What's to Automate? A Task Analysis of AI-enabled Start-ups

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Abstract

Automation of tasks as a result of advances in Artificial Intelligence (AI) is currently one of the major economical drivers. However, the varying effectiveness of AI usage across occupations and industries suggests that the impact of AI diffusion is uneven. Thus, it is imperative to understand which types of tasks are more or less prevalent in AI-enabled businesses. Using a cross-sectional dataset of 27,700 start-ups and occupation data, we utilize word embedding to link start-ups to their respective underlying tasks. We compare the task types of AI-enabled with non-AI start-ups in the services and platforms domain using a suitability for machine learning metric. The results show that analytical, logistical, and statistical tasks predominate among AI-enabled start-ups while services with customer proximity have a smaller share and the overall task diversity is lower. The implications of our findings are discussed in the light of labor theory and the economies of scale of AI start-ups.

1. Introduction

Artificial intelligence (AI)—as a general-purpose technology (GPT) [1]—has been characterized as being able to generate significant economic value and transform companies that successfully establish an AI factory [2]. The productivity gains stem from increased efficiency, where many decisions and tasks can be augmented or automated across the value chain [3]. At the core of contemporary AI are machine learning (ML) technologies that have greater autonomy, deeper learning capacity, and are more opaque than earlier software artifacts described as "intelligent" [4].

However, it is unclear to which degree these potential benefits are actually realized among digital start-ups that claim AI technology to be at the core of their value proposition and thereby their business model. Economists argue that the realized economic effects still appear to be small [5]. The implementation of AI technologies requires access to expert developers who design algorithms that make use of data. At the same time, skilled workers such as data scientists as well data are not easily available or deployable [6]. Moreover, another fundamental issue is that AI technology affects occupations by demand for specific tasks within this occupation and not taken as a whole [7]. And some tasks, obviously, seem to be better suited for AI automation than others, so this paper analyzes *which tasks in start-up practice are prevalent in AI-enabled businesses and how suitable they seem to be for machine learning*.

To address this question, we examine how the underlying tasks of AI-enabled start-ups differ from those in the same domain and industry that do not deploy AI. We use a dataset collected from the Crunchbase database of 27,700 start-ups utilizing both Crunchbase business categories as well as non-negative matrix factorization (NMF) topic modeling in combination with word embedding to assign them to the AI, platform, and professional services domains. We identify platform and service start-ups that deploy AI technology in their business model, which we will call AI-enabled platform and service start-ups, and contrast them with non-AI platform and service start-ups that are not characterized by the use of AI. Utilizing BERT word embedding models, we relate the start-up description texts to the descriptions of occupations in the O*NET database to gain an understanding of the task types most commonly underlying the start-ups. Hereinafter, we compare these task types using the suitability for machine learning metric [1] assigned to the O*NET occupations to identify similarities and differences in start-up practice empirically. To further narrow down the conditions for AI technology's capability to automate specific tasks, it stands to reason that context matters, such as the industry or ecosystem in which the start-up competes by using AI [2].

Our findings indicate that (i) in most industries, AI-enabled start-ups indeed have more tasks that have been labeled as generally more suitable for machine

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learning compared to non-AI start-ups; (ii) these machine learning suitable tasks that are prevalent in entrepreneurial practice most often fall into the analytics category, such as operations research analyst, logistician, statistician, or industrial engineer; (iii) domain-specific skills that require a closer connection to the customer are less prevalent for AI-enabled start-ups, such as jobs as a counselor, coordinator or community health worker; (iv) the difference in the number of tasks suitable for machine learning is higher in AI-enabled service start-ups (compared to non-AI service start-ups) than in AI-enabled platform start-ups (compared to non-AI platform start-ups); and (v) there are further industry-specific differences in the degree of suitability for machine learning of tasks.

This study thus provides a computationally intensive method of linking tasks, occupations, or work activities to organizations—given that the data about them includes meaningful description texts. The application of this method in this AI-focused study showcases how significant differences in task characteristics can be empirically detected. This paper adds to the studies on the effect of AI on work by suggesting that the AI-enabled tasks and business processes are currently centered around a more analytically focused and less customer-facing service offering to customers. As [1] argue, managers and entrepreneurs should not focus exclusively on automation: to realize the full potential of AI technology, the task content of most jobs still needs to be significantly re-engineered. Our results, however, also detect a general shift towards more analytical service types when automating with AI in start-up practice.

We discuss the implications of our results in the light of the labor force and AI economy studies. First, AI applications lead to changes within firms and have particular implications for the labor force. Since the currently argued technology deskilling effect of AI seems to be more pronounced in the service sector [8], we can surmise that the "deskilled tasks" in the service sector are primarily and counterintuitively statistics- and analytics-based, while occupations, such as public relations specialists, rehabilitation counselors or agents and business managers of artists, performers, and athletes, play a less dominant role. It stands that AI is pulling the scope of a service start-up further away from a career field that is in personal, close customer support.

Second, it is important to understand the implications of AI to "reshape the operational foundations of firms" [2] and the extent to which it is enabling new economies of scale, scope, and learning. Irrespective of the current hype on AI, scaling up an AI venture does not always meet expectations, as complementarities of AI innovations have not diffused widely enough to yield higher productivity. However, there is little empirical evidence to show that deploying AI technology seems to have a relatively higher effect on scaling for start-ups with a service business model than for platform start-ups [9]. Our study complements this research question by showing that the difference in tasks suitable for machine learning also seems to be larger for AI-enabled compared to non-AI service start-ups than for AI-enabled compared to non-AI platform start-ups.

2. Literature Overview

AI technology is capable of enabling augmentation and automation processes in organizations, yet not every task lends itself equally well to automation. We provide a brief overview on the topic of task automation in AI start-ups.

2.1. AI Start-ups

The object of consideration in this paper is AI start-ups, which we define as a digital start-up that uses AI as a core part of its value proposition. Thereby, we consider start-ups where AI technology enables the start-up's primary activities and its business model [10]. In contrast, we do not consider digital start-ups where AI technology merely provides context and start-ups engage with AI technology in secondary activities, such as their work processes. Examples of AI start-ups include companies that provide products or customer services using technologies, such as machine learning and deep learning [11], intelligent systems [12], natural language processing [13], and predictive analytics [14].

When considering the automation capabilities of AI start-ups, prior literature has pointed to two key aspects. First, AI has been characterized as the next GPT, credited with enabling significant complementary investments that include business process redesign, co-invention of new business models, and human capital [1]: First, AI models allow for high predictive quality and can therefore identify and meet customer requirements faster [15]. Second, data-based learning helps create user value [16]. This is a pertinent value to complement those well-documented direct and indirect network effects. Data-based learning occurs when the AI platform becomes more valuable to each user, the more it learns about users from the data it collects. Finally, it has been noted that once a mature AI model is set up, it can be transferred to other business applications via Transfer Learning [2].

In turn, as [17] noted, talent and data seem to be the scarcest, yet crucial, resources for a thriving AI start-up. From an economical point of view, AI does not always live up to high expectations. Scholars and industry reports indicate common issues for AI start-ups: There is significant uncertainty for businesses regarding how to manage AI [18]. The complexity of AI seems to exceed that of traditional, fewer data-intensive IT applications [19]. [2] highlight barriers to creating and capturing value through AI technologies, such as unclear business cases for AI implementations, lack of leadership support, and limited technological capabilities. In addition, recent industry reports underline practical issues arising from the above [20]: First, expensive cloud infrastructure is often necessary, requiring ongoing human support. Second, numerous edge cases pose a problem for the initial model setup—hence, it has been surmised that AI lives in the long tail [21].

Literature has further noted the difference in augmentation and automation of tasks: Whereas automation means that machines take over a human task, augmentation means that humans work closely with machines to accomplish a task. If we follow [22], we could say that task augmentation cannot be cleanly separated from task automation, as they seem to be interdependent: augmentation steps could lead to automation over time. Hence, the question of which tasks are more or less amenable to both augmentation and automation by AI deserves further attention.

2.2. AI Task Automation

As far as task automation is concerned, there is growing worries about the wave of automation and its impact on the workforce. Although we are not yet at the point of artificial general intelligence, which can match humans in most cognitive areas, industry reports suggest that about 50% of the tasks currently performed by people could be automated [23]; further, 60% of all jobs consist to 30% of activities that could be automated [23]; finally, automation could eliminate 47% of jobs in the US economy by 2033 [24]. Given that the impact of automation on the workforce is already significant, the question of which tasks will be most affected by machine learning and which will remain relatively unaffected is all the more important.

The spectrum of job automation ranges from information acquisition to information analysis and decision-making to action implementation [25]. As noted by [26], occupations in any organization consist of tasks with varying degrees of automation capability. Automation of tasks in these fields has always had a significant impact on productivity and the workforce in the past [1, 27]. It has predominantly been argued that it is mainly routine tasks that will be automated and substituted by information technology [26]. However, while in the past, automation was usually achieved by extracting the rules of a business process and designing the algorithm or machine accordingly, today, machine learning models no longer need to rely on a priori codified rules, but derive those rules themselves based on output and input data—often in opaque ways that are not easy to interpret. Nevertheless, the extent of machine substitution of human labor may still usually be overestimated because it remains extremely difficult to fully automate human workers in their full spectrum of tasks, which usually require aspects of flexibility, judgment, and common sense. It is still the complementarities that seem to increase productivity, raise earnings and drive demand for skilled labor [7].

Given the differences in how tasks are automated compared to past automation, it stands to reason that the types of tasks that can be automated are also different and that the level of automation varies for different tasks [25]. Some tasks can be automated with no additional human labor, while most of the time task automation requires some kind of human in the loop, which in turn creates work roles that may demand both technical and professional skills on the part of the workforce. [28] argue that products of an intermediate level of novelty (neither too novel nor too incremental) in drug discovery benefit most from AI assistance. And some categories of tasks may not be automated at all, as [24] suggest: tasks that center around perception and manipulation and creative or social intelligence. However, it is argued that AI entails many more differences from traditional disciplines that have not been unearthed since AI can be much more comprehensive and interactive than previous generations of IT [29]. [18] summarized the facets of AI task automation using the key concepts of (i) autonomy: AI making autonomous decisions without human intervention; (ii) learning: automatic improvement of AI models through data and experience; and (iii) inscrutability: AI algorithms being increasingly unintelligible to different audiences. Thus, AI algorithms are on their way to automating not only routine tasks but also more complex tasks with greater uncertainty—sometimes in new and surprising ways. Prospectively, [30] describe that AI autonomy is increasingly generative. AI-enabled autonomous agents are performing tasks more akin to those of knowledge workers [31]. It has been argued that humans, in turn, are taking over more and more integrative sensemaking [32].

To arrive at a clearer picture of which types of tasks are automated in start-up practice, we chose to make use of an exploratory, computationally intensive research approach [33] by comparing start-ups that use AI ("AI-enabled") with start-ups that do not claim to use AI ("non-AI"). In particular, we analyze whether the suitability for machine learning (SML) metric by [1] is higher for AI-enabled start-ups compared to non-AI start-ups, as expected. Moreover, we inspect if the differences in the SML metric are higher for AI-enabled service than for AI-enabled platform start-ups, as could be expected by the line of reasoning laid out above. Finally, we zoom into industry-specific differences in tasks and their respective suitability for machine learning.

3. Data and Measures

We used topic modeling and word embedding to identify the differences between AI-enabled and non-AI start-ups in job tasks.

3.1. Data Sources and Variables

We gathered start-up data from Crunchbase and occupation data from the O*NET Resource Center for information regarding job types and occupations. The Crunchbase database is an open-source directory that contains community-generated data on global technology start-ups and investors. We used Crunchbase's 'business group' categories to capture AI-enabled and non-AI start-ups in the service and platform category. We could use the Crunchbase business group category "Artificial Intelligence" and "Professional Services". However, the Crunchbase business group category "Platform" lists firms that offer complementary services to the most well-known platforms, such as Amazon, eBay, etc., which do not represent platform start-ups we are interested in this research. Hence, we included start-ups that fit the following criteria: "description text" contains any of $\{$*Platform*, *Marketplace*, *Forum*, *Aggregator*$\}$ AND "business category" element of $\{$*E-commerce*, *Internet*, *Logistics*, *Marketplace*, *Retail*, *Wholesale*$\}$.

Using topic modeling via NMF [34], we validated the categorization of AI, platform, and service start-ups as depicted in Figure 1. We compared the description texts of these start-up groups with the description texts of the complete Crunchbase start-up dataset. These start-up description texts give a brief description of the core business and activities of about one paragraph in length. The results yield a high face validity between the underlying topics discovered in the business description text since we found no topics from Crunchbase to be missing that we expected to be present in the topics we obtained for the selected start-up groups. We further validated the start-up groups by comparing the service start-ups with the most frequent themes in service research based on the topic modeling results for 22 years of service research [35]. Customer- and service-centric consulting themes are reflected in both service research and the NMF topics in our data, while topics such as business analytics and AI solutions are not yet present in the service research literature but are found in the NMF topics in our dataset. It should be noted that although we develop a good understanding of the content of the start-up description texts, they may not cover the entire set of tasks for start-ups' business, but reflect only those related to their key products or services and, thus core business model.

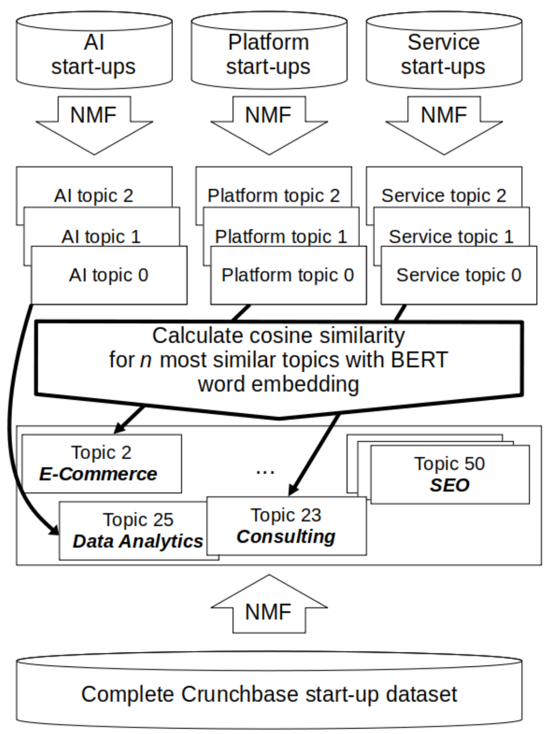

Figure 1. Checking the validity of the start-up groups by (i) Non-Negative Matrix Factorization of the description texts and (ii) mapping the emergent topics of the start-up group samples to the topics of the entire Crunchbase start-up database using cosine similarity of the embedded vectorized topic content via BERT word embedding

In total, the dataset comprised 27,700 start-ups, of which 6,230 fell into the AI group, 16,002 into the platform group, and 5,468 into the service group. These groups are not mutually exclusive. We further split the dataset into sets of start-ups that fall into the platform or service group while using AI at the same time ("AI-enabled start-ups") and sets of platform or service start-ups that do not use AI ("non-AI start-ups"). The dataset comprises 3,213 non-AI and 2,520 AI-enabled platform start-ups as well as 3,021 non-AI and 877 AI-enabled service start-ups. For the in-depth analyses, we grouped the start-ups by their respective industry sectors that they are engaging in. Additional descriptive statistics are presented in Table 1.

Table 1. Start-up summary statistics

	AI-enabled platform	Non-AI platform	AI-enabled service	Non-AI service
Age	5.25 (2.18)	6.57 (2.18)	5.56 (2.17)	7.23 (1.91)
Region				
North Am.	1,456 (.58)	5,655 (.47)	480 (.55)	1,548 (.51)
Asian-Pac.	278 (.11)	2,024 (.17)	84 (.10)	372 (.12)
Europe	336 (.13)	1,864 (.16)	135 (.15)	370 (.12)
Sector				
Services	2,218 (.88)	8,404 (.70)	769 (.88)	842 (.28)
Retail	634 (.25)	6,401 (.54)	108 (.12)	223 (.07)
Management	390 (.15)	2,134 (.18)	74 (.08)	313 (.10)
Arts	417 (.17)	4,360 (.37)	118 (.13)	573 (.19)
Finance	265 (.11)	1,359 (.11)	129 (.15)	485 (.16)
Transport	278 (.06)	769 (.06)	29 (.03)	47 (.02)
Education	126 (.05)	607 (.05)	65 (.07)	280 (.09)
Health	278 (.11)	557 (.05)	22 (.02)	88 (.03)
Count	2,520	11,912	877	3,021

As for the reliability of the start-up data, Crunchbase monitors its data in particular through three different data curation mechanisms [36]: first, editors are part of the business environment to control the validity of the data. Second, Crunchbase uses machine learning algorithms to compare data against publicly available information. Finally, data analysts recruited by Crunchbase manually take care of data validation. Crunchbase data has been used in several studies, e.g. to measure dyadic business proximity of firms [13], to analyze collaboration between organizations [37], and for various ecosystem analyses (e.g. [38]).

The O*NET database contains variables describing labor and worker characteristics and was developed under the sponsorship of the U.S. Department of Labor/Employment and Training Administration. It has immense scope and is useful for reflecting economic aspects of the labor market [39]. The database includes the O*NET-SOC taxonomy, which lists job occupations and tasks associated with them. It is revised at regular intervals, the last revision was in 2019.

The latter dataset was used by [1] to create the SML metric, which we further utilized for the task analysis in this paper. The authors assigned a value between 1 ("not suitable for machine learning") and 5 ("very suitable to machine learning") to 684 tasks from 964 occupations in the U.S. economy joined to 18,156 specific tasks, which are further mapped to 2,069 direct work activities spread across occupations. The metric is based on eight key criteria by [40] that help to identify tasks that are more suitable for machine learning and focuses entirely on the technical feasibility. The SML scores were generated by the task crowdsourcing platform CrowdFlower. Table 2 summarizes the SML measures for tasks of the AI-enabled and non-AI start-up groups. We subsequently present the methodology we used to analyze the data.

Table 2. SML summary statistics for the ten tasks most likely to be associated with AI-enabled and non-AI start-ups

	AI-enabled	Non-AI
Task SD	.019	.013
Mean SML	3.48	3.45
Weighted Mean SML	3.51	3.47
SD SML	.101	.101
Weighted SD SML	.13	.17
Min SML	3.33	3.33
Max SML	3.60	3.60

3.2. Methodology: Task Automation Analysis

This study aims to uncover tasks that are more or less prevalent in AI-based ventures by comparing global start-up practices with the survey-based SML metric in different industries for platform and service start-ups. Figure 2 provides a schematic overview of the methods and analyses presented in this paper. We measured the similarity between the start-ups' description texts and the description of job tasks from the O*NET database. Start-ups provide comprehensive descriptions of their company and business model in the length of a paragraph. Therefore, the description of the start-ups can be a good representation of the application areas of the different job occupations and closely connected to underlying job tasks. When checking the face validity of the start-up-task matches start-ups in more easily identified industries yielded traceable task matches, such as "community health workers" or "healthcare social workers" in the healthcare sector.

We further build on the work of [1], who created the SML measure for labor input based on tasks within occupations in the O*NET database. An important criterion for determining whether a task is suitable for machine learning is that the set of actions and the corresponding set of outputs for the task can be measured such that an algorithm can learn the mapping between the two sets. To associate job tasks with a start-up, we make use of Natural Language Processing to build a connection between the description of start-ups and job tasks. We decided to use a BERT vector space model [41] in the main analysis because vector space models overcome the data sparsity issues and because the results in benchmarking tests work well with BERT models that rely on large pre-trained

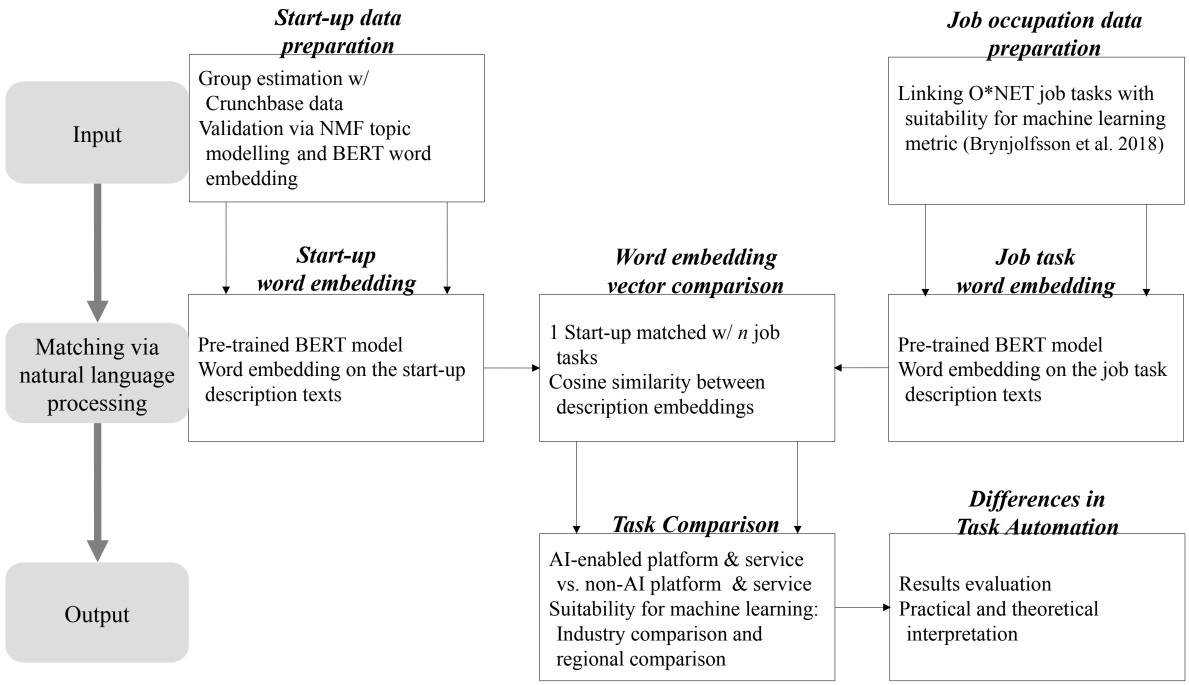

Figure 2. Overview of the different analyses and methods

text datasets, such as Wikipedia, that we were able to use. To ensure a high level of agreement between the descriptions of start-ups and job tasks, we computed the ten most fitting matches of job tasks for every start-up and removed every match that was not in the top 10% quantile in the entire cross table of cosine similarities (minimum 0.618). We conducted further sensitivity analyses on the number of tasks matched to each start-up and the minimum cosine similarity.

In a similar approach, [42] recently linked O*NET task data to Occupational Employment Statistics (OES) by the U.S. Bureau of Labor Statistics for occupational employment at the industry level and in metropolitan statistical areas. The authors applied network analysis to construct one-mode skill and two-mode job-skill networks and propose a data-driven approach to construct task-level automation indices to track how automation affects occupations and communities over time. In terms of their method [42] take the path from an occupation to a set of a priori assigned tasks, whereas we assign tasks directly to start-ups—unmediated, but with some fuzziness in the natural language processing approach.

4. Results

We conducted the task automation analysis by linking start-up occupations to O*NET job tasks and their respective SML values developed by [40]. Empirical evidence suggests that, although machine learning technologies will be pervasive, the SML of work tasks varies widely within occupations. We found that there is a greater variety of tasks in the non-AI start-up groups compared to the AI-enabled datasets, as depicted in Table 2. Since the two-sided F-test is highly significant, we can assume that the two standard deviations are different. Table 4 presents the top tasks for AI-enabled compared to non-AI platform and service start-ups. We only considered tasks that fell outside the range of five ranks of the other group—hence focusing on differences between AI- and non-AI-related tasks rather than similarities. Since we already found that there is a significant difference in the variance of the task types, we manually searched for a meaningful value for the minimum rank difference to explicate group differences without omitting too much information.

The major focus of the AI-enabled start-up seems to be on analytics, logistics, and statistics—both in the platform and service start-up groups. The predominant tasks in the non-AI start-up groups are customer-oriented, exemplified by the "Public Relation

Table 3. Tasks most commonly associated with the AI-enabled and non-AI start-up samples, based on cosine similarity of the word embeddings of the start-up and task descriptions

	Task	Freq	SML value
AI			
Task 1	Operations Research Analysts	.11	3.55
Task 2	Credit Analysts	0.07	3.59
Task 3	Logisticians	0.07	3.54
Task 4	Industrial Engineers	.06	3.53
Task 5	Team Assemblers	.06	3.38
Task 6	Sales Managers	.05	3.55
Task 7	Food Scientists & Technologists	.05	3.36
Task 8	Cost Estimators	.04	3.33
Task 9	Cartographers & Photogrammetrists	.04	3.54
Task 10	Commercial & Industrial Designers	.03	3.37
Non-AI			
Task 1	Team Assemblers	.07	3.38
Task 2	Sales Managers	.06	3.60
Task 3	Public Relations Specialists	.06	3.42
Task 4	Operations Research Analysts	.06	3.55
Task 5	Wholesale and Retail Buyers	0.05	3.48
Task 6	Credit Analysts	.05	3.59
Task 7	Commercial and Industrial Designers	.04	3.37
Task 8	Cost Estimators	.04	3.33
Task 9	Food Scientists & Technologists	.03	3.37
Task 10	General & Operations Managers	0.02	3.47

Note: Task {1,..,5} refers to the top 5 tasks associated with AI-enabled and non-AI start-ups, respectively, matched via O*NET job tasks. Excluding the top two job tasks "Market Research Analysts and Marketing Specialists" and "Marketing Managers", with frequencies ranging from .32 to .35 in both the AI-enabled and non-AI groups.

Table 4. Tasks most commonly associated with AI-enabled/non-AI platform and service start-ups

	AI-enabled platform	Non-AI platform	AI-enabled service	Non-AI service
Task diff 1	Operations Research Analysts	Public Relations Specialists	Logisticians	Public Relations Specialists
Task diff 2	Logisticians	Wholesale, Retail Buyers	Industrial Engineers	Training Specialists
Task diff 3	Industrial Engineers	Industrial Designers	Food Scientists, Technologists	Instructional Coordinators
Task diff 4	Food Scientists, Technologists	Advertising Managers	Cartographers	Wholesale, Retail Buyers
Task diff 5	Statisticians	Community Health Workers	Management Analysts	Credit Counselors

Note: Task diff. {1,..,5} refer to the top 5 associated tasks matched with O*NET job tasks—comparing AI-enabled vs. non-AI start-ups of the respective platform and service group omitting tasks within the range of five ranks of the other group.

Specialists" at the top of both table columns. In general, the diversity of tasks appears to be greater in the non-AI start-up groups than in the AI-enabled groups. Figure 3 outlines an overview of the differences. The group differences between the platform and service groups of non-AI start-ups show tasks that are prominent exclusively in the service group, such as "Rehabilitation Counselors", "Lawyers" or "Agents and Business Managers of Artists, Performers, and Athletes", indicating more domain-specific occupations with a focus on specific service themes, such as customer relationship management and service encounter (compare service themes in [43]). In the platform non-AI start-up group, tasks such as "Wholesale and Retail Buyers", "Advertising and Promotions Managers", "Fashion Designers", "Demonstrators and Product Promoters", "Hosts and Hostesses" prevail, again indicating customer-oriented, but also traditional trade occupations.

The 20 highest SML values of the tasks, weighted by their occurrence in the corresponding start-up groups, are indeed higher for the AI-enabled compared to the non-AI start-up groups. Since this tendency of analytics- and statistics-based tasks can be observed for both platform and service business models and across different industry sectors and especially this kind of task seems to have an above-average SML value [42], it explains the higher SML values that our results provided for AI-enabled vs. non-AI start-ups. However, the difference is more pronounced in the service group (AI-enabled: 3.458 vs. non-AI: 3.382) than in the platform group (AI-enabled: 3.460 vs. non-AI: 3.417). However, the absolute difference in the SML score of AI-enabled service and platform start-ups is very small, as not only the tasks of the service but also the platform start-ups seem to be more cognitive and knowledge-intensive side. It is the difference between tasks of "classic" non-AI service-oriented start-ups and AI-enabled start-ups that stands out.

Most tasks that are more prominent in the AI-enabled start-up groups have an SML score above the overall mean across all tasks (3.470)—with a few exceptions such as "Cost Estimators" (3.334). For the non-AI start-up groups, the picture is less clear: Most tasks that are more prevalent here are below the SML average, such as "Public Relations Specialists" (3.422) or "Personal Financial Advisor" (3.391), but others have an above-average SML value, such as "Wholesale and Retail Buyers" (3.482) or "Advertising Managers" (3.597).

Looking at industry differences in underlying tasks, we find certain industries to have higher differences in the weighted SML between AI-enabled and non-AI start-ups than others, such as Transportation, Manufacturing, Utilities, and Finance. In the case of Finance, we find a shift from hard-to-automate service tasks, such as "Personal Financial Advisors" (3.391), to more analytically oriented tasks. In the following, we want to discuss our findings and relate them to the current dialogue in the field of AI and the workforce as well as economies of scale.

5. Discussion

The literature suggests that AI affects different parts of the workforce than earlier waves of automation [1]. Automation has been one of the primary drivers of economies of scale, and the potential for productivity gains from automation using AI is also vast; however, measured productivity growth has declined by half within the past decade [5]. Tasks within jobs have typically been shown to have considerable variability in their suitability for machine learning, and most jobs can not be automated completely at the moment. We thus propose a method of linking start-ups to their underlying task types and were able to gain an understanding of the predominant task types of AI jobs. Our results suggest that the tasks associated with AI-enabled occupations in start-ups are related to a more pronounced focus on analytics, statistics, and logistics. At the same time, the results uncover that tasks of AI-enabled start-ups cover a less broad range of different activities; in particular, fewer of the kind that requires particular proximity to customers. Similarly, [1] suggest that this variability at the task-level regarding SML values indicates the potential to reorganize and combine task with high and low suitability for machine learning, respectively. And indeed, archetypal business model patterns of AI start-ups have shown that providing data analytics seems to be the most prominent pattern, followed by AI model-based products and services, and developing customizable AI solutions and basis AI technology [44]—reflecting the analytics-based characteristics of value capture and delivery. This is also evidenced by the vast amount of machine learning and analytics topics emerging in the NMF topic analysis. This result echoes the findings of [42], who claim that especially cognitive tasks, which were previously considered being more complementary to automation technology, now seem to be more suitable for machine learning. As the current hype surrounding AI technology still prevails [22], it stands to reason that many start-ups currently either integrate AI technologies—or at least claim to do so in their self-description.

As indicated above, AI automation has already disrupted the labor force. However, [1] have already pointed out that the correlation coefficients of the SML metric with wage percentiles are very low. It has also been argued that automation in most cases simplifies jobs and allows less-skilled workers to do them [45]. The main argument is that most tasks require some degree of human interaction required, so full automation is rarely possible. Since service tasks often involve higher levels of knowledge intensity, customization, and human engagement, it has been argued that the level of automation following AI applications in the service sector may be lower than in other sectors, such as manufacturing [8]. The authors reason that, due to a lower level of automation, there should be more jobs for less-skilled workers, as the remaining tasks that still call for human support can often be performed by less analytically qualified workers. In turn, the service sector should be more heavily affected by de-skilling effects in the labor force. The analysis of task automation in this study suggests this effect in two ways. First, by emphasizing the focus of AI on analytical, knowledge-intensive tasks that are susceptible to service process automation, and second, because of the greater difference in AI-enabled vs. non-AI SML values in the service sector compared to the platform sector. It is still unclear whether AI differs substantially from past automation technology, which also fostered inequality and wage polarization by exclusively automating routine cognitive tasks [46].

[42] argue that to get a clearer picture of automation and the future of work, it is vital to understand not only which and to what extent a human task is automated but also labor demand for occupations

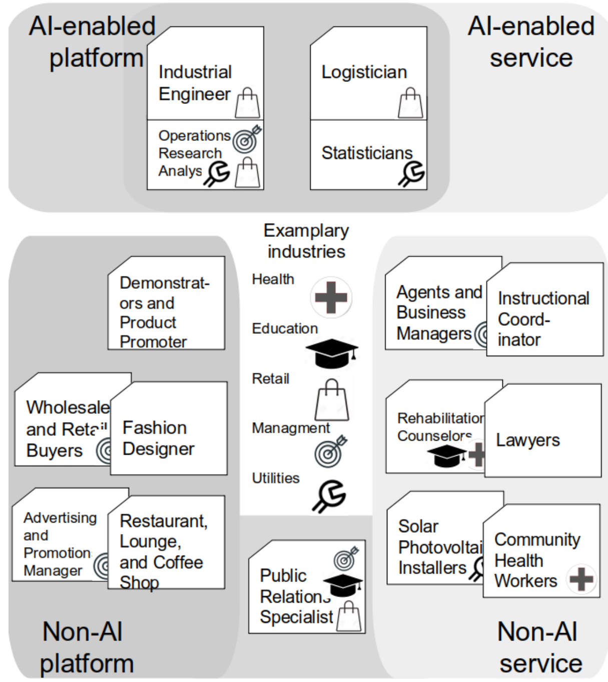

Figure 3. Tasks that are more prevalent when comparing AI-enabled vs. non-AI service and platform start-ups with exemplary industry sectors, in which they are primarily carried out.

performing a task. Our study provides some insight into the characteristics of tasks performed by AI-enabled start-ups and therefore allows tentative inferences to be made about labor requirements. When analyzing sector-specific differences, we noticed that weighted average SML values are higher in the financial sector, for which market entry and data sharing are proving especially difficult. Moreover, scaling analysis has suggested that not only the stakes but also the payoffs for automation with AI could be larger in the financial and healthcare sectors [9]. In summary, though AI is a GPT, both the capability to automate tasks and the economies of scale and scope of AI vary across sectors and require further research.

It is noteworthy to point out that differences between AI-enabled and non-AI tasks as measured in this study setup could still have several causes: either tasks have been automated or they have been omitted, respectively are redundant. We do not discern these two types of task differences in our study. Furthermore, an important limitation of this study is that the Crunchbase start-up descriptions mostly describe the start-ups' business models and key products or services and not likely all of the underlying business tasks. To avoid having to rely on the start-ups' self-description texts, the method proposed in this paper could be put to use for analyzing firm's job postings, which have been increasingly adopted in studying AI, skills, and labor markets [47]. An important application for the proposed method could thus be to empirically analyze which AI tasks have a positive or negative effect on a firm's employment of (non-)academically-trained workers in line with the work of [8].

6. Conclusion

We provide a word embedding-based method to associate start-ups with their underlying task types and ran it on a dataset of start-ups and job occupations to provide a task-based overview of AI-enabled and non-AI start-ups in the service and platform businesses. Our results indicate that tasks related to AI-enabled occupations are associated with a more pronounced focus on analytics, less variety, and less in that kind of service domain, which requires particular proximity to customers. Moreover, the relative difference in tasks with high suitability for machine learning when comparing AI-enabled to non-AI service start-ups, we conclude, is due to the increasing automation of cognitive and knowledge-intensive tasks. Our proposed method provides further research opportunities in the field of AI and labor theory.

7. References

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