# Future of Jobs in China under the Impact of Artificial Intelligence [1]

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**Abstract**

This study presents a new task-based quantification method for constructing Chinese occupational dataset based on the features of US jobs. Furthermore, we estimate the impact of artificial intelligence (AI) on jobs in China by determining substitution probability using a LightGBM-based prediction model. The results show that 54% of jobs in China would be substituted by AI in the following decades. Relatively speaking, unit heads are the safest jobs in China, whereas jobs intensive in perceptive and manipulative tasks are highly susceptible to substitution.

*Keywords:* Artificial intelligence; labor markets; task-based quantification; substitution probability; LightGBM

[1]This work is supported by Beijing Municipal Social Science Foundation (No. 21JJB018) and 2022 Project of the Central University of Finance and Economics Education Reform Fund (No. 011450722001/036).

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## 1. Introduction

AI as a new technological revolution (Aghion et al., 2018) is experiencing a rapid advance in recent decades, and the impact of AI on employment has aroused widespread interest (Goos et al., 2009; David, 2017; Oschinski and Wyonch, 2017; Acemoglu et al., 2022). All these studies focus on the impact of AI on developed countries, such as Europe, Japan, Canada, and the US. Although these studies explore the substitutive and creative effects of new technologies on jobs across different countries, AI influences distinct labor markets differently. For example, only 1.7% of employment is at a high risk of automation in Canadian labor market; by contrast, the proportion of total occupations vulnerable to computerization is up to 47% in the US and 55% in Japan. Therefore, the results are not fully transposable.

Few studies have been conducted for developing countries because there are few quantified features of jobs in these countries. One example is Zhou et al. (2020), who exploit the results of Frey and Osborne (2017) directly by matching the occupational codes between China and the US to examine the influence of AI in China without using the quantified features of Chinese jobs. Because China is a developing country with the largest population, the impact of AI on Chinese labor market deserves more attention, especially from the viewpoint of quantified features.

This study contributes to the literature in two ways. First, we develop a task-based quantification method for constructing a relationship between Chinese and US job features not based on occupational codes. Thus, the first Chinese occupational dataset with quantified features is created. To analyze the impact of AI, the linkage between quantified features and substitution probability is another important factor. Therefore, the second contribution of our study is that a novel machine learning method, a LightGBM[2]-based prediction model, is developed to improve the timeliness and accuracy of the substitution probability of jobs. According to our estimation, 54% of jobs in China are at a high risk of being substituted. Particularly, jobs with perception- and manipulation-intensive tasks are highly susceptive to substitution.

## 2. Models

### 2.1. Task-based quantification model

The quantified features of jobs are the basis of the substitution evaluation. Some countries have quantified job features, but some do not. For example, the US has O*NET, an online service developed for the US Department of Labor, but China does not have a similar service. Therefore, it is necessary to use the known quantified features of jobs to describe unknown ones. Two close jobs in different countries may have different names; however, they share the same key features. We propose a task-based quantification model to obtain the quantified features of jobs without them using the known quantified features of the associated jobs in other countries.

Suppose there is a similarity matrix $\mathbf{\Lambda} = (\lambda_{ij})_{N_1 \times N_2}$ between jobs in a labor market $\mathcal{L}^{(un)}$ without quantified features and those in a labor market $\mathcal{L}$ with them, where $\lambda_{i,j}$ represents the similarity between Job $i$ in $\mathcal{L}^{(un)}$ and Job $j$ in $\mathcal{L}$, and $N_1$ and $N_2$ are the respective numbers of jobs in $\mathcal{L}^{(un)}$ and $\mathcal{L}$. For Job $j$ in $\mathcal{L}$, its key features are known as $\mathbf{o}_j = (v_{j,1}, \cdots, v_{j,M})$, where $M$ denotes the number of features in $\mathcal{L}$. Then the feature matrix

[2]LightGBM is the abbreviation of Light Gradient Boosting Machine.

of jobs in $\mathcal{L}$ is

$$\mathbf{O}_v = (\mathbf{o}_1, \cdots, \mathbf{o}_{N_2})^{\mathbf{T}}_{N_2 \times M} .$$

For jobs in $\mathcal{L}^{(un)}$, the quantified features can be obtained by

$$\mathbf{O}_v^{(un)} = \mathbf{\Lambda} \cdot \mathbf{O}_v.$$

There are several methods to establish the similarity matrix $\mathbf{\Lambda}$; for example, by expert scoring or assigning corresponding occupational codes, such as the Standard Occupational Classifications. However, these methods depend heavily on either expert experience or forced pairing. In fact, job descriptions contain information about tasks performed on the job. For example, the job description for a dishwasher includes task descriptors such as "wash dishes" and "place clean dishes." In this study, we employ task descriptors as a mediator to establish the matrix $\mathbf{\Lambda}$.

Suppose that all task descriptors of $\mathcal{L}$ constitute the task set $\{t_j\}_{j=1}^m$ and those of $\mathcal{L}^{(un)}$ constitute $\{t_i^{(un)}\}_{i=1}^n$, where $m$ and $n$ are the respective number of tasks in $\mathcal{L}$ and $\mathcal{L}^{(un)}$.

We denote an indicator coefficient vector of tasks for Job $l$ in $\mathcal{L}$ as $\mathbf{\Delta}_l = (\delta_{l,1}, \cdots, \delta_{l,m})$, where $\delta_{l,k}(l = 1, \cdots, N_2)$ equals 1 if $t_k$ is a task of Job $l$, otherwise 0. The coefficient matrix of tasks in $\mathcal{L}$ is $\mathbf{\Delta} = (\mathbf{\Delta}_1, \cdots, \mathbf{\Delta}_{N_2})^{\mathbf{T}}_{N_2 \times m}$. Similarly, the coefficient matrix of tasks in $\mathcal{L}^{(un)}$ is $\mathbf{\Delta}^{(un)} = \left(\mathbf{\Delta}_1^{(un)}, \cdots, \mathbf{\Delta}_{N_1}^{(un)}\right)^{\mathbf{T}}_{N_1 \times n}$. We identify the similarity coefficient matrix of tasks as

$$\mathbf{S} = (s_{i,j})_{n \times m} ,$$

where $s_{i,j}$ represents the similarity of pairwise tasks $t_i^{(un)}$ and $t_j$. Then, we define $\mathbf{\Gamma} = \mathbf{\Delta}^{(un)} \cdot \mathbf{S} \cdot \mathbf{\Delta}^{\mathbf{T}} = (\gamma_{i,j})_{N_1 \times N_2}$, which is responsible for transferring the quantified features of jobs in $\mathcal{L}$ to those in $\mathcal{L}^{(un)}$ with $\mathbf{S}$ as an intermediate variable. However, $\mathbf{\Gamma}$ includes the features of all jobs in $\mathcal{L}$ for a job in $\mathcal{L}^{(un)}$. To focus on the key jobs, we first identify the closest jobs in $\mathcal{L}$ to a job in $\mathcal{L}^{(un)}$, that is[3], $\mathcal{I}(\mathbf{\Gamma}) \triangleq \left(\mathbb{I}_{\max\{\gamma_{i,\cdot}\}}(\gamma_{i,j})\right)$. Usually, the jobs that are the closest to the job in $\mathcal{L}^{(un)}$ are not unique, and the final result corresponding to the job in $\mathcal{L}^{(un)}$ takes the mean of the closest jobs in $\mathcal{L}$. Therefore, we normalize the associated closest jobs in $\mathcal{L}$; that is, normalize each row of the matrix $\mathcal{I}(\mathbf{\Gamma})$, defined by[4] $\mathcal{N}(\mathcal{I}(\mathbf{\Gamma}))$. Hence, the similarity matrix of jobs $\mathbf{\Lambda}$ is obtained using the nonlinear mapping $\mathcal{G} = \mathcal{N} \circ \mathcal{I}$ with $\mathbf{S}$ as an intermediate variable; that is,

$$\mathbf{\Lambda} = \mathcal{G}(\mathbf{\Gamma}) = \mathcal{G}\left(\mathbf{\Delta}^{(un)} \cdot \mathbf{S} \cdot \mathbf{\Delta}^{\mathbf{T}}\right).$$

The following is a simplified example of using the known quantified features of four tasks of two jobs in the US to quantify the features of two jobs with three tasks in China. Suppose

$$\mathbf{\Delta}^{(chn)} = \begin{pmatrix} 1 & 0 & 1 \\ 1 & 1 & 0 \end{pmatrix}, \quad \mathbf{\Delta}^{(us)} = \begin{pmatrix} 1 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \end{pmatrix},$$

and

$$\mathbf{S}^{(chn,us)} = \begin{pmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}.$$

Intuitively, Job 1 in China, which includes Tasks 1 and 3 of China should be matched with a job that includes Tasks 1, 3, and 4 of the US, that is, Job 2 in the US, because by $\mathbf{S}$, Task

[3] $\mathbb{I}_{\max\{\gamma_{i,\cdot}\}}(\gamma_{i,j})$ equals 1 if and only if $\gamma_{i,j} = \max\{\gamma_{i,\cdot}\}$, otherwise 0.

[4] $\mathcal{N}(A)$ denotes the normalization of the rows in $A$, which means replacing $a_{i,j}$ by the quotient of $a_{i,j}$ and $\sum_j a_{i,j}$, where $A = (a_{i,j})_{N_1 \times N_2}$.

1 of China is the closest to Tasks 1 and 3 of the US, and Task 3 of China is the closest to Task 4 of the US. Similarly, Job 2 in China, which includes Tasks 1 and 2 of China should be matched with Job 1, which includes Tasks 1, 2, and 3 of the US.

Using our task-based quantification method, the similarity matrix $\mathbf{\Lambda}$ between China and the US labor markets is

$$\mathbf{\Lambda} = \mathcal{G}\left(\mathbf{\Delta}^{(chn)} \cdot \mathbf{S}^{(chn,us)} \cdot \mathbf{\Delta}^{(us)\mathbf{T}}\right) = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}.$$

Suppose that each job in the US is equipped with 3 O*NET variables:

$$\mathbf{O}_v^{(us)} = \left(\mathbf{o}_1^{(us)},\ \mathbf{o}_2^{(us)}\right)^{\mathbf{T}}_{2\times 3} = \begin{pmatrix} v_{1,1} & v_{1,2} & v_{1,3} \\ v_{2,1} & v_{2,2} & v_{2,3} \end{pmatrix}.$$

Then, the quantified features of jobs in China are

$$\mathbf{O}_v^{(chn)} = \left(\mathbf{o}_1^{(chn)},\ \mathbf{o}_2^{(chn)}\right)^{\mathbf{T}}_{2\times 3} = \mathbf{\Lambda} \cdot \mathbf{O}_v^{(us)} = \begin{pmatrix} v_{2,1} & v_{2,2} & v_{2,3} \\ v_{1,1} & v_{1,2} & v_{1,3} \end{pmatrix} = \left(\mathbf{o}_2^{(us)},\ \mathbf{o}_1^{(us)}\right)^{\mathbf{T}}_{2\times 3}.$$

This implies that $\mathbf{o}_1^{(chn)}$ ($\mathbf{o}_2^{(chn)}$) shares the variable values of $\mathbf{o}_2^{(us)}$ ($\mathbf{o}_1^{(us)}$), which is consistent with the intuitive results. Therefore, the method developed in this study is valid.

### *2.2. Prediction model*

To calculate the substitution probability of jobs, a prediction model is required to connect the quantified features of jobs with the latent variable using binary values, taking 1 if a job is substituted and otherwise 0. Considering the problem with the binary dependent variable, logistic regression and random forests are usually used in applied economics; for example, Frey and Osborne (2017) and David (2017). In this study, we adopt LightGBM proposed by Ke et al. (2017), using boosting strategy to achieve ensemble learning. Additionally, K-fold cross validation and hyperparameter optimization based on grid search are exploited to promote the accuracy and generalization ability of the prediction model.

Table 1: Performance of the prediction model

| Prediction models | AUC* | Accuracy |
|---|---|---|
| LightGBM-based | **0.986** | **0.922** |
| Logistic regression | 0.939 | 0.889 |
| Random forests | 0.961 | 0.911 |
| Naïve Bayes | 0.938 | 0.867 |

* AUC denotes the area under the receiver operating characteristics curve, which is a model performance evaluation index. The performance of the model is better as AUC approaches 1.

Table 1 lists the performances of our LightGBM-based prediction model, compared with logistic regression, random forests and naïve Bayes under the same conditions. The results show that the LightGBM-based prediction model exhibits the best performance compared to its rivals.

## 3. Data and empirical results

### *3.1. Data*

The data on Chinese and US jobs are obtained from the China's Seventh National Population Census across six major categories and O*NET, respectively. Frey and Osborne (2017) propose that AI technology is confined by three strong engineering bottlenecks. Further, they identify nine key O*NET variables as proxies for describing the attributes of the three bottlenecks[5]. As jobs change over time, we update the data of these nine variables based on O*NET and expand the dataset from 70 to 91 occupations. Through the task-

[5]More details on the three bottlenecks and nine O*NET variables and their relationships see Columns 1 and 2 of Table 3.

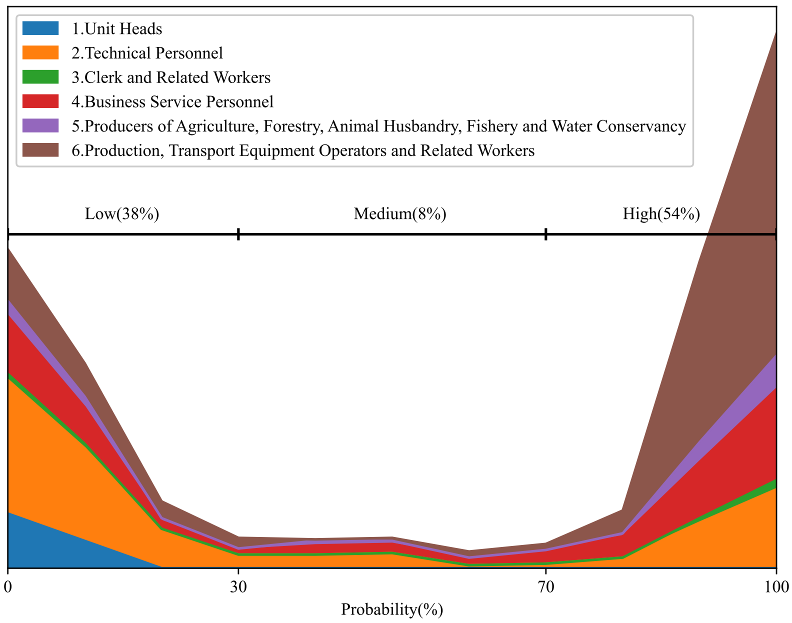


Figure 1: Employment affected by AI

based quantification model described in Section 2.1, we use the US occupations, with nine O*NET variable values for each occupation, to construct Chinese occupational dataset with quantified characteristics. Then the substitution probabilities of jobs are estimated using the LightGBM-based prediction model.

### *3.2. Empirical results*

The empirical results show the properties of substitution probability based on the two aspects of job characteristics and O*NET variables.

First, jobs are divided into three groups by thresholding at probabilities of 0.3 and 0.7, according to our estimation, as illustrated in Figure 1.

In the short-term future, 54% of jobs in China are at a high risk of being substituted with AI, and they are mainly related to the engineering bottlenecks that are easy to overcome, such as routine, auxiliary, or processing works. Figure 1 shows that most workers in

Table 2: Examples of jobs in each category

| Risk Levels | Categories | Jobs |
|---|---|---|
| High ($p > 0.7$) | 6 | Down and feather processing and product manufacturing personnel |
| | 3 | Administrative business handling personnel |
| | 4 | Road transport service personnel |
| Medium ($0.7 > p > 0.3$) | 2 | Music conductor and actor |
| | 2 | Gardening technicians |
| | 6 | Civil aviation equipment operators |
| Low ($p < 0.3$) | 3 | Chief executive of public institutions |
| | 2 | Legal counsel |
| | 2 | Public health and health physician |

production and transport equipment operations and related workers (e.g., down and feather processing and product manufacturing personnel), together with the bulk of business service personnel (e.g., road transport service personnel), are highly susceptible to substitution.

As bottlenecks are broken through, jobs at medium risk, which are usually specialized operating and research works, will begin to be substituted. This type of jobs accounts for only 8% of Chinese jobs and is mainly professional technical personnel such as music conductors, actors, and gardening technicians.

The 38% of jobs that will be substituted last are at a low-risk level and are characterized by heuristics, professional technology, and social interactions. For example, unit heads that are typically engaged in management are in the low-risk interval. These types of jobs require a high degree of social intelligence and are very difficult to substitute. In addition, some highly professional types of technical personnel, such as legal counsel and health physician, are low-risk jobs that require creative and social intelligence. More jobs in each group are listed in Table 2.

Second, for every O*NET variable, the variable scores of the jobs across different risk levels were measured using means and standard deviation, as presented in Table 3.

Table 3: Variable distributions

| Bottlenecks | O*NET Variables | High | Medium | Low |
|---|---|---|---|---|
| Perception and manipulation | Finger dexterity | 50.04 | 47.10 | 37.64 |
| | | (13.71) | (13.62) | (14.60) |
| | Manual dexterity | 50.21 | 41.97 | 30.32 |
| | | (18.10) | (18.57) | (19.54) |
| | Cramped work space, awkward positions | 32.81 | 34.27 | 22.19 |
| | | (19.05) | (23.09) | (14.67) |
| Creative intelligence | Fine arts | 5.57 | 10.67 | 9.50 |
| | | (10.11) | (20.60) | (13.82) |
| | Originality | 34.22 | 47.67 | 54.67 |
| | | (9.06) | (8.48) | (7.76) |
| Social intelligence | Social perceptiveness | 46.10 | 50.80 | 61.94 |
| | | (5.74) | (5.44) | (11.10) |
| | Persuasion | 35.11 | 42.73 | 51.45 |
| | | (9.51) | (8.59) | (8.65) |
| | Negotiation | 31.85 | 40.67 | 49.95 |
| | | (8.87) | (8.42) | (11.46) |
| | Assisting and caring for others | 40.12 | 42.87 | 46.42 |
| | | (10.25) | (12.13) | (19.67) |

Manual and finger dexterity variables representing bottleneck attributes of perception and manipulation have the highest scores at the high-risk level. This implies that jobs that require manipulation of objects are the most susceptible to AI substitution. As AI develops, industrial robots with enhanced senses and dexterity may penetrate more industries to fulfill a wider range of nonroutine manual tasks.

However, cramped work space and awkward positions belonging to perception and manipulation bottleneck and fine arts belonging to creative intelligence have the highest scores at the medium-risk level. This indicates that jobs that require knowledge of art theory and/or special working environment will be substituted in the long run.

Except for originality, which belongs to creative intelligence, the remaining O*NET variables belong to the bottleneck of social intelligence. They have the highest scores at the low-risk level. This means that most jobs with social intelligence and some with creative intelligence, such as unit heads, health physicians, and legal counsels, are not easy to sub-

Table 4: Comparison of risk levels between the US and China

| Risk Level | Ratio | | Bottlenecks (O*NET Variables) | |
|---|---|---|---|---|
| | US | China | Commons | Differences |
| High | 47% | 54% | Perception and manipulation (Finger dexterity, Manual dexterity) | - |
| Medium | 19% | 8% | Perception and manipulation (Cramped work space, awkward positions) | China: Creative intelligence (Fine arts) |
| Low | 33% | 38% | Creative intelligence (Originality); Social intelligence (Persuasion, Negotiation, Social perceptiveness, Assisting and caring for others) | US: Creative intelligence (Fine arts) |

stitute.

Compared with the ratios of jobs at different risk levels in the US given by Frey and Osborne (2017), the ratios of jobs at the high- and low-risk levels in China are larger, while the ratio of jobs at the medium-risk level is smaller. As to the related bottlenecks, the biggest difference between China and the US is the creative intelligence of fine arts which is at the medium-risk level in China and at the low-risk level in the US. The result differences could rely on the differences in labor market structure, number of jobs and task composition in different countries. However, this is beyond the scope of this study, so we will leave it for future research.

## 4. Conclusions

This study considers the task similarity between jobs to construct Chinese occupational dataset based on O*NET variables for the US and estimates the substitution probability of jobs by AI in China based on the LightGBM-based prediction model, which provides new evidence for developing countries. The results show that 54% of jobs in China are at a high risk of substitution. In particular, production and transport equipment operators and related workers are most susceptible, whereas unit heads are the safest jobs in China, with the lowest substitutional probability. Additionally, jobs that require perception and manipulation are in danger because they have the largest substitution probability, whereas those that require social intelligence will be substituted relatively late. Therefore, the development in AI will put a large number of jobs at risk in the next few years. As jobs evolve alongside the development of AI, workers will need to adapt to activities that require more creativity and social intelligence. Policymakers will need to provide more midcareer job training and income support for workers caught in the flood of AI to fulfill job transition.

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