Collaborative Robots in the Workplace: Occupational, Geographic, and Demographic Opportunities for Technology Adoption

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July 30, 2024

Research Summary: We develop an index, which we call the *Cobot Adoption Potential Index (CAPI)*, of the potential that occupations have for the adoption of collaborative robots, or "cobots." Using data from O*NET, American Consumer Survey (ACS), and the Bureau of Labor Statistics (BLS), we estimate the feasibility of cobot adoption across occupations of various characteristics. We illustrate how CAPI can be used to assess (1) cobot adoption potential at regional levels (2) evaluate how easily cobots integrate with workers in these occupations based on worker characteristics and (3) the potential of cobots to improve workplace safety.

Managerial Summary: Collaborative robots, or "cobots," hold the potential to create new job opportunities, increase the flexibility of work, and improve worker conditions across a range of industries. The extent to which this new technology can actualize on this promise is unknown due to a lack of appropriate metrics that consider both technical possibilities and compatibility with labor. To address this gap, we develop a metric that we call *Cobot Adoption Potential Index (CAPI)* that can be used to assess both the feasibility of incorporating cobots into different types of work. We discuss the potential uses of this metric by researchers and managers to inform decisions about cobot adoption and integration.

*Unicersity of Wisconsin–Madison. We are grateful to Bilge Mutlu, Rob Radwin, Andrew Schoen, Tim Smeeding, and Shiyu Zhou for numerous helpful discussions and comments. This work has been supported by NSF Future of Work Grant FW-HTF-RM: Human-Robot Collaboration for Manual Work). Corresponding author: Lindsay Jacobs, lpjacobs@wisc.edu.

1 Introduction

New robotic technologies hold significant potential for improving worker productivity and working conditions [Schmidtler et al., 2015]. In this paper, we focus on one emerging technology: collaborative robots. Collaborative robots, or "cobots," are robotic technologies "designed for direct interaction with a human" [ISO, 2016] and offer flexible, safe, and user-friendly automation in manual tasks [Vicentini, 2021]. Thus, unlike traditional robotic automation solutions that are designed to minimize human interaction, cobots offer work configurations that are "collaborative" [Pearce et al., 2018]. Furthermore, cobots offer businesses safe, low-cost, do-it-yourself (DIY), re-configurable integration of the technology, making them more attractive than traditional robotic automation that requires significant expertise to effectively and safely integrate and utilize [Magalhaes and Ferreira, 2022]. The cobot market share is expected to expand between 2023 and 2030 at a compound annual growth rate (CAGR) of 29.9% in the U.S. and 32.0% globally [Grand View Research, 2023].

Despite the significant promise of and interest in cobot technology, best practices for robot integration are yet to be established. Most manufacturers see cobots as a safe, low-cost automation solution [Michaelis et al., 2020], however due to the collaborative nature of cobots additional investments in training may be required. Where the "collaborative" capabilities of cobots might be best utilized and how easily workers will adapt to working with cobots remain open questions. We seek to contribute to these discussions by developing an index that can be used by researchers and practitioners to evaluate the occupations where cobot adoption is feasible, who currently works in these occupations, where they are located, and what the implications are from a management perspective.

Using data from O*NET on detailed occupational tasks as well as expert information on cobot compatibility for select occupations from prior work [Liu et al., 2022], we develop an index—the *Cobot Adoption Potential Index*, or *CAPI*—as an instrument that can be used by researchers and practitioners. First, looking at the occupations where cobots can be adopted, similar to other automatic robots, cobots have the highest potential in occupations that require repetitive physical tasks. However, unlike other types of automatic robots, cobots have greater potential outside of manufacturing occupations in the areas of hospitality and agriculture.

We then illustrate the use of this index through three applications. First, we apply it to detailed regional data from the Bureau of Labor Statistics (BLS) in order to estimate where we can expect cobots to be adopted most intensely. This is particularly important for managers considering how cobots may affect competition in their local markets. Second, we show how the index can be used to consider how easily cobots can integrate with the current workforce based on worker characteristics using data from the American Community Survey (ACS). Cobot success requires collaborative relationship with workers, so it is even more important for managers to understand the adaptability of the workforce. Lastly, we consider the potential of cobots to improve workplace safety, which has the promise of both reducing employment costs and making jobs more appealing to potential workers.

Our exercises highlights several key insights about the future potential of cobots. Geographically, we show that cobots could transform competition among firms in the Western part of the US. Our second exercise highlights how easily cobots might integrate with the current workforce. Workers in occupations most likely to use cobots tend to be younger. This is promising for the integration potential of cobots, as young workers tend to seek new skills at a higher rate. However, the workers most likely to work with cobots also tend to have lower education on average. Workers with lower education may require additional training to most effectively use cobots. Finally, we show that the occupations with a high potential for cobot adoption also have higher injury rates which highlights the potential of cobots to improve workplace safety by handling the more risky tasks.

2 Relation to the literature

Researchers have identified several barriers to cobot adoption. In particular, among decision makers there is a lack of knowledge on the business uses and benefits of collaborative robots [Miller, 2021]. There is also a lack of expertise to effectively work with, reconfigure, and troubleshoot cobot applications [Michaelis et al., 2020, Moffat and Gray, 2015]. These different factors contribute to poor adoption and utilization of cobots. Simões et al. [2020] notes that assessing cost-benefit measures and making a business case for the integration of cobots is a particular challenge to gaining acceptance from internal stakeholders. Our work seeks to address these barriers by providing a simple index to evaluate the potential of cobots.

There are several management considerations in the integration of cobots and other types of technologies. Internal factors include structural characteristics, receptiveness to change, and readiness of the organization. External factors include competitive pressure, business partner pressure, government directives, regulatory environment, and technology infrastructure [Sinha and Noble, 2008, Bennett, 2020, Kopp et al., 2021, Sundaresan et al., 2023]. We primarily draw on literature focused on how management considers both technological and employee-centered considerations when deciding whether and how to integrate cobots into manufacturing environments.

Managers take into account a multitude of technological considerations when evaluating the potential adoption of cobots. Technological considerations that have been studied with regards to cobots include a desire for safety, flexibility, adaptability, and capacity in their processes [Brettel et al., 2014]. Other work has analyzed how easily cobots can be integrated into existing manual processes [Ponda et al., 2010, Pearce et al., 2018, Casalino et al., 2019, Bogner et al., 2018, Pupa and Secchi, 2021, Zhang et al., 2022, Schoen et al., 2020]. We build on this literature by distilling the multiple dimensions of cobot technological capacities into an index that can be used to understand cobot feasibility at the occupation level.

When investing in a new technology, complementary investment in human capital is often required [Riley et al., 2017]. Employee-centered considerations when adopting cobots include social factors [Sauppé and Mutlu, 2015]; team dynamics [Kopp et al., 2023]; worker trust and acceptance of the robot [Kopp et al., 2023, Panchetti et al., 2023]; and worker skills and training to fully utilize the collaborative capabilities of the robot [Moffat and Gray, 2015, Michaelis et al., 2020]. While automation replaces some worker tasks, it also helps workers specialize and better perform their remaining tasks [Gong and Png, 2024]. Further, the introduction of new technology has the potential to change the organizational structure of firms. Dixon et al. [2021], for instance, study the managerial impact of robots on firms as well as employment. They estimate increases in employment as robots are introduced, along with a reorganization where managers constitute a small share of firm employment.

Firms may also consider how the introduction of cobots could have beneficial or maladaptive effects on workers depending on the job characteristics [Liu et al., 2022], and what levels of collaboration might be feasible for collaborative robots [Michalos et al., 2015, Malik and Bilberg, 2019, Kopp et al., 2021, Christiernin, 2017, El Zaatari et al., 2019, Franklin et al., 2020]. Workers themselves can be reluctant to work with robots, but their reluctance tends to decrease over time as threats and risks of robots are better understood [Wurhofer et al., 2015, Arntz et al., 2017, Frey and Osborne, 2017, Kawaguchi, 2021]. We analyze cobot compatibility with workers by analyzing the characteristics of workers in occupations with the highest potential for cobot adoption.

In terms of methods and goals, our work is related to the literature evaluating other types of task automation. Our work is most closely related to Felten et al. [2021] who develop an index using task data to analyze the potential use of artificial intelligence. Similar to cobots, artificial technology is an emerging technology and tools are still being developed to evaluate its impact and future potential [McElheran et al., 2022]. The work of Jia et al. [2024] shows how artificial intelligence enhances productivity, and that the effects are greater for employees with greater skill. Other work looks to instances of automation adoption for more direct evidence of the how automation affects firms and workers and documents challenges to successful adoption [Tong et al., 2021, Feigenbaum and Gross, 2024]. As cobot adoption progresses, similar methods can be used to evaluate their impact.

3 Methods

Our objective in developing CAPI is to quantify the potential for cobot integration for hundreds of detailed occupation categories. In this section, we describe how we construct the CAPI index. We first identify the tasks within occupations that would be potentially suitable for cobots based on prior work. Then, we construct several possible indices using these identified tasks. We choose our preferred index by testing how well each index can replicate the categorization of occupations in a small sub-sample that has been expertly identified in prior work as having a high potential for cobot adoption. Finally, we use our preferred index to categorize a wider range of occupations. Each occupation is assigned a CAPI value from this index, and with this we carry out our analysis in the next section to demonstrate how the index can be used to evaluate cobot potential and feasibility.

3.1 Identifying Tasks

To construct CAPI, we first identify which tasks have cobot potential. We use task and occupation data from O*NET. The O*NET data contains abundant occupational information for 892 occupations, including detailed descriptions of occupation-specific attributes, such as *abilities* and *skills* required by certain occupations, *work activities*, and *work context*.[1]

We identify potential tasks from O*NET that can be used to develop the index, focusing on O*NET measurements under *work context* in particular, which are the "physical and social factors that influence the nature of work." Table 1 lists the O*NET tasks in this category. While there are additional O*NET measures available (e.g. *skills* and *work activities*), we focus especially on *work context* for two primary reasons: 1) Physical aspects of an occupation are important in measuring the usefulness for cobot integration, and *work context* module has reasonable amount of related measurements over those aspects. 2) Some of the information is redundant and repeated between modules, and we found that using more modules and more measurements did not necessarily increase the precision.

The variability of occupations, and the components of their work means that cobots may not necessarily serve the same types of functions in each occupation. For example, cobots may be used in photography, leaning on their ability to repeatedly execute complex maneuvers with held cameras, or in packaging or stocking applications (*e.g.,* pick-and-place

[1] The Occupational Information Network (O*NET) provides a public data set developed under the sponsorship of the U.S. Department of Labor's Employment and Training Administration. Each occupation has a distinct Standard Occupational Classification (SOC) System code.

Table 1: Key O*NET Work Context measures determining the cobot suitability

physical related measurements (+)	
(4.C.2.d.1.e)	Spend Time Kneeling, Crouching, Stooping, or Crawling
(4.C.2.d.1.g)	Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls
(4.C.2.d.1.h)	Spend Time Bending or Twisting the Body
repetitiveness (+)	
(4.C.2.d.1.i)	Spend Time Making Repetitive Motions
interpersonal skills (–)	
(4.C.1.a.2.c)	Public Speaking: How often do you have to perform public speaking in this job?
(4.C.1.a.4)	Contact With Others: How much does this job require the worker to be in contact with others in order to perform it?
(4.C.1.b.1.e)	Work With Work Group or Team: How important is it to work with others in a group or team in this job?
(4.C.1.b.1.f)	Deal With External Customers: How important is it to work with external customers or the public in this job?
(4.C.1.b.1.g)	Coordinate or Lead Others: How important is it to coordinate or lead others in accomplishing work activities in this job?
(4.C.1.c.1)	Responsible for Others' Health and Safety: How much responsibility is there for the health and safety of others in this job?
(4.C.1.c.2)	Responsibility for Outcomes and Results: How responsible is the worker for work outcomes and results of other workers?
(4.C.1.d.1)	Frequency of Conflict Situations: How often are there conflict situations the employee has to face in this job?
(4.C.1.d.2)	Deal With Unpleasant or Angry People: How frequently does the worker have to deal with unpleasant, $\cdots$ individuals $\cdots$?
(4.C.1.d.3)	Deal With Physically Aggressive People: How frequently does this job require the worker to deal with *cdots*?
decision making (–)	
(4.C.3.a.1)	Consequence of Error: How serious would the result usually be if the worker made a mistake that was not readily correctable?
(4.C.3.a.2.a)	Impact of Decisions on Co-workers or Company Results: What results do your decisions usually have on other people or $\cdots$?
(4.C.3.a.2.b)	Frequency of Decision Making: How frequently is the worker required to make decisions that affect other people, $\cdots$?
(4.C.3.a.4)	Freedom to Make Decisions: How much decision making freedom, without supervision, does the job offer?
physical proximity (–)	
(4.C.2.a.3)	Physical Proximity: To what extent $\cdots$ worker to perform job tasks in close physical proximity to other people?
autodegree (–)	
(4.C.3.b.2)	Degree of Automation: How automated is the job?

tasks), due to the ability to clearly define or augment the environment to support robot automation. In contrast, cobots are less suitable when extremely heavy objects need to be manipulated, for example, in some automotive manufacturing tasks, where the reduced payloads of collaborative robots relative to conventional robots hinders their utility.

We use the O*NET data to more concretely categorize the potential of cobots to perform different work tasks. Broadly, our index will be made up of elements that either enhance or detract from cobot implementation. Given the physical capabilities of cobots, we expect that occupations with physical tasks—shown in the upper panel of Table 1—are more likely to be suitable for robot or cobot integration. Further, if repetitive motions are required in an occupation, suitability is even greater for two reasons. First, repetitive tasks will generally be less costly for the engineers to set up due to reuse of functionality. Second, repetitive motions performed by human workers are frequent sources of ergonomic concerns Armstrong et al. [1986], Bernard and Putz-Anderson [1997], and offloading these tasks present good opportunities for improvement. As interpersonal skills are very unlikely to be learned and cultivated by the robot, cobot potential would be lower in occupations requiring these skills. Similarly, the more freedom required in the decision making process, the harder it could be to collaborate with the cobot, given trade-offs between creative decision making and predictability. For physical proximity, if the task needs to be operated in a very close physical proximity to other people, the combination of tight spaces and high precision will make it hard to introduce cobots into the operation. In order to rule out those occupations which have already been or are soon likely to be automated, we add the O*NET "auto-degree" as another key category.

3.2 Potential Indices

Next, we create several potential indices which are constructed using different combinations of the work context categories. We use both linear and non-linear combinations of the context measures. To begin, we first standardize each of the work context measurements with mean zero and standard deviation of one. This is to eliminate the concern that the range of different measurements can be different, and to make preparations for constructing *cobot indices.*[2] We discuss five versions in detail below. Table 8 of Appendix A.1 describes all the other versions that have been considered.[3] In the next section, we will discuss how we choose our preferred index from among these different options.

Index 1. The first candidate index version uses *physical related measurements* and *repetitiveness*. And for a given occupation o, the index is calculated in the following way. Conditional on repetitiveness being the same, the more physical related tasks included in the occupation, the higher the score. However, if very few of the tasks are repetitive, it will be hard to set up the function and use the cobot to assist which will lead to a low CAPI. This is true no matter how high the *physical measurements* are.

$$index1_o = \sum_{j \in \text{physical measurements}} j_o \times \text{repetitiveness}_o \tag{1}$$

In the equation, for the first term we use the sum of all physical measurements instead of using the mean. This is because we think that the "number" of tasks that are physically related are also vital in determining cobot compatibility and could have significance.

Index 2. Instead of using the product form, the second version uses the sum of *physical related measurements* and *repetitiveness*. Thus, this method separately considers the

[2]We do not re-weight each measurement based on the occupational labor supply. Since whether an occupation has the potential to be compatible with cobot should depend on the occupational technology attributes but not on how many workers are working in that occupation. From this perspective of view, it is not necessary to put more weights on occupations with larger size when constructing CAPI.

[3]Whenever it is in product form, we adjust so that product of two negative terms does not achieve the same outcome as the product of two positive terms. For visual clarity, it is not explicitly written out in the equation.

physicality of the task and how repetitive the tasks are.

$$index2_o = \sum_{j \in \text{physical measurements}} j_o + \text{repetitiveness}_o \tag{2}$$

Index 3. This version extends **Index 2** by including the need for interpersonal skills as an attenuating factor.

$$index3_o = \sum_{j \in \text{physical measurements}} j_o + \text{repetitiveness}_o - \sum_{j \in \text{interpersonal skills}} j_o \tag{3}$$

Index 4. This version brings *physical proximity* and *auto-degree* into consideration. Conditional on everything else being the same, if the job requires the worker to perform tasks in a very close physical proximity to other people, it will be hard to set up the cobot under this situation. In the O*NET data, the higher the *physical proximity*, the closer the distance. Therefore, *physical proximity* is negatively correlated with cobot collaboration potential. *Auto-influence* is created based on the auto-degree. If the auto-degree of a certain occupation is too high or too low relative to the median auto-degree of all the occupations, the value of *auto-influence* will be very negative and decrease the CAPI. When auto-degree is too high, it might have already been automated and have no room for cobot collaboration. When the auto-degree is too low, it may be extremely hard to assign any of the tasks to robot or cobot.

$$\begin{aligned} \text{auto-influence}_o &= -\left[\text{auto-degree}_o - \text{median(auto-degree)}\right]^2 \\ index4_o &= \sum_{j \in \text{physical measurements}} j_o + \text{repetitiveness}_o \\ &\quad - \sum_{j \in \text{interpersonal skills}} j_o - \text{physical proximity}_o + \text{auto-influence}_o \end{aligned} \tag{4}$$

Index 5. In the fifth version, we substitute the *interpersonal skills* of **Index 3** with *decision making* as an alternative attenuating factor. If an occupation requires the worker to frequently make decisions that have impacts on other people, if the consequence of each decision is serious, or if any errors can lead to a severe outcome, then this occupation may not be a good candidate and be with low CAPI.

$$index5_o = \sum_{j \in \text{physical measurements}} j_o + \text{repetitiveness}_o - \sum_{j \in \text{decision making}} j_o \tag{5}$$

3.3 Choosing the CAPI Index

Next, we test how well each potential index performs and choose our preferred index. We first identify a subset of occupations that have been already analyzed with respect to cobot potential in prior work. Then, we analyze how well each potential index identifies cobot potential in our identified occupations.

3.3.1 Occupation test sample

First, we identify a subsample of occupations that can be used to verify the performance of our indices. We use the subsample of occupations in Liu et al. [2022]. Liu et al. used [O*NET OnLine, 2023] data and information about cobot ability to devise a rating system that attempts to predict the possible extent of collaborative utility in different occupations.The index that best matches the assessment of Liu et al. [2022] will be our cobot-potential assigning index, CAPI.

Liu et al. [2022] uses the O*NET data and the detailed descriptions and tasks mentioned under each selected occupation to categorize these occupations as having "high" or "low" cobot compatibility. An occupation (e.g. packaging and filling machine operators and tenders) is defined as a good potential candidate for cobot adoption if the occupational tasks have the following attributes: 1) Some of the tasks require physical work (e.g. packaging the product in the form in which it will be sent out); 2) Some aspects of those physical related works are easily modeled (e.g. having well-defined workspace organizations/processes or highly capable sensing capabilities); 3) The work features a low proportion of tasks which need frequent human-level judgement, inspection, or analysis, or otherwise require interpersonal connections with others. Under these criteria, nine occupations are categorized under the "high" cobot compatibility group and seven occupations are characterized as having "low" cobot compatibility, as shown in the rightmost column of Table 2.

3.3.2 Testing the Indices

Our goal is to find—among all candidate indices—the one that best matches the expert assessment from Liu et al. [2022] for the subsample of occupations. Using the constructed candidate indices, we generate an indicator for cobot compatibility which equals one when

Table 2: Qualitative Assessment of Cobot Compatibility for Selected Occupations

SOC Code	Occupation Title	Compatibility
512011	Aircraft structure, surface, rigging and systems assemblers	high
536051	transportation inspectors	low
516041	Shoe and leather workers and repairers	low
512061	Timing device assemblers and adjusters	low
473011	Helpers—brickmasons, blockmasons, stonemasons, and tile and marble setters	high
172111	Health and Safety Engineers, Except Mining Safety Engineers and Inspectors	low
519071	Gem and diamond workers	low
514071	Foundry mold and coremakers	high
518091	Chemical plant and system operators	high
512021	Coil winders, tapers, and finishers	high
519192	Cleaning, washing, and metal pickling equipment operators and tenders	high
492091	Avionics technicians	low
513022	Meat, poultry, and fish cutters and trimmers	high
516011	Laundry and dry-cleaning workers	low
519111	Packaging and filling machine operators and tenders	high
537062	Recycling and reclamation workers	high

Table 3: Example of how we pick the threshold

occ	1	2	3	4	5	6	7	8	9	10	
cobot potential	low									high	
true compatibility	0	0	0	0	0	0	1	1	1	1	
constructed index(e.g.)	0.5	1.3	4.6	5.1	6.2	6.8	10.5	12.2	14.2	16	
Pick a specific threshold.											
Compatible indicator = 1 If the index value $\geq$ threhold											
	indicator for compatible or not										precision rate
30th quantile	0	0	1	1	1	1	1	1	1	1	0.6
50th quantile	0	0	0	0	1	1	1	1	1	1	0.8
70th quantile	0	0	0	0	0	0	1	1	1	1	1
90th quantile	0	0	0	0	0	0	0	0	1	1	0.8

the candidate index is above the p-th quantile of the index distribution; and equals to zero if the candidate index is below the threshold.

$$\mathbf{I}(\text{compatible with cobot})_o = \begin{cases} 1 & \text{if } \text{CAPI}_o \geq p\text{-th quantile} \\ 0 & \text{if } \text{CAPI}_o < p\text{-th quantile} \end{cases} \tag{6}$$

For each candidate cobot index, we can generate the corresponding indicator. The selected sub-sample is then used to test the precision of each index. Various p-th quantiles are also tested in this process.

If, for instance, there are 10 occupations ordered based on their cobot compatability, and suppose only the top 30%(three out of ten) occupations can actually be compatible in reality as is shown in Table 3. Assume the constructed index reflects the truth and the order of the index value perfectly aligns with the true order of occupation cobot potential, so that the occupation with the highest cobot potential is with the highest constructed index value and vice versa. We then use different thresholds to test which one can provide us with the highest precision rate. Theoretically, the closer to the true threshold the higher precision rate we will be, and the *index-quantile* bundle which provides the highest precision rate should be the closest to the true *index-quantile*.

We apply this logic to our sub-sample data over several combinations of indices and thresholds. Table 4 provides an example of the precision rate when we use the 70th quantile as the threshold.[4] Among all, the most precise measurement is provided by index *5* with the 70th quantile as the threshold, and the precision rate is 87.5%. We adopt index *5* as our CAPI and 70th quantile as the cutoff.

Table 4: Precision rate of all the indices when threshold is the 70th quantile

index version	data source	precision rate	assessments matched
1	work context	0.813	13 out of 16
2	work context	0.750	12 out of 16
3	work context	0.688	11 out of 16
4	work context	0.688	11 out of 16
5	work context	0.875	14 out of 16
6	work context	0.625	10 out of 16
7	work context	0.750	12 out of 16
8	work context	0.750	12 out of 16
9	work context	0.813	13 out of 16
10	work context	0.688	11 out of 16
11	work context	0.813	13 out of 16
12	work context	0.688	11 out of 16
13	work context	0.750	12 out of 16
14	work context	0.750	12 out of 16
15	work context	0.750	12 out of 16
16	work activities	0.563	9 out of 16
17	work activities	0.625	10 out of 16

Given the results above, we selected candidate **Index 5** as the CAPI index formula (5), such that

$$CAPI\ Index = index5_o = \sum_{j \in \text{physical measurements}} j_o + \text{repetitiveness}_o - \sum_{j \in \text{decision making}} j_o\,, \quad (7)$$

[4]Table 9 in Appendix A.2 provides all versions across threshold levels.

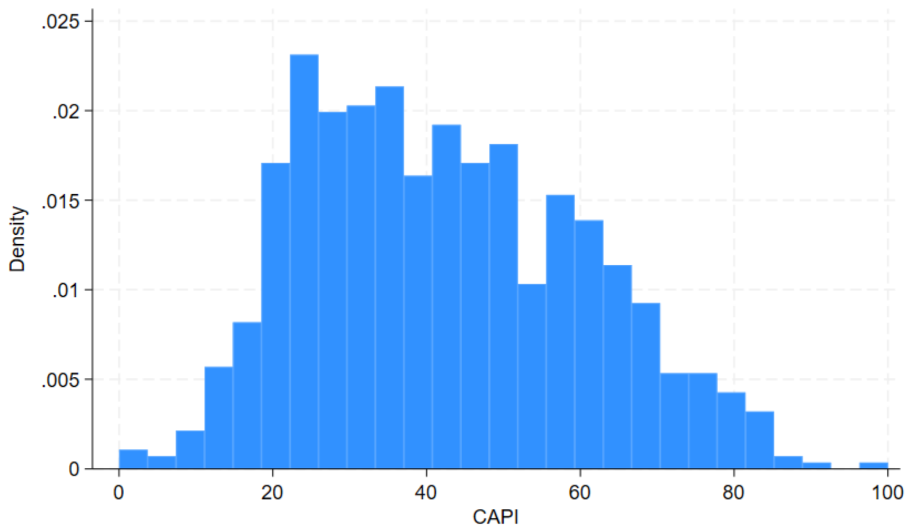


Figure 1: Distribution of CAPI

3.4 Categorizing Occupations

Finally, we can use our preferred index to categorize the full sample of occupations in the O*NET data. We then apply our index to each occupation, expressing it in terms of its CAPI score. The index is normalized to be between 0 and 100, and the distribution of scores across occupations is shown in Figure 1. We will use these occupation level categorizations in the next section to show how the index can be applied to gain further insights on the potential of cobots.

Table 5 shows a subset of occupations, organized by CAPI in descending order and divided by quartile. For the purposes of presenting many findings, we categorize having "high" cobot adoption potential as occupations that have CAPIs within the top 30 percent, where there is the most significant gap in CAPIs. Occupations below this cutoff will be categorized as having "low" cobot adoption potential. The top "high" occupations include those in the upper part of Table 5, including "Maids and Housekeeping Cleaners" down to "Stockers and Order Fillers". The "low" cobot adoption potential occupations range from those with reasonable high CAPIs, such as "Telecommunications Equipment Installers and Repairers" to those with the extremely low CAPIs, such as "Judges, Magistrate Judges, and Magistrates" and "Family Medicine Physicians ".

Table 5: Examples of Occupations in Different CAPI Quartile

Occupation Title*	CAPI Quartile	CAPI	Compatible with Cobot
Maids and Housekeeping Cleaners	4	100.00	high
Fiberglass Laminators and Fabricators	4	92.29	high
Textile Knitting and Weaving Machine Setters, Operators, and Tenders	4	88.04	high
Shoe Machine Operators and Tenders	4	87.52	high
Tile and Stone Setters	4	83.87	high
Floor Sanders and Finishers	4	83.67	high
Painters, Construction and Maintenance	4	83.34	high
Terrazzo Workers and Finishers	4	82.90	high
Cement Masons and Concrete Finishers	4	82.75	high
Pressers, Textile, Garment, and Related Materials	4	81.92	high
...			
Carpenters	3	55.95	high
Word Processors and Typists	3	55.92	high
Photographers	3	55.91	high
Earth Drillers, Except Oil and Gas	3	55.71	high
Stockers and Order Fillers	3	55.63	high
...			
Telecommunications Equipment Installers and Repairers, Except Line Installers	3	51.66	low
Animal Caretakers	3	51.58	low
Proofreaders and Copy Markers	3	51.23	low
Dental Laboratory Technicians	3	51.14	low
Food Service Managers	3	51.05	low
...			
Telemarketers	2	40.61	low
Counter and Rental Clerks	2	40.49	low
Insurance Appraisers, Auto Damage	2	40.45	low
Exercise Physiologists	2	40.39	low
Automotive Engineering Technicians	2	40.39	low
Aerospace Engineering and Operations Technologists and Technicians	2	40.39	low
Environmental Engineering Technologists and Technicians	2	40.38	low
Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	2	40.35	low
Retail Salespersons	2	40.31	low
Museum Technicians and Conservators	2	40.27	low
...			
Instructional Coordinators	1	27.82	low
Concierges	1	27.69	low
Materials Scientists	1	27.58	low
Interior Designers	1	27.47	low
Atmospheric and Space Scientists	1	27.40	low
...			
Real Estate Brokers	1	4.91	low
Judges, Magistrate Judges, and Magistrates	1	4.00	low
Psychiatrists	1	1.32	low
Neurologists	1	0.37	low
Family Medicine Physicians	1	0.00	low

* Occupations are listed based on the descending order of CAPI. Contains a subset of the 892 occupations, specifically those at the top of each quartile by CAPI, and at the top of the occupations categorized as having “low” cobot adoption potential.

4 Applications

Having estimated what occupations have potential for cobot integration, we show how the index can be used to 1) identify where cobots have the highest potential to be adopted, 2) analyze how easily cobots might be integrated into the workforce in these occupations based on worker characteristics, and 3) the potential for cobots to improve workplace safety.

For these exercises, we use additional data from the American Community Survey (ACS) and the Bureau of Labor Statistics (BLS). We connect the CAPI and cobot-compatible groups constructed using the O*NET data to the IPUMS ACS [2015-2019] data to summarize the age, income, and other characteristics by CAPI scores for occupations. We also show the relationship between cobot compatibility and injury incidence rates across occupations, specifically the Injuries, Illnesses, and Fatalities (IIF) data from the Bureau of Labor Statistics, U.S. Department of Labor [2020].

4.1 Geography of Cobots

We first apply our index to evaluate which geographic areas have the greatest potential for cobot adoption based, as the geography of cobots can help inform managers about the potential for changing competition in local markets. We show the geographic variation of occupations with cobot potential by linking our occupation CAPI scores to occupational employment data from the May 2019 Occupational Employment and Wage Statistics (OEWS) by Bureau of Labor Statistics, U.S. Department of Labor [2019]. We construct an aggregate, occupation-weighted CAPI for both Metropolitan Statistical Areas (MSAs) and states.

4.1.1 Metropolitan Statistical Area Level

Figure 2 shows the CAPI score levels across metropolitan areas in the United States. Dark blue corresponds to an occupational composition with an aggregate CAPI showing low average cobot adoption potential, while red corresponds to an MSA with high occupation-weighted cobot adoption potential.[5]

Figure 3 presents some detailed examples. Those figures the intensity of cobot adoption potential is not related to the size or population density of an MSA. For instance, the larger cities of San Francisco, Los Angeles in Figure 3a, Milwaukee, Madison in Figure 3b, Detroit

[5] It is important to note that these show the relative intensity of cobot adoption potential, but do not reflect absolute numbers. For instance, the Chicago MSA might show lower average cobot adoption potential than, say, the Fresno MSA in the central valley of California, but there are in fact a higher number of people working in occupations with high CAPIs in Chicago. A graph showing absolute numbers would be primarily reflecting population density rather than cobot adoption potential.

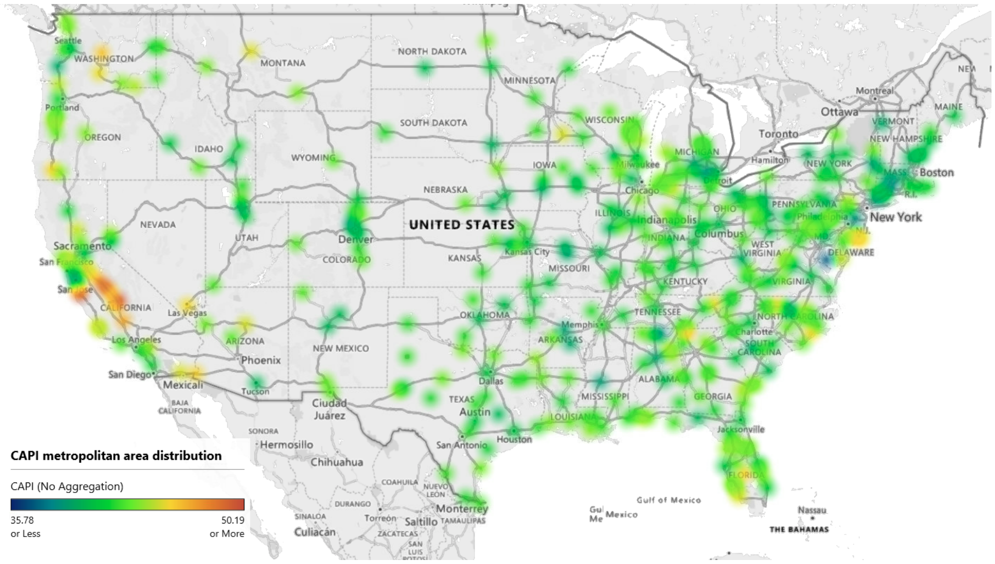
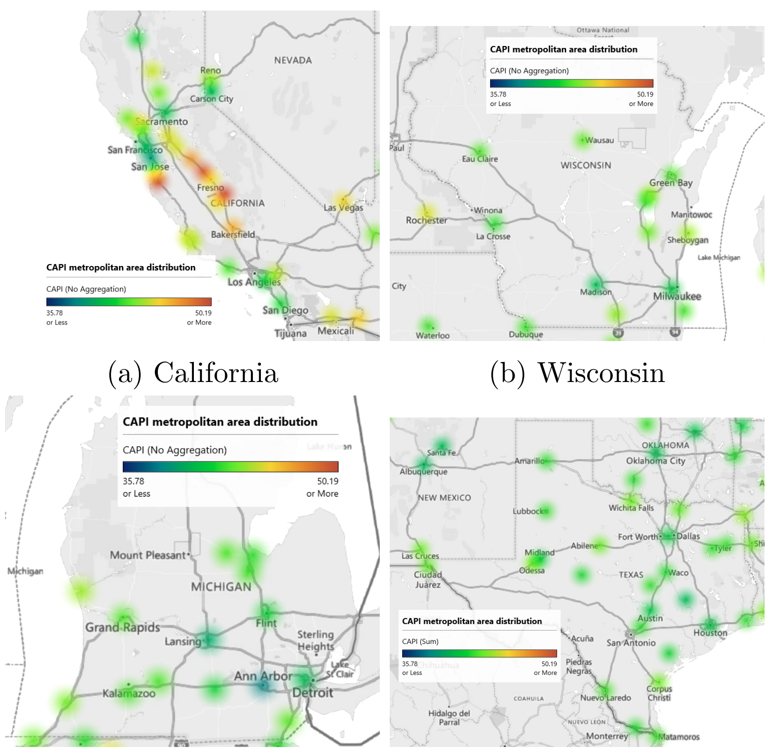


Figure 2: The Distribution of MSA-level CAPI Scores



(a) California (b) Wisconsin

(c) Michigan (d) Texas

Figure 3: CAPI distribution at metropolitan statistical area level, detailed examples

in Figure 3c, and Houston, Austin in Figure 3d have relatively moderate cobot adoption potential compared to surrounding areas.

4.1.2 Occupations in High CAPI MSAs

Table 6 lists the ten MSAs with the highest cobot adoption potential and, for the top 5 MSAs, the largest occupations within the MSA based on total current employment level and rate per 1,000 jobs. These are all MSA with highly specialized local economies, with the top three (Madera, Salinas, and Visalia-Porterville, California) being agricultural. The MSA with the fourth highest CAPI is Kahului-Wailuku-Lahaina, Hawaii, specializing in tourism, with the fifth highest, Dalton, Georgia, specializing in carpet manufacturing.

4.1.3 State Level

Similar to our exercise above that considered MSAs with the highest predicted cobot adoption potential, we now look at U.S. states by cobot adoption potential. Figure 4 provides State level information and presents the relative average CAPI for each State. The states with the highest potential are closer to the red end of the spectrum, while states with the lowest average potential are dark green-blue. Table 7 lists the top 10 States which are with the highest cobot adoption potential along with, for the five states with the highest average CAPI, the largest occupations by employment. Not too surprisingly, there is less variation across states in the largest occupations compared to the variation across smaller and more specialized MSAs. However, the top two states, Nevada and Hawaii, host a large tourism industry, while the next three—Wyoming, Indiana, and South Dakota—host more agricultural, manufacturing, and natural resources activity.

4.2 Worker and Cobot Compatibility

Next, we use the index to analyze how easily cobots can integrate with the existing workforce. Firms should consider whether additional investment in training may be required to utilize cobots in production. The adapatbility of the workers will determine how costly these additional expenditures might be. Generally, younger workers and those with higher educations will have an easier time learning how to use cobots. While we use national occupation level data, firms can perform a similar exercise using information on their own workforce.

For this exercise, we use the American Community Survey (ACS) to connect the CAPI with worker demographic information. The ACS data is a nationally representative individual level dataset which is released annually and includes information about jobs and occupations, demographic characteristics, social characteristics like disability status and educational

Table 6: The top ten metropolitan areas with the highest CAPI

CAPI Rank	Metropolitan Statistical Area	High Potential Occupations	CAPI	Total Employment	The Number of Jobs in the Given Occupation per 1,000 Jobs in the Given Area
1	Madera, CA	Farmworkers and Laborers, Crop, Nursery, and Greenhouse	81.48	6,340	135.8
		Cashiers	54.65	1,200	25.7
		Fast Food and Counter Workers	65.15	1,110	23.9
		Packers and Packagers, Hand	67.57	1,010	21.6
		Janitors and Cleaners, Except Maids and Housekeeping Cleaners	61.38	980	21.0
		Laborers and Freight, Stock, and Material Movers, Hand	61.05	820	17.5
		Maintenance and Repair Workers, General	60.60	490	10.5
		...			
2	Salinas, CA	Farmworkers and Laborers, Crop, Nursery, and Greenhouse	81.48	30,880	168.8
		Cashiers	54.65	4,900	26.8
		Fast Food and Counter Workers	65.15	4,390	24.0
		Laborers and Freight, Stock, and Material Movers, Hand	61.05	4,200	22.9
		Waiters and Waitresses	67.21	3,990	21.8
		Maintenance and Repair Workers, General	60.60	2,130	11.6
		Maids and Housekeeping Cleaners	100.00	2,070	11.3
		...			
3	Visalia-Porterville, CA	Farmworkers and Laborers, Crop, Nursery, and Greenhouse	81.48	24,650	158.3
		Cashiers	54.65	4,820	31.0
		Fast Food and Counter Workers	65.15	3,680	23.6
		Laborers and Freight, Stock, and Material Movers, Hand	61.05	2,660	17.1
		Stockers and Order Fillers	55.63	2,300	14.8
		Industrial Truck and Tractor Operators	52.30	2,280	14.7
		Packers and Packagers, Hand	67.57	1,870	12.0
		...			
4	Kahului-Wailuku-Lahaina, HI	Waiters and Waitresses	67.21	4,100	53.8
		Maids and Housekeeping Cleaners	100.00	3,210	42.1
		Fast Food and Counter Workers	65.15	2,180	28.5
		Cashiers	54.65	2,160	28.3
		Cooks, Restaurant	70.82	1,980	26.0
		Landscaping and Groundskeeping Workers	71.95	1,650	21.7
		Maintenance and Repair Workers, General	60.60	1,470	19.3
		...			
5	Dalton, GA	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders	78.36	4,530	70.3
		Laborers and Freight, Stock, and Material Movers, Hand	61.05	3,270	50.8
		Cashiers	54.65	1,800	27.9
		Industrial Truck and Tractor Operators	52.30	1,530	23.8
		Customer Service Representatives	56.53	1,350	21.0
		Fast Food and Counter Workers	65.15	1,330	20.7
		Industrial Machinery Mechanics	61.03	1,200	18.6
		...			
6	Ocean City, NJ				
7	San German, PR				
8	Wenatchee, WA				
9	Yuma, AZ				
10	Sebring, FL				
	...				

Table 7: The top ten States with the highest CAPI

CAPI Rank	Metropolitan Statistical Area	High Potential Occupations	CAPI	Total Employment	The Number of Jobs in the Given Occupation per 1,000 Jobs in the Given Area
1	Nevada	Fast Food and Counter Workers	65.15	43,310	31.1
		Waiters and Waitresses	67.21	37,300	26.8
		Cashiers	54.65	37,060	26.6
		Laborers and Freight, Stock, and Material Movers, Hand	61.05	37,000	26.6
		Janitors and Cleaners, Except Maids and Housekeeping Cleaners	61.38	29,360	21.1
		Customer Service Representatives	56.53	28,200	20.2
		Maids and Housekeeping Cleaners	100.00	25,140	18.1
		...			
2	Hawaii	Waiters and Waitresses	67.21	19,500	30.7
		Fast Food and Counter Workers	65.15	17,070	26.9
		Cashiers	54.65	13,270	20.9
		Maids and Housekeeping Cleaners	100.00	13,230	20.8
		Janitors and Cleaners, Except Maids and Housekeeping Cleaners	61.38	11,910	18.7
		Cooks, Restaurant	70.82	11,220	17.7
		Food Preparation Workers	61.15	9,290	14.6
		...			
3	Wyoming	Cashiers	54.65	6,350	23.2
		Fast Food and Counter Workers	65.15	6,000	21.9
		Waiters and Waitresses	67.21	4,740	17.4
		Janitors and Cleaners, Except Maids and Housekeeping Cleaners	61.38	4,530	16.6
		Maintenance and Repair Workers, General	60.60	3,480	12.7
		Stockers and Order Fillers	55.63	3,300	12.1
		Nursing Assistants	56.34	3,200	11.7
		...			
4	Indiana	Fast Food and Counter Workers	65.15	101,290	33.0
		Laborers and Freight, Stock, and Material Movers, Hand	61.05	93,040	30.3
		Cashiers	54.65	69,340	22.6
		Customer Service Representatives	56.53	53,480	17.4
		Waiters and Waitresses	67.21	49,690	16.2
		Stockers and Order Fillers	55.63	46,490	15.1
		Janitors and Cleaners, Except Maids and Housekeeping Cleaners	61.38	43,230	14.1
		...			
5	South Dakota	Fast Food and Counter Workers	65.15	13,130	30.9
		Cashiers	54.65	12,550	29.5
		Customer Service Representatives	56.53	8,810	20.7
		Janitors and Cleaners, Except Maids and Housekeeping Cleaners	61.38	8,250	19.4
		Waiters and Waitresses	67.21	7,020	16.5
		Nursing Assistants	56.34	5,990	14.1
		Laborers and Freight, Stock, and Material Movers, Hand	61.05	5,720	13.4
		...			
6	Montana				
7	Wisconsin				
8	Kentucky				
9	South Carolina				
10	Alabama				
	...				

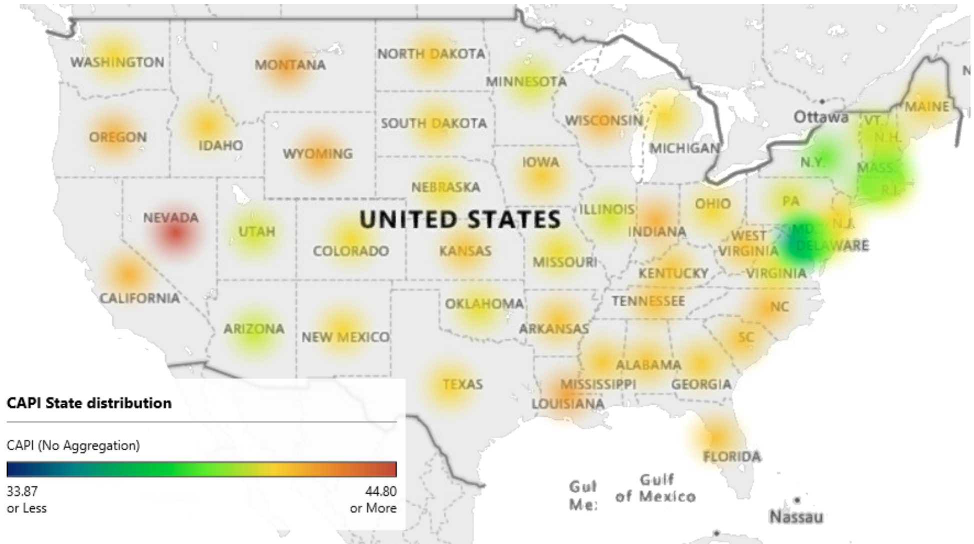


Figure 4: CAPI distribution at State level

Data Source: O*NET is used to construct the Cobot Adoption Potential Index (CAPI). Occupational employment information by metropolitan statistical area and by state comes from the May 2019 Occupational Employment and Wage Statistics (OEWS) by U.S. Bureau of Labor Statistics (BLS).

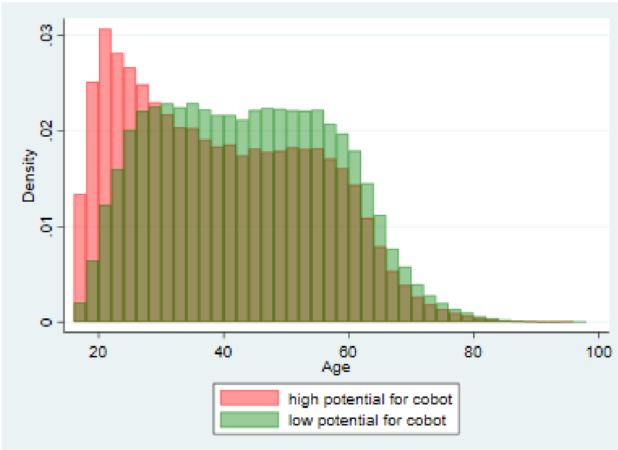
attainment, and economic characteristics like income. The rich information provided by the ACS data together with the constructed CAPI score allow us to analyze and understand the characteristics of people who are currently working in occupations with high cobot potential and with low cobot potential.

First, we consider the age distribution of workers in high- and low-cobot potential occupations. Figure 5, panel (a) shows the age distributions for those who are in occupations with a CAPI that indicates high or low potential of cobot adoption.[6] Among those in occupations with high CAPIs, the age distribution shows much younger average and modal ages (in red) compared to those in occupations with low CAPIs (in green). A young workforce is promising for the ability and willingness of workers to adapt to new technology, since investment in human capital is more intense for an individual with more potential working years ahead. We also consider the income level of workers in these occupations. The graph in panel (b) shows, more strikingly, that the total annual income among those in high-cobot potential jobs have lower annual income on average. Income levels may be of interest when considering the financial trade-offs of adopting cobots.

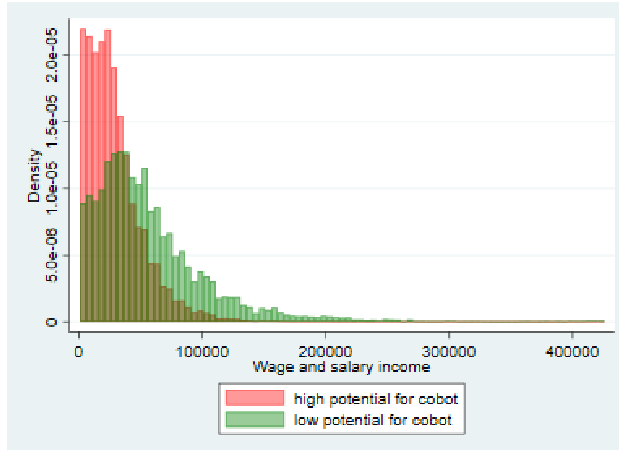
Next, we analyze demographic factors using the full range of CAPI scores instead of a binary measure. In the set of graphs in Figure 7, each point represents, for all occupations with a given small range of CAPI score around that point, the average level of the variable

[6]ACS individual-level personal weights are used in the summary table and all the following graphs.

Figure 5: Graph by Group



(a) age



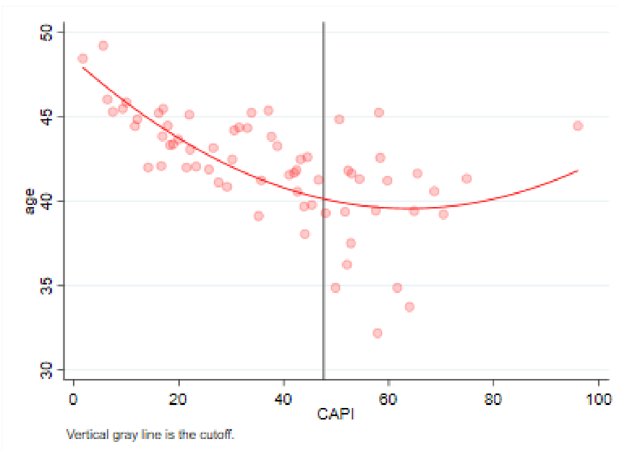
(b) income

being measured. In panel (a), we see the average age of workers in occupation by CAPI score, where for occupations with CAPI scores that would be considered high, the average age is more dispersed and the trend is flatter. For occupations with low CAPI scores, the average age is not only higher overall, but also shows a less dispersed pattern with a clear trend downward as CAPI scores increase. Still, the lower overall age for occupations with higher CAPI scores suggests that workers will be at a stage of their careers where they can easily adjust their skills and adapt to new technologies.

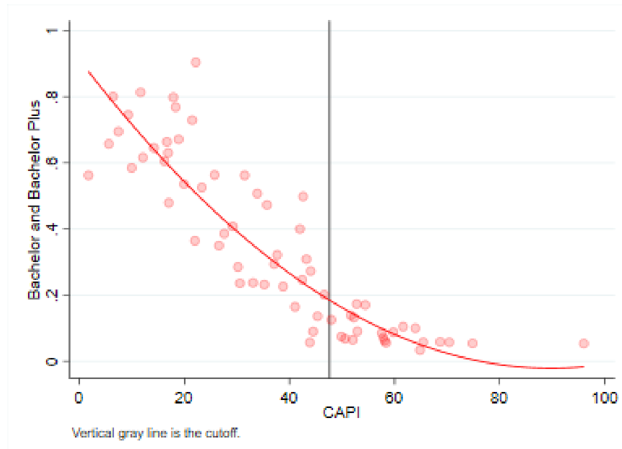
Another way of analyzing the adaptability to workers is by education level. Figure 7 (b) reports the average share of workers with at least a bachelor degree. The graph shows a more striking trend than age, with workers in high cobot potential occupations having lower education on average. In terms of implications, a workforce with lower education may need more investment in training to utilize cobots, particularly if the cobots require computer programming to adapt them to new environments.

Finally, we highlight a few other demographic characteristics that we can observe from the ACS data. Graph (c) plots the patters for average income. As we saw with the binary measure, workers in higher CAPI occupations also tend to receive lower wages. Graph (d) of Figure 7 shows the patterns for other demographic variables on percent married, percent female, and race. Occupations with CAPI scores that predict high potential for cobot adoption are made up of workers who are more likely to be Hispanic and less likely to be married.

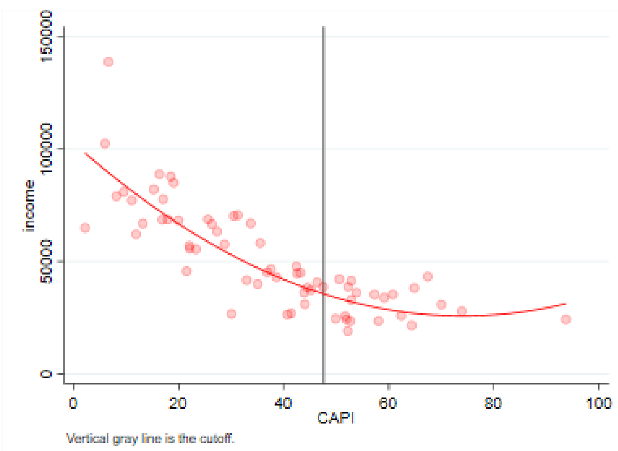
Figure 6: Relationships Between Demographics and Occupation CAPI Scores



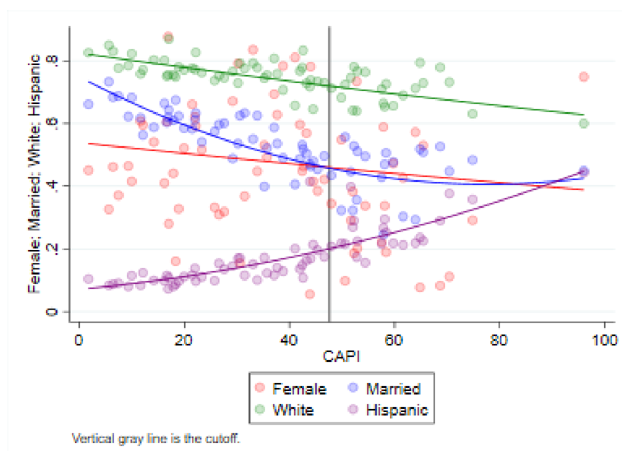
(a) age



(b) education (proportion of workers with bachelor and bachelor+ degree)

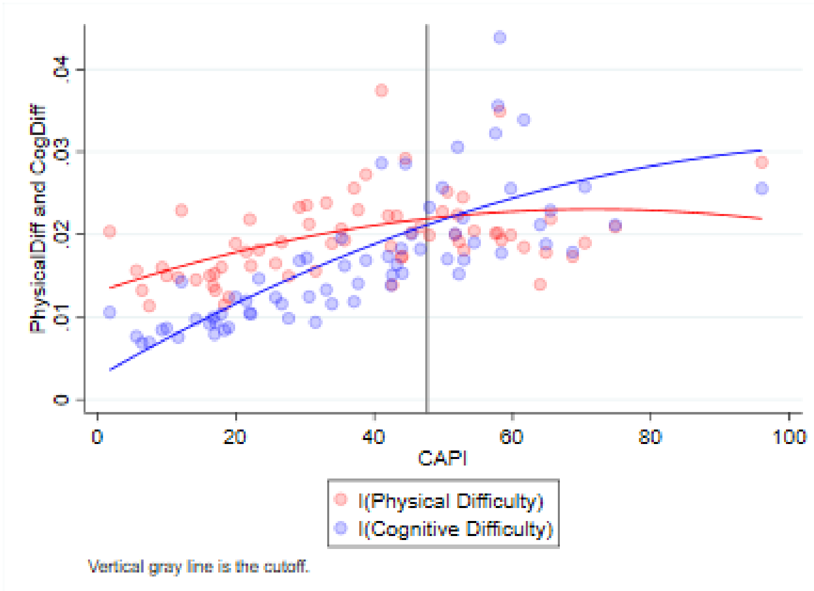


(c) income



(d) other demographic indicators

Figure 7: Relationships Between cognitive and physical difficulty and Occupation CAPI Scores



4.3 Physical assistance, Injury Rates, and Cobots

Finally, we use our index to analyze the potential for cobots to improve the physical work environment. Cobots have the potential to make physical tasks more ergonomic and safe for workers.[7] In this application, we focus on they types of workplace barriers workers might face as well as injury rates in the occupations with the highest potential for cobots.

Integration of cobots may allow some people to work longer; some with disabilities may have a wider range of occupations they are able to perform. Reduction of potential injury rates very attractive to both prospective workers and firms. Using the ACS data, Figure 7 shows that workers in occupations with higher CAPI scores are more likely to have cognitive difficulties and somewhat more likely to have physical difficulties. Cobots have the capacity to ameliorate some of these physical difficulties.

Next we connect occupation CAPI scores to data on injury and exertion by occupation with the Injuries, Illnesses, and Fatalities (IIF) 2020 data from the Bureau of Labor Statistics (BLS). The adoption of cobots has the potential to reduce net injury and strain. As we show, occupations with high CAPI scores—being more physically involved—have on average higher total injury incidence rates. Cobots have the potential to improve workplace safety

[7]For instance, using data from the US and Germany, Gihleb et al. [2022] find that the introduction of robots reduced the physical intensity and injury rates of workers exposed to industrial robots in their workplaces.

and reduce the rate of workplace injury. All the following analyses use the injury incidence rate as the measurement for injury-related questions.

The relationship between occupational CAPI scores and various incidence rates per 10,000 workers is shown in the graphs in Figure 8 and in Table 11. Looking first at Figure 8, we see that in the top green trend lines in panels (a) and (b), the total injury and total average overexertion rates increase as CAPI score increases. In these same graphs, sub-categories show a similar, though muted, pattern. In panel (c), we see a weak relationship between CAPI and injury through exposure to harmful substances or environments in the blue trend line, with a positive relationship between CAPI scores and injury by contact with objects or equipment. Finally, panel (d) shows a weak relationship between inpatient hospitalization and CAPI scores (in red), but strong relationships between emergency room visits and CAPI scores, as well as total treatments at medical facilities and CAPIs.

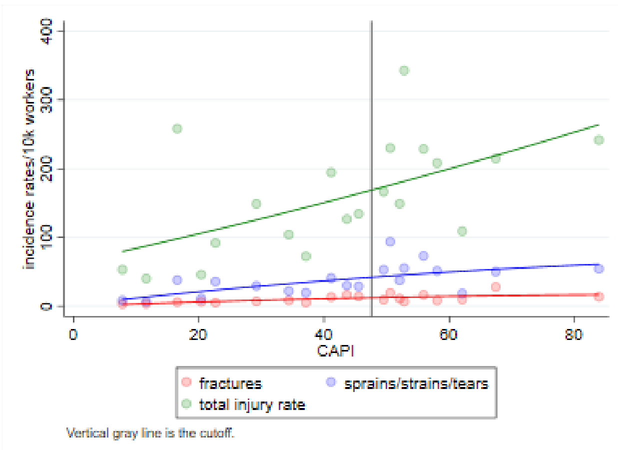
Table 11 in the Appendix tabulates the summary for the same data where occupations are grouped as having either high or low cobot adoption potential. Here too we can see that occupations with high cobot adoption potential have significantly higher rates of injury, with the total injury incidence rate per 10,000 workers being 102.8 for workers in occupations with low CAPI scores and 188.7 for workers in occupations with high CAPI scores. In all injury-related aspects, as well as medical treatment facility visits, the average incidence rate is significantly higher for occupations with high cobot potential. This is relevant because, on net, cobots have the potential to reduce injuries if integrated strategically, which is highly valuable for all parties.

5 Discussion and Conclusion

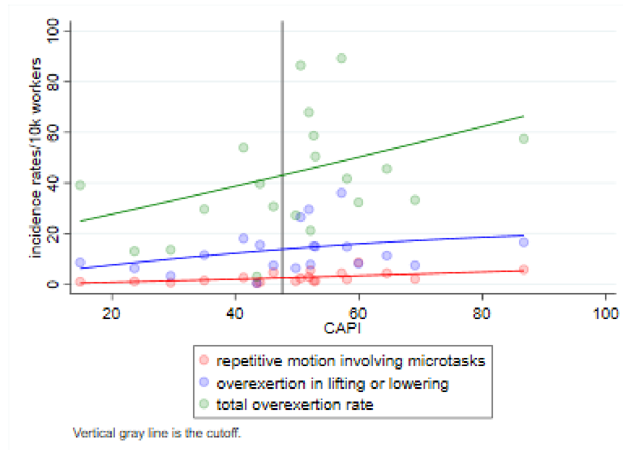
Cobots are an expanding type of automation technology that require more collaboration from workers than prior types of automation. Best practices for the adoption and uses of cobots are still being determined. In this paper, we create a simple index that can be used to analyze the potential for cobot adoption in multiple areas. The CAPI is constructed using detailed information on the tasks that cobots perform. We show how the index can be easily applied to understand where cobots might be adopted geographically, how easily workers may adapt to cobots, and their potential to improve workplace safety.

We make several contributions to prior research and for managers evaluating the benefits of cobot integration. Despite growing evidence of the benefits of cobot in production, barriers to adoption remain, and the adoption of new technologies will also consider external factors and competitive pressure. We show how the CAPI can be used to analyze geographic markets where cobots are most likely to be adopted, and that these are also the markets where

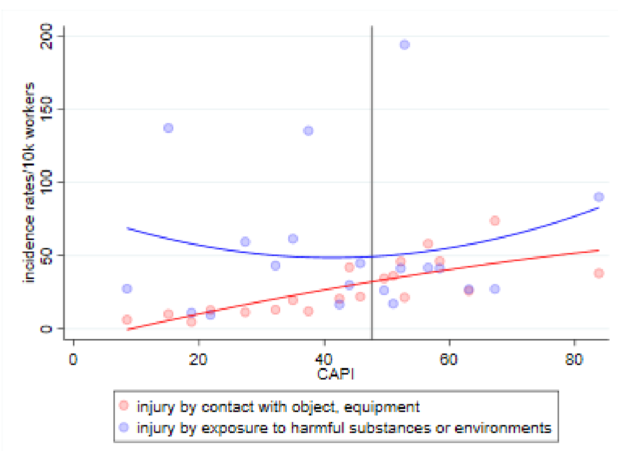
Figure 8: How injuries are correlated with CAPI



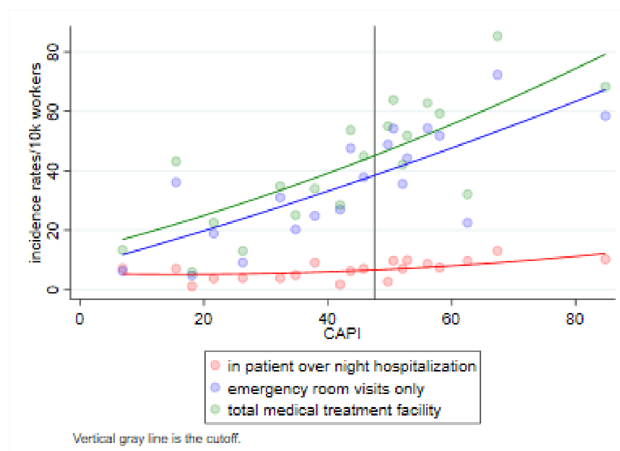
(a) total injury rate



(b) total overexertion rate



(c) other injury



(d) total medical treatment

business pressure is most likely to affect cobot adoption. In particular, we highlight the large potential for expansion in the Western part of the United States. Managers need to also consider how cobots will integrate with their current workforce. We show how CAPI can be used to address these issues. The first is that cobots have the ability to improve workplace safety. Secondly, the education profile of workers in occupations where cobots are used suggests that additional investment in training may be required for firms to most effectively utilize this new technology. A clearer understanding of the benefits and potential barriers of cobots can help mangers move forward confidently with adoption.

While this study highlights opportunities given the capabilities of cobots, it is limited in that information on the costs of cobots relative to local labor market conditions would be necessary to determine if cobot adoption is beneficial. In that sense, CAPI, in focusing on potential, is an upper bound on ultimate adoption. At the same time, the CAPI is particular to current cobot capabilities, which could evolve and grow just as workplace integration moves forward.

Cobots offer a unique combination of automation and collaboration. The CAPI index has the capacity to streamline analysis for managers and other practitioners interested in evaluating the potential of cobots. Understanding the potential for implementation, cobots have the potential to complement workers in production across a large number of occupations and industries.

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A Appendix

A.1 Alternative Indices

Table 8: Different cobot indicies

version	data source	description
1	work context	$\sum$ physical measurements × repetitiveness
2	work context	$\sum$ physical measurements + repetitiveness
3	work context	$\sum$ physical measurements + repetitiveness - $\sum$ interpersonal skill measurements
4	work context	$\sum$ physical measurements + repetitiveness - $\sum$ interpersonal skill measurements - physical proximity + auto-influence)
5	work context	$\sum$ physical measurements + repetitiveness - $\sum$ decision making freedom
6	work context	$\sum$ physical measurements + repetitiveness - $\sum$ interpersonal skills - $\sum$ decision making freedom
7	work context	$\sum$ physical measurements + repetitiveness - $\sum$ decision making freedom - physical proximity
8	work context	$\sum$ physical measurements + repetitiveness - $\sum$ decision making freedom + auto-influence
9	work context	$\sum$ physical measurements + repetitiveness - $\sum$ decision making freedom + auto-influence
10	work context	[$\sum$ physical measurements + repetitiveness - $\sum$ decision making freedom] × $\sum$ interpersonal skills
11	work context	[$\sum$ physical measurements + repetitiveness - $\sum$ decision making freedom] × auto-influence
12	work context	PCA(physical measurements) + repetitiveness - PCA(interpersonal skills) - PCA(decision making freedom) - physical proximity + auto-influence
13	work context	PCA (physical measurements) + repetitiveness - PCA(interpersonal skills) - PCA(decision making freedom)

14	work context	PCA(physical measurements) + repetitiveness - PCA(interpersonal skills)
15	work context	PCA(physical measurements) + repetitiveness - PCA(decision making freedom)
16	work activities	$\sum$ physical measurements - $\sum$ Interaction with people - $\sum$ decision making
17	work activities	PCA(physical measurements) - PCA(Interaction with people) - PCA(decision making)

Notes: Other versions using mean instead of sum have also been tested, while the precision rate is no higher than 87
'*mean*' version is listed in the Table 10 in Appendix.

Notes: PCA standards for principle component analysis.

A.2 Precision Rates of Candidate Indices Across Thresholds

Table 9: Precision rate of all the indices conditional on different thresholds

			precision rate | threshold=x^{th} quantile										
version	data source	$\cdots$	60^{th}	62^{th}	64^{th}	66^{th}	68^{th}	70^{th}	72^{th}	74^{th}	76^{th}	78^{th}	80^{th}	$\cdots$
1	work context		0.750	0.813	0.813	0.813	0.813	0.813	0.813	0.750	0.688	0.688	0.688	
2	work context		0.750	0.688	0.750	0.750	0.750	0.750	0.750	0.813	0.813	0.813	0.750	
3	work context		0.625	0.625	0.688	0.625	0.688	0.688	0.688	0.625	0.563	0.625	0.500	
4	work context		0.563	0.563	0.563	0.563	0.688	0.688	0.625	0.625	0.688	0.625	0.563	
5	work context		0.750	0.813	0.813	0.813	0.813	0.875	0.813	0.688	0.625	0.500	0.500	
6	work context		0.625	0.625	0.688	0.625	0.563	0.625	0.625	0.688	0.625	0.563	0.500	
7	work context		0.750	0.750	0.813	0.813	0.813	0.750	0.750	0.750	0.688	0.688	0.500	
8	work context		0.750	0.750	0.750	0.813	0.750	0.750	0.750	0.688	0.688	0.688	0.563	
9	work context		0.750	0.813	0.813	0.813	0.813	0.813	0.813	0.688	0.625	0.500	0.500	
10	work context		0.688	0.688	0.688	0.750	0.750	0.688	0.688	0.688	0.625	0.625	0.500	
11	work context		0.750	0.813	0.750	0.813	0.813	0.813	0.813	0.750	0.750	0.625	0.563	
12	work context		0.688	0.688	0.688	0.688	0.688	0.688	0.688	0.688	0.688	0.688	0.688	
13	work context		0.625	0.625	0.688	0.688	0.688	0.750	0.750	0.750	0.688	0.688	0.750	
14	work context		0.625	0.625	0.688	0.688	0.750	0.750	0.750	0.750	0.813	0.813	0.688	
15	work context		0.688	0.750	0.750	0.750	0.750	0.750	0.750	0.750	0.813	0.813	0.813	
16	work activities		0.688	0.688	0.625	0.563	0.563	0.563	0.563	0.563	0.500	0.500	0.500	
17	work activities		0.688	0.688	0.688	0.688	0.688	0.625	0.625	0.563	0.625	0.563	0.625	

A.3 Other Versions of Indices

More measurements do not necessarily mean more information, and can sometimes introduce too much noise into the calculation or provide redundant information. Other than using the sum of the measurements as the measure for each dimension, we considered other versions such as simple averages or using the principle component analysis to reduce the dimension and to construct the components which can expressing the maximum information from the original measurements to improve the quality of the information.

Principle Component Analysis. Using the Kaiser-Guttman criterion, we only keep those components whose eigenvalues are above 1.0 and believe that these components can capture considerable amount of information in the data. Take the *interpersonal skill* dimension for example. Under this dimension there are ten measurements and principal component analysis reveals that only the first three components are with eigenvalues greater than 1.0. By the rule of thumb, we only keep those three components and therefore the dimension for interpersonal skill measurements decreases from ten to three. Inside Table 8, PCA(physical measurements) is then calculated in the following way.

$$\text{PCA(physical measurements)} = \textit{component}1 + \textit{component}2 + \textit{component}3 \tag{8}$$

The same logic applies to other principle component analysis listed in the table.

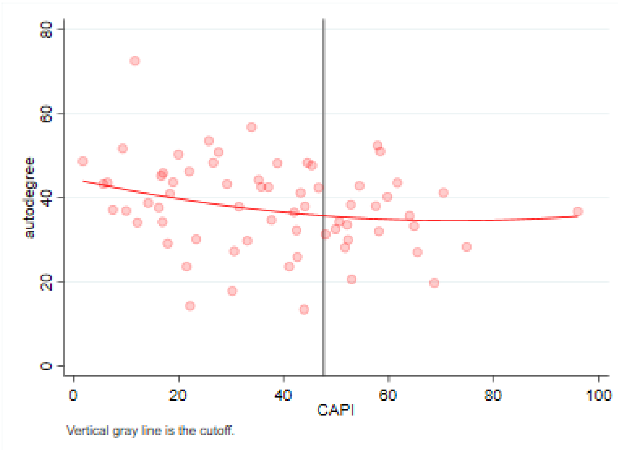
Using the mean instead of the sum to construct the CAPI. Comparing with all the '*sum*' versions listed in Table 8, the '*mean*' versions' precision rates are no higher than 87.5%. It is found that *Index5* consistently provides the best results, though the threshold is at the 80th quantile under this '*mean*' version. For worries that if the threshold of dividing the whole population into high and low cobot potential group is too high(or too low), we may have fewer information for the high potential group(or low potential group). We have preference for the threshold to be somewhere near the middle. Therefore, we keep using '*sum*' version with *Index5* and 70th quantile as the threshold to construct our CAPI in later analysis.

Table 10: Using the mean instead of the sum, precision rate of all the indices conditional on different thresholds

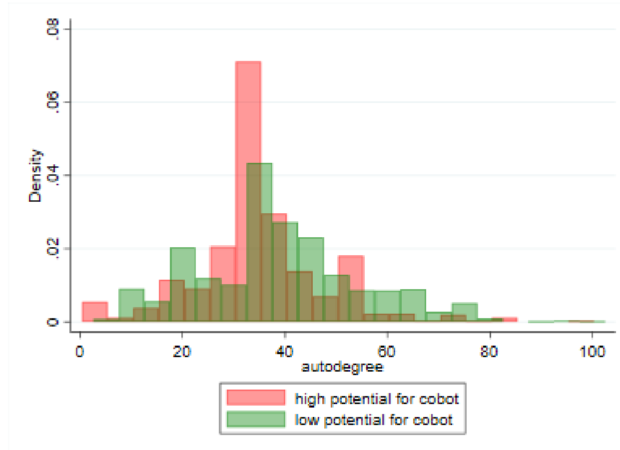
		precision rate | threshold=x^{th} quantile											
version	data source	⋯	60^{th}	62^{th}	64^{th}	66^{th}	68^{th}	70^{th}	72^{th}	74^{th}	76^{th}	78^{th}	80^{th}	⋯
1	work context		0.750	0.813	0.813	0.813	0.813	0.813	0.813	0.750	0.688	0.688	0.688	
2	work context		0.750	0.750	0.750	0.750	0.750	0.813	0.813	0.813	0.813	0.750	0.750	
3	work context		0.688	0.688	0.688	0.688	0.625	0.625	0.625	0.688	0.625	0.688	0.750	
4	work context		0.625	0.625	0.625	0.625	0.563	0.563	0.563	0.563	0.563	0.688	0.688	
5	work context		0.688	0.688	0.688	0.688	0.750	0.813	0.813	0.813	0.813	0.813	0.875	
6	work context		0.625	0.625	0.625	0.625	0.625	0.625	0.625	0.688	0.625	0.563	0.625	
7	work context		0.688	0.688	0.750	0.750	0.750	0.750	0.750	0.813	0.813	0.813	0.750	
8	work context		0.688	0.688	0.688	0.750	0.750	0.750	0.750	0.813	0.813	0.750	0.750	
9	work context		0.688	0.688	0.688	0.688	0.750	0.750	0.813	0.813	0.813	0.813	0.813	
10	work context		0.625	0.625	0.625	0.688	0.688	0.688	0.688	0.750	0.750	0.688	0.688	
11	work context		0.750	0.750	0.750	0.750	0.750	0.813	0.750	0.750	0.813	0.813	0.813	
12	work context		0.688	0.688	0.688	0.688	0.688	0.750	0.688	0.688	0.688	0.688	0.688	
13	work context		0.688	0.688	0.688	0.750	0.750	0.750	0.688	0.688	0.688	0.750	0.688	
14	work context		0.688	0.688	0.750	0.750	0.750	0.750	0.750	0.813	0.750	0.688	0.625	
15	work context		0.750	0.750	0.750	0.750	0.750	0.750	0.813	0.813	0.813	0.813	0.813	
16	work activities		0.625	0.563	0.563	0.563	0.563	0.563	0.500	0.500	0.500	0.500	0.500	
17	work activities		0.688	0.688	0.625	0.625	0.625	0.563	0.625	0.625	0.563	0.563	0.500	

B Correlation between CAPI and Autodegree

Auto-degree



(a) auto degree



(b) auto degree by cobot compatible group

Figure 9: Auto degree

Table 11: Summary statistics in occupations based on CAPI group

compatible with cobot	low potential	high potential	Total
Demographics			
age	43.2	38.8	41.9
annual wage and salary income($)	58,544	29,703	49,576
female	0.50	0.43	0.48
married	0.57	0.41	0.52
white	0.76	0.69	0.74
Hispanic	0.14	0.25	0.17
high school degree	0.96	0.84	0.92
some collage	0.70	0.36	0.59
bachelor plus	0.45	0.10	0.34
ambulatory difficulty	0.02	0.02	0.02
cognitive difficulties	0.01	0.03	0.02
Injury related aspects*			
total injury rate	102.8	188.7	132.2
sprains/strains/tears	28.1	45.3	34.7
fractures	9.1	12.7	10.5
total injury rate for overexertion and body reaction	23.5	45.8	31.8
overexertion in lifting or lower	10.2	14.5	12.1
repetitive motion involving microtasks	1.6	3.6	2.5
other affiliated injuries			
contact with object, equipment	17.1	42.4	27.6
exposure to harmful substances or environments	45.1	60.3	50.4
Medical treatment facility visits**			
total medical treatment facility	27.7	52.5	36.6
emergency room visits only	24.6	45.2	32.2
inpatient/overnight hospitalization	5.5	8.3	6.6

* Incidence rates of nonfatal occupational injuries and illnesses involving days away from work by occupation and medical treatment facility visits, all U.S., private industry, 2020. *Source: Bureau of Labor Statistics*

** Incidence rates for nonfatal occupational injuries and illnesses involving days away from work per 10,000 full-time workers by occupation and selected nature of injury or illness, private industry, 2020. *Source: Bureau of Labor Statistics*