their competitive advantage and letting their business grow in competition with multiple process mining providers. Last but not List, our approach and the methodology we proposed could be repeatable in other BPM-related roles.

5.2 Research Limitations and Future Work

Despite our in-depth descriptive analysis of process mining vacancies in all countries without considering the language, our research still faces some limitations. First, our dataset is limited to vacancies in May 2022. Although the extraction was performed twice within 10 days, it is a sample of the real world at a certain moment in time. Therefore, evolution over time and seasonal changes are not considered. Nevertheless, a longitudinal dataset containing vacancies across several months or different seasons will be beneficial. It will also give the opportunity for chronological research which compares the change and evolution of vacancies and job types during the time. Second, we extracted data from LinkedIn, which is yet the most popular platform for process mining vacancies. Other platforms like Monster.com or local job portals will also give a deeper insight into vacancies in certain geographical areas in the case of the latter. Third, we tried to homogenize job titles by considering the original job title and job description. This objective can only be fully explored by performing further research through skills extraction, text mining and/or conducting an expert panel. Fourth, there might be a potential bias regarding our search terms due to LinkedIn algorithms, although our query terms were searched in all vacancies' metadata.

For our next step and as future research, we are going to extend this study further on standardizing job roles and deriving individual skills and competencies that are required within process mining projects in organizations. Further, there might be a novel opportunity to investigate mapping such competencies with the levels of Augmented BPM pyramid [2] or a pre-defined maturity model.

6 Conclusion

Although process mining has matured as a research field over the past decade from a technical standpoint, there is a limited understanding of process mining from an organizational perspective [8]. In this study, we have conducted empirical and analytical research on vacancies in process mining practices throughout the world. Based on Section 2, we could argue that there has been no study on this topic so far and it remains unclear what kind of job types, job positions and skills with what kind of orientation exists or is required in process mining practices. Since vacancies are considered an appropriate source of data for studying job specifications, we argue that they can reflect the current needs of organizations by linking needs and demands. We studied 921 vacancies and tried to make clear what the state of job market demand for process mining at the moment in time is. Novelty in this study lies in considering real data from a well-known job portal and focusing on geographical distribution, employer specifications, job titles and their characteristics, presenting facts underlying vacancies and the job market.

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