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Displaced or Augmented? How does Artificial Intelligence Affect Our Jobs: Evidence from LinkedIn

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Displaced or Augmented? How does Artificial Intelligence Affect Our Jobs: Evidence from LinkedIn

Short Paper

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Abstract

With the rapid advances of artificial intelligence (AI), increasingly more job tasks can be automated. Despite the AI hype, we know little about the extent to which AI may destroy or augment the career of different occupations of professionals. Although most existing literature focused on creating AI automation scores for each occupation, AI may automate non-critical tasks for many occupations which indirectly increases the productivity and value creation of jobs. Therefore, we develop a novel method to estimate the AI automation scores for core and supplemental work activities of all major occupations and analyze how employees' human capital characteristics may lead to different results: being augmented or displaced by AI. Particularly, skills accumulated from prior work experiences and excellent educational background can reduce the automation risks. Additionally, professionals with major in computing, law, and medicine are more likely to be augmented since only their supplemental work activities may be automated.

Keywords: Artificial intelligence, intelligence augmentation, job automation, human capital

Introduction

The last two decades have witnessed the rapid advances in artificial intelligence (AI), machine learning (ML), and mobile robotics. According to Garner, the world's leading research and advisory company, the global business value derived from AI is projected to total $1.2 trillion, an increase of 70 percent from 2017. Therefore, there has been a keen interest among academics and practitioners in understanding the impact of AI on all aspects of our society and life, especially on the labor markets. This may be because AI increasingly shifts the frontier between the job tasks performed by humans and those performed by machines and algorithms; thus, labor markets are undergoing dramatic transformations. On one hand, the recent declines in wage and employment in the United States (U.S.) and the decrease of middle-skill occupations are typical evidence for the claims that advanced digital technologies, robotics and AI will make labor redundant (Acemoglu and Restrepo 2018; Brynjolfsson and McAfee 2014; David and Dorn 2013). On the other hand, AI can serve as a platform to create new job tasks and new employment opportunities, which provides a powerful countervailing force that increase the labor demand (Acemoglu and Restrepo 2018). For instance, Garner estimates that AI technologies are expected to create 2.3 million jobs and eliminate 1.8 million, leading to a net positive job creation. Notwithstanding these concerns and expectations, we are far from a comprehensive understanding of the extent to which specific work activities (WAs) are affected by AI automation and the key antecedents of the job automation risk at the individual level. Even worse, there is a notable dearth of empirical research on these issues.

In this paper, we build on Frey and Osborne (2017) to develop a more nuanced understanding of how automation in AI impact the WAs that belong to each different occupations. Further, motivated by gaps in extant literature on jobs augmented by AI, we aim at identifying jobs that may be augmented by AI, defined as jobs with only supplemental work activities being automated by AI. This is because augmentation intelligence enables people to accomplish core job tasks more efficiently and accurately and substitute for some trivial and routine tasks using advanced computer algorithms (Chui and Francisco 2017). For instance, some lawyers have used sophisticated algorithms and system to identify and preprocess the relevant legal documents, which can save a lot of time (Markoff 2011). In addition, this study plans to investigate how individual characteristics may affect the susceptibility to AI automation risk by utilizing both Occupation Information Network (O*NET) data and LinkedIn profile data.

Using O*NET dataset, we start with a novel ML-based method for constructing AI automation score at the WA level and then aggregate WA-level scores to the occupational level. A critical difference of our method is that we do not hand-label the AI automation scores at the occupation level (Frey and Osborne 2017). Instead, we estimate the AI automation risk from more fine-grained O*Net data including abilities, skills, interests, work styles, and work context. We try to code at the more granular level based on the literature to minimize the amount of subjective coding. Furthermore, we compute AI automation scores of two types of work activities: core and supplemental WAs categorized by O*NET. This is because AI cannot fully automate all work activities of most occupations and AI usually substitutes for specific tasks. Moreover, augmentation intelligence have the potential to improve work productivity since it enables people to focus on higher-level job tasks by automating some tedious and routine tasks (Chui and Francisco 2017). Consequently, at the heart of our study is the idea that if a job's core WAs are replaced by AI, then that job may be completely destroyed by AI whereas if only supplemental WAs are replaced by AI, the employee can become more productive in core WAs, and thus benefiting from AI advances. In this way, we are able to identify occupations which may be augmented by AI, and thus enhancing current understanding of impacts of AI automation in workforce. Additionally, drawing upon human capital theory, we construct and highlight several key individual characteristics from our rich datasets, which may determine whether the person will be replaced by or augmented from AI. In particular, we analyzed the effects of individuals' demographic information such as gender and race, education background, the prior work experience and the different skills accumulated from the prior work experiences. Our preliminary results suggest that the social skill, nonroutine analytical skill, artistic skill, and IT skill accumulated from prior wok experience, educational background such as the highest educational degree, the ranking of the university, and the major (in science, computing, law, and medicine) can correlate with working with jobs that are less likely to be replaced by AI in the near future. More interestingly, professionals with social skill, artistic skill and IT skill accumulated from prior work experience tend to have higher probability of being augmented by AI. In addition, employees with majors in computing, law, and medicine are more likely to be augmented by AI advances.

To the best of our knowledge, our paper is the first study to perform a detailed analysis on how likely an individual's specific job roles may be augmented or destroyed by AI. By merging LinkedIn and O*NET, we also extensively examine the factors that may correlate with working in occupations with higher AI automation risk. This stream of research is of great importance because people are concerned about whether they may become unemployed due to AI advances. By taking a more granular approach, our study not only offers an interesting lens for the study of AI automation in labor markets by distinguishing the core and supplemental WAs, but also espouses a better understanding of jobs that may be augmented by AI, which has been neglected by extant studies. More importantly, we identify several key characteristics which may determine whether a person will be destroyed or augmented by AI advances drawing upon human capital theory. In this way, our study can add new insights to the body of knowledge on AI automation and intelligence augmentations, as well as provide crucial practical implications for the job candidates and employers in the labor markets.

The remaining of the paper is organized as follows. First, we explain the data context and then review the works related to our study. Next, we present the details of our measures and empirical model. Then, we report and analyze our empirical results. Finally, the conclusions and future work are discussed.

Data

In this paper, we employ two sources of data: O*NET and LinkedIn.com. Following the recent literature on labor market (Arntz et al. 2017; Deming 2017), we gather data available from O*NET version 23.1. O*NET is a publicly available dataset collected by a survey administered by the U.S. Department of Labor. O*NET documented a comprehensive list of occupations and by survey workers in that occupation, O*NET provides detailed occupation-level characteristics including abilities, skills, knowledge, interests, work styles, and work contexts. In this paper, we use two terms "occupation" and "jobs" interchangeably and it is the key variable in O*NET. O*NET also provides a hierarchical structure to decompose each occupation into 3 different levels: generalized work activities (WA), detailed work activities (DWA), and tasks required in all major occupations. In O*NET, a large number of occupations shared the 41 WAs, 2,070 DWAs, and 19,387 job tasks. Since there are 1,110 O*NET occupations, most WAs are shared by many occupations whereas DWAs and tasks are more specific to each occupation. We will construct the AI automation score at the WA-level in this study. For most of the variables described earlier, O*NET disclose two different ratings: the "importance" and the "level" scores of each job characteristic (e.g., skills or WAs) for each occupation. The "importance" scale indicates the degree of importance a particular characteristic is to the occupation while the "level" scale represents the knowledge level to which a characteristic is required to perform the occupation. For example, bank teller may require a lot of human communication (high importance) but the level of communication is easier than the level of communication for CEO. In our study, we employ both scales when constructing AI automation scores.

The O*NET data is essentially an occupation-level dataset, which cannot be utilized to answer individual-level research questions. Therefore, we collected millions of resumes of U.S. workers from LinkedIn. After we process the raw profile data, the useful information includes employment experience (such as the employer of each job, job title, starting and ending year, industry, total work experience, tenure, etc.), education background (such as university, degree, major, and start/end year of each degree), as well as connections to other members of the network. Next, we match LinkedIn's self-reported job titles with those in O*NET based on job title's similarity calculated from Google Word2Vec (Mikolov et al. 2013) and GloVe pre-trained model (Pennington et al. 2014). In this way, we can merge LinkedIn work experience with O*NET to construct variables based on the current and prior work experiences. Finally, we select a sample of workers whose prior job titles can be mapped to O*NET, and compile the cross-sectional dataset which comprises around 461,270 users in 2013.

Literature Review

AI advances are poised to generate dramatic economic value and transform numerous occupations and industries. Accordingly, many researchers focus on economic models or the speculative forecasts about the potential influence of AI. For instance, Aghion et al. (2017) speculate on how AI affect economic growth by modeling AI as the latest automation of the production of goods and services. Further, Acemoglu and Restrepo (2018) develop a more nuanced conceptual framework to study how machines replace human labor and why this might or might not lead to lower employment and stagnant wages in a task-based model. These studies provide a significant insight in the impact of AI; however, there is a paucity of additional empirical evidence. This is consistent with the paradox stressed by Brynjolfsson et al. (2018b): "we see transformative new technologies everywhere but in the productivity statistics". Fortunately, our research aims at providing empirical evidence on the effects of AI on the workforce.

Our paper draws upon literature on the susceptibility of specific job tasks to the rapid technological advances. A key insight from Autor et al. (2003) is that an occupation can be viewed as a bundle of tasks, and these tasks can be classified into routine versus nonroutine tasks, and manual versus cognitive tasks. Different types of job tasks can be automated to different degrees by current technologies. To date, the range of job tasks that can be automated are expanding rapidly from automated financial tax preparation and personalized financial advice generation to legal document preprocessing to cancer diagnosis and treatment (Brynjolfsson and McAfee 2014; Frey and Osborne 2017; Markoff 2011; Remus and Levy 2017). In order to understand which type of tasks are susceptible to ML, Brynjolfsson and Mitchell (2017) establish eight key criteria that help classify tasks which have high suitability for ML. For instance, most suitable tasks for ML do not require for specialized dexterity, physical skills, or mobility and the long chains of reasoning or explanations. Those demanding flexibility, judgment, creativity, and common sense that we understand only tacitly are most vexing to automate (David 2015). This is because human values could change over time and vary across circumstances, making it challenging to be represented clearly in programmed rules (Boden 2004; Frey and Osborne 2017). Apart from these, it is vexing for AI to displace the social interaction tasks because it involves team cooperation, with workers taking advantage of each other's strengths and adapting flexibly to turbulent circumstances (Deming 2017).

There exist three closely related papers that analyze similar research questions. As a pioneering study, Frey and Osborne (2017) manually coded 70 O*Net occupations as a binary variable indicating whether a job will be automated by current technologies or not. Next, they applied a supervised learning method (Gaussian process classifier) to estimate the probability of automation for all 702 detailed occupations listed in O*NET. They use nine O*NET variables as the predictors, including finger dexterity, originality, fine arts, negotiation, persuasion, etc. They conclude that 47% of US jobs are at high risk of being automated, including the book-keepers, cashiers, clerks, or even the taxi and bus drivers, without considering the complementarity between AI and human labors in that AI may replace only different proportions of tasks of occupations to different degree. To address this concern, Arntz et al. (2017) replicated and re-estimated the automation probability of occupations. They first estimate the effects of job and worker characteristics on occupation-specific automation risk obtained from Frey and Osborne (2017) and then predict the automation potentials for each individual job using OECD skills survey data. In other words, they do not directly construct the automation risk at task level. Accordingly, they found that the automation risk of US jobs drops to 9% when allowing for workplace heterogeneity. Consistent with Arntz et al. (2017), Brynjolfsson et al. (2018a) show that tasks within jobs exhibit considerable variability in suitability for ML and few jobs can be fully automated using ML. In particular, Brynjolfsson et al. (2018a) explore which detailed work activities (DWAs) will be most affected by ML and which will be relatively unaffected. Using O*NET data for 964 occupations and 2,069 DWAs shared across occupations, they rate each DWA for its suitability for ML by human coders from a crowdsourcing platform. Next, the DWA-level scores are aggregated back to the occupation level by weights provided in O*NET.

Our paper is different from the literature in the following ways. When compared with related works in the labor economics literature, our paper is different in that the dependent variable in labor economics is usually wage, level of analysis is at occupation-level or individual-level, and the key independent variable is one or more focal skills. In this study, the dependent variable is the AI automation risk and the level of analysis is at individual level. Our independent variable includes a comprehensive list of variables including skills and other variables constructed by literature. When compared with those three relevant recent papers, our study has three important differences. First, we attempt to estimate AI scores at the core and supplemental WA level so that we can identify occupations that may be augmented by AI. Second, although those three studies highlight the importance of tasks and DWAs in predicting the automation risk of occupation, they ignore the other sets of job characteristics including abilities, skills, work styles, and work context required in occupations. Consistent with the labor economics literature that study the effects of automation by Autor et al. (2003), we code the effects of ML algorithms at the skills level, not the occupation, DWA, or task level. In other words, rather than labeling or scoring the DWAs and occupation directly, we consider the more fine-grained elements required by occupations closely following the literature. Third, by LinkedIn dataset, our study can analyze a larger set of individual characteristics that may affect the susceptibility of being displaced or augmented by AI.

Measures

Dependent variables. Our analysis is conducted at the individual level and the dependent variables include various cases of the AI automation scores of the current job title of each individual. We construct three AI automation scores at the occupation level (*AI_all*), the core WAs level (*AI_core*), and the supplemental WAs (*AI_noncore*) level, separately. Specifically, we firstly code the AI automation scores on different O*NET skillset elements (e.g. abilities, skills, interests, work styles, and work context) of the occupation on a 5-point scale from "very likely to be replaced by AI given the current technology" to "can never been replaced by AI in the next decade" closely following the guidelines in the literature (Autor et al.

2003; Brynjolfsson and Mitchell 2017; Brynjolfsson et al. 2018a; Deming and Kahn 2018; Frey and Osborne 2017). For instance, we code the elements of "originality", "innovation", "persuasion", "negotiation", and "social perceptiveness" as those skills that may not be replaced by AI in the next decade. This is because these elements are relevant with creative intelligence and social skill, which are difficult to be automated by current technologies (Deming 2017; Frey and Osborne 2017). For another example, we code the elements of "static strength", "operation monitoring", and "spending time making repetitive motions" as those elements that are very likely to be replaced by AI given the current technology. This is because these elements are more relevant with routine tasks which can be completed by advanced machines or algorithms following explicit programmed rules (Autor et al. 2003; Frey and Osborne 2017). For each coding task, two researchers participate in coding separately and if the results are inconsistent, then the third researcher will join in the coding. Finally, we take the average of these rating scores. At the same time, we employ a simple neural network method to learn a weight matrix between detailed skillset elements and WA. Specifically, use a neural network without hidden layer and with the constraint of non-negative weights to learn weights for skill elements. This is because WA-level weights for abilities or skills are not available in the original O*NET dataset while weights are given only at the occupation level. Given the estimated WA-level weights for the detailed elements such as abilities, skills, interest, work context, and work style, we multiply by the hand-labelled AI automation scores at the detailed elements level, and thus obtaining the WA-level AI automation score. The WA-level AI automation scores are normalized to 0 to 1. For example, results show that the WA of "handling and moving objects" has high probability of being automated. On the contrary, the examples of the WAs that are less likely to be automated include "thinking creatively" and "establishing and maintaining interpersonal relationships". Next, given the importance and level score of each WA on occupations disclosed in O*NET data, we compute an AI automation score for each occupation (denoted by *AI_all*) by aggregating the WA-level AI scores. In addition, O*NET classifies the tasks into the core and supplemental tasks within an occupation and job tasks can be directly linked to WAs. Consequently, we are able to classify the WAs into core and supplemental WAs and construct the AI automation scores at the core WA level (*AI_core*) and the supplemental WAs (*AI_noncore*) level, respectively.

Independent variables. First, we construct individual's various skills accumulated from their prior work experiences. Specifically, we focus on the social skill (*Social*), the nonroutine analytical skill (*Analytical*), the artistic skill (*Artistic*), and the IT skill (*IT*). We followed Autor et al. (2003) and Deming (2017) and calculate the skill intensity of each occupation utilizing O*NET data. For example, the social skill intensity of an occupation is defined as the average of the following four items in the O*NET data on "social skills": coordination, negotiation, persuasion, and social perceptiveness (Deming 2017). The measure for nonroutine analytical skill intensity is the average of three O*NET variables that capture an occupation's mathematical reasoning requirements: the mathematical reasoning ability, the mathematics ability and skill (Autor et al. 2003). Then we define an occupation's artistic skill intensity as the knowledge of fine arts and the IT skill intensity was measured by the item of programming skill. Following the prior studies, we rely on the "level" rating and then normalize the skill intensity to 0 to 1. Given the specific skill intensity at the occupational level, we multiply by the total years of work experience for each prior occupation and then add the skill intensity accumulated from different occupations in the professionals' prior career path. In this way, we can measure individual's specific skill accumulated from their prior work experiences. Drawing on human capital theory, we construct other independent variables on individual's education background (degree, major, and the university ranking). Specifically, we consider a professional's highest degree by using three dummy variables (*Associate*, *Undergraduate* and *Graduate*). For the major types, we mainly analyze individuals from school of science (*Science*), engineering (*Engineer*), computing (*CS_IS*), business (*Business*), arts and design (*Arts*), social science (*Social_science*), law (*Law*), education (*Education*) and medicine (*Medicine*). Meanwhile, we use *QS_100* to capture whether the rank of university is within top 100 in a QS World University Rankings.

Control variables. At the individual level, we control for gender, race, the number of connections (*lnconnection*), the total years of prior work experiences (*Work_exp*), the total years of senior leadership work experience (*Leader_exp*), and the average turnover rates (*Turnover*). In particular, we construct individual's turnover experience based on Ge et al. (2016). Additionally, we construct "Erraticism" to investigate how the order of job histories affect worker's AI automation risk based on Leung (2014). Also, we control for the company size measured by the total number of employees (*Firm_size*), and industry dummies (*Industry*).

Empirical Model for Preliminary Analysis

To investigate the effects of individual characteristics on the AI automation risk, we specify a standard cross-sectional linear model of the following form:

$$Y_i = \beta_0 + \beta_1 Social_i + \beta_2 Analytical_i + \beta_3 Artistic_i + \beta_4 IT_i + \beta_5 Associate_i + \beta_6 Undergraduate_i + \beta_7 Graduate_i + \beta_8 QS\_100_i + \beta_9 Major\_type_i + \beta_{10} Controls_i + e_i \quad (1)$$

where Y_i are the AI automation scores at different levels (AI_all_i, AI_core_i, $AI\_noncore_i$). The higher the AI automation scores, the higher the probability of being replaced by AI for a specific occupation. $Social_i$ and $Analytical_i$ capture the accumulated social skill and nonroutine analytical skill obtained from prior occupations. Similarly, $Artistic_i$ and IT_i capture the accumulated artistic skill and IT skill accumulated from prior work experience. As for the educational degree, we mainly analyze three types of highest degree: the associate degree ($Associate_i$), the bachelor's degree ($Undergraduate_i$), the master or PhD's degree ($Graduate_i$). We use QS_100_i to capture whether the rank of university is within top 100 in a QS World University Rankings. In terms of the major types, we focus on individuals from school of science ($Science_i$), engineering ($Engineer_i$), computing (CS_IS_i), business ($Business_i$), arts and design ($Arts_i$), social science ($Social\_science_i$), law (Law_i), medicine ($Medicine_i$), and education ($Education_i$). $Controls_i$ is a set of control variables, including the individual's gender, race, and the order of his or her job history (*Erraticism*). Specifically, $Female_i$ is a dummy variable to denote whether a person is a female. In terms of race, we focus on the African American, the Hispanic, and Asian. $Erraticism_i$ was used to measure the average distance between different job titles individual has consecutively worked in their career path. Also, we control for individual's connections ($lnconnections_i$), years of prior work experiences ($Work\_exp_i$), average turnover rates ($Turnover_i$), the firm size ($Firm\_size_i$), and the industry dummies ($Industry_i$). β is the coefficients of interest; and e_i is the error term associated with each individual i.

Results of Preliminary Analyses

Table 1 presents the standard OLS regression results of equation (1). Four models are reported in this table. Dependent variable in the Model 1 is the AI automation score at the occupational level (*AI_all*). In Model 2, the dependent variable (*AI_core*) captures the susceptibility of AI automation at the core WA level, which is our main model. The dependent variable (*AI_noncore*) in Model 3 and 4 is AI automation score at the supplemental WA level. Model 3 includes all employees whose supplemental WAs that may be automated by AI. Model 4 includes only professionals whose *AI_core* falls within the top 25% percentile. In other words, the sample in Model 4 only includes the individuals who benefit from AI the most because their supplemental WAs are automated by AI while their core WA are less likely to be automated by AI. This is because we are interested in characterizing the main beneficiaries of AI technologies in the labor market. In Table 1, most of the results are consistent in different models. Specifically, all models suggest that individuals with high social skill and nonroutine analytical skills accumulated from prior work experience are less likely to be displaced by AI at the occupational level, core WA level, and supplemental WA level. Meanwhile, Models 1 and 2 suggest that employees' artistic and IT skills can alleviate the concerns of being automated at the occupational level and core WA level. However, further sub-sample analysis from Model 4 reveals that employees with higher level of social, artistic and IT skill accumulated from prior work experience are more likely to be augmented by AI.

As for the education background, Model 4 suggests that the professionals who have a master or PhD degree are more likely to be augmented by AI automation. Moreover, if the professionals come from the university that ranks at top of QS 100, then they have lower probability of being replaced. More interestingly, we consider the effects from the education major. We take the major of "social science" as the benchmark major. It can be seen from Model 2 that compared with the major of social science, professionals come from the school of science, computing, law, and medicine are significantly correlated with a low AI automation risk for their core WAs. Model 4 presents that compared to the majors in social science, employees who come from the school of computing, law, and medicine are more likely to be augmented by AI because only their supplemental WAs have higher probability of being replaced. These findings are consistent with the fact that advanced AI algorithms are successfully applied in legal document preprocessing and cancer diagnosis and treatment (Brynjolfsson and McAfee 2014; Frey and Osborne 2017).

In addition, compared with male workers, the female is correlated with higher AI automation risk (Model 1, 2, and 3) and lower probability of being augmented (Model 4). As for race, Models 1 and 2 show that the African American and the Hispanic have higher probability of being replaced by AI. On the contrary, the Asians are less likely to be replaced by AI. From Models 1 and 2, we can also infer that when individuals move erratically between very different job titles, they have higher probability of being replaced by AI automation at the occupational and core WA level. This is consistent with the findings in Leung (2014) arguing that employers prefer workers who move incrementally between similar jobs over those with highly erratic job histories. Differently, as shown in Model 4, employees who move erratically between different job titles exhibit a lower probability of being augmented by AI.

Also, we can observe that social connections and senior leadership experience are likely to significantly reduce the AI automation risk. To sum up, our results indicate that the different skills accumulated from prior wok experience, excellent educational background, and with a degree from the school of science, computing, law, and medicine can alleviate employees' risk that they may become unemployed due to AI advances. More interestingly, professionals' social, artistic and IT skill accumulated from prior work experience, and master or PhD degree are positively related to being augmented by AI advances. In addition, compared to major of social science, employees graduated from school of computing, law, and medicine are more likely to benefit from AI advances.

Table 1. Empirical Results

Variable	Model 1 *AI_all* Full sample	Model 2 *AI_core* Full sample	Model 3 *AI_noncore* Full sample	Model 4 *AI_noncore* Top 25% *AI_core*
Social	-0.0064***	-0.0035***	-0.0036***	0.0049***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Analytical	-0.0054***	-0.0053***	-0.0091***	-0.0109***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Artistic	-0.0010***	-0.0053***	0.0049***	0.0017***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
IT	-0.0027***	-0.0036***	0.0018***	0.0092***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Associate	0.0014***	0.0010*	0.0007	-0.0060***
	(0.0005)	(0.0006)	(0.0006)	(0.0014)
Undergraduate	-0.0162***	-0.0173***	-0.0156***	-0.0026**
	(0.0005)	(0.0005)	(0.0005)	(0.0011)
Graduate	-0.0302***	-0.0301***	-0.0236***	0.0026**
	(0.0005)	(0.0005)	(0.0005)	(0.0012)
QS_100	-0.0033***	-0.0022***	-0.0016***	-0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0004)
CS_IS	-0.0003	-0.0040***	0.0025***	0.0199***
	(0.0003)	(0.0003)	(0.0004)	(0.0006)
Science	-0.0051***	-0.0042***	-0.0049***	-0.0077***
	(0.0004)	(0.0004)	(0.0004)	(0.0006)
Engineer	0.0016***	0.0012***	-0.0021***	-0.0007
	(0.0003)	(0.0003)	(0.0003)	(0.0005)
Business	0.0003	0.0046***	-0.0055***	-0.0127***
	(0.0002)	(0.0003)	(0.0003)	(0.0004)
Arts	0.0050***	0.0051***	0.0083***	-0.0045***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Law	-0.0063***	-0.0070***	0.0224***	0.0593***
	(0.0003)	(0.0003)	(0.0004)	(0.0006)
Education	0.0093***	0.0004	-0.0099***	-0.0060***
	(0.0004)	(0.0004)	(0.0004)	(0.0007)
Medicine	0.0025***	-0.0061***	0.0111***	0.0198***

	(0.0003)	(0.0004)	(0.0004)	(0.0007)
Erraticism	0.0065***	0.0187***	0.0034***	-0.0241***
	(0.0006)	(0.0006)	(0.0007)	(0.0011)
Female	0.0059***	0.0058***	0.0044***	-0.0021***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)
African American	0.0017**	0.0025***	-0.0010	-0.0004
	(0.0007)	(0.0007)	(0.0007)	(0.0011)
Asian	-0.0045***	-0.0040***	-0.0067***	-0.0032***
	(0.0003)	(0.0003)	(0.0004)	(0.0005)
Hispanic	0.0014***	0.0019***	0.0000	-0.0051***
	(0.0004)	(0.0004)	(0.0004)	(0.0007)
lnconnections	-0.0057***	-0.0047***	-0.0045***	-0.0015***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Leader_exp	-0.0027***	-0.0010***	-0.0020***	-0.0010***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Work_exp	0.0051***	0.0041***	0.0044***	0.0012***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Trunover	0.0193***	0.0164***	0.0217***	0.0122***
	(0.0005)	(0.0005)	(0.0006)	(0.0010)
Firm_size	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Observations	461270	461270	461030	128141
Robust Standard error is in second row bracket. Significant levels * p<0.1, ** p<0.05, *** p<0.01				

Conclusions and Future Work

This paper not only analyses the effects of AI automation on work activities in different occupations, but also exploit the jobs that be benefited from intelligence augmentation. Further, utilizing O*NET and LinkedIn public profiles, we are able to identify the important factors such as the crucial human capital characteristics of professionals that may correlate with AI automation risk and increase or decrease the probability of being augmented. We complement and add to previous studies in several aspects. The first contribution involves the estimations for the AI automation risk by a more sophisticated approach. We estimate AI scores at the core and supplemental WA levels by coding detailed skills and abilities required for each occupation. Secondly, the findings suggest that the important skills accumulated from prior work experience, the excellent educational background, and major in the right areas can alleviate employees' concerns that they may become unemployed due to AI advances. The findings above provide important implications for younger generations to prevent themselves from being displaced by AI advances. For education policy makers, this could provide policy guidelines for equipping employees the right skills for the future. Third, we identify the key determinants of the probability of being augmented by AI, which enriches our understanding of the positive AI impact on labor force.

We believe that future works should explore more in depth the impact of AI automation on workforce and the labor demand for different skills that are hard to be replaced by AI advances. As this is an ongoing research, we plan to further identify another type of jobs that may be directly augmented by AI. Specifically, we attempt to explore the jobs with core WAs that can be augmented by AI. This is because we believe that the performance of some work activities may become better when human beings and machines work together. For instance, oncologists have used IBM's Watson computer to assist in providing chronic care and cancer treatment diagnostics in healthcare industry (Frey and Osborne 2017). Meanwhile, we are interested in analyzing the dynamics of AI automation risks over years. Comparing our estimates of the AI automation scores with the results from the prior studies occupation-by-occupation is another important research-in-progress. The other possible research direction is to analyze the effects of AI at the firm level. Given the AI automation risk of each occupations, we can derive the percentage of the AI-destroyed job titles and AI-augmented job titles at a firm. Therefore, we can explore how AI affect the firm productivity, innovation, and hiring strategy influenced by the workforce automation.

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