The Changing Importance of Technology Skills for Accountants in the Context of Artificial Intelligence

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Abstract: The goal of this study is to demonstrate the impact of the changing importance of technology skill under the evolution of artificial intelligence on the job requirements for accountants. The analysis is based on data from the Chinese employment market from 2012 to 2022 under different educational backgrounds. The research objectives are achieved through multiple regression and relative importance analysis. The analysis indicates that the changing importance of technology skills have significant effects on the job requirements of accountants. Trends show that from 2012 to 2020, the relative importance of technology skills decreased. However, this trend was reversed in 2020. Differences exist in both overall characteristics and trend features for job seekers with different educational backgrounds. The research findings provide insights for recommendations on how job seekers and educational institutions should take actions in the context of AI to promote employment and personal development.

1 INTRODUCTION

In 2012, deep Convolutional Neural Network (CNN) models achieved significant success in the ImageNet Large Scale Visual Recognition Challenge. In the same year Microsoft and Google began employing deep learning approaches to enhance their speech recognition systems. In 2020, GPT-3 was launched for commercial operations, and as a continuation of GPT-3, OpenAI introduced ChatGPT in 2022. With the rapid development of Artificial intelligence (hereinafter referred to as AI), technology skills are receiving increasing attention. For accountant positions, technology skills primarily encompass proficiency in accounting, ERP systems, financial analysis, taxation, and word processing software operations. Due to its profound impact, AI has become a central theme in business education and practice (Xue et al., 2020). The application of AI can be found across various business functions (Bejaković et al., 2020). However, existing research lacks in-depth insights into the evolution of AI technology and often overlooks differences in educational backgrounds during the research process, making it challenging to thoroughly examine the impact of AI on job skills requirements. The accounting industries serve as an example with high levels of automation in business practices, where computing technologies have replaced a significant amount of human simple repetitive labour, giving rise to demands for technology skills. It is generally believed that repetitive labour is more prevalent in accounting roles, making technology skills most essential. Has the evolution of AI changed this situation? How does the situation differ for job seekers in the context of AI? These are intriguing and worthy questions for in-depth exploration.

Therefore, we use the introduction of CNN in 2012 and GPT-3 in 2020 as demarcation points, conducts an analysis of the impact of the evolution of AI on the job skills requirements of accountants by examining the changes in the relative importance of technology skills. To showcase and analyse developments in a specific scientific field, the paper reviews relevant literature and constructs a research framework based on critical analysis. The research focuses on the evolution of concepts related to the impact of AI on the job requirements of accountants. This is detailed in the section 2 ('Literature Review').

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After reviewing and presenting literature relevant to the research theme, the section 3 ('Data and Methods') introduces the details for creating task importance variables (TI) and skill importance variables (SI) used for the numerical evaluation of relationships between the studied phenomena. The basis for the presented measurable indices is online recruitment data from the Sina Weibo platform spanning from 2012 to 2022. The analysis of the impact of SI on TI is achieved through panel regression with random effects, and the analysis of changes in the relative importance of job skills is conducted through Relative Importance Analysis (RI). The results are presented in the section 4 ('Results'). Additionally, the research findings enable the formulation of recommendations on how accountant employees and educational institutions can take action to adapt to the impact of AI, as discussed in the section 5 ('Conclusion').

2 LITERATURE REVIEW

2.1 AI in Accounting

As a burgeoning force the impact of AI on society has long garnered widespread attention from researchers (McAfee et al.,2016). As a crucial component of the business community, the accounting profession has also been impacted by AI. Chukwuani and Egiyi (2020) studied the impact of AI on the accounting industry, showcasing advancements in automating accounting processes. Huang (2018) investigated the application of AI in Chinese tax matters. Chukwudi et al. (2018) demonstrated the positive impact of AI on the functions of company accountants in the southeastern region of Nigeria. Lee & Tajudeen (2020), through research on the use of various AI-based accounting software in Malaysian organizations, found that AI adoption is not limited to large organizations. They observed organizations using AI-based accountant software to store invoice images and fully automate the information capture process. Luan et al. (2020) discussed the challenges and directions of AI and big data in education research, policymaking, and industry, including accounting and auditing education, policy, and industry. They argued that effective collaboration among academia, decision-makers, and professionals from various disciplines is necessary to fully realize the potential progress of AI and big data in the face of the innovations and challenges brought about by the AI and big data revolution.

Regardless of the future disruptions that AI may bring to this industry, accountants cannot be replaced by AI in exercising human creativity and judgment (Hasan, 2021). AI can help businesses achieve three key objectives: automate business processes, gain insights through data analytics, and connect with consumers and employees. The marginal benefits and costs of achieving these three goals are crucial considerations for businesses applying AI (Kokina et al., 2017).

While the significance of the above studies varies due to different research perspectives, they provide not only descriptive but also predictive insights, offering stakeholders such as employers and schools valuable insights for decision-making in the AI revolution (Huang, 2018). Hindered by the characteristics of early AI technologies, many small and medium-sized enterprises were unable to afford or develop customized and dispersed AI systems. Cost factors and technology barriers limited the full demonstration of AI potential in the accounting industry. In June 2020, OpenAI launched the first commercially available large-scale language model product, GPT-3. By providing a large language model interface, developers and users can obtain high-quality feedback with only basic software skills. However, researchers after 2020 have not fully recognized the impact of this breakthrough in AI on the marginal benefits and costs of the three key objectives for businesses. Research perspectives mostly remain confined to the pros and cons, leading to conclusions that have not kept pace with technology advancements.

2.2 Research Problem & Hypotheses

The impact of AI on the roles of accountants has been widely discussed from a business competency perspective. From a skills standpoint, the relationship between AI and technology skills has garnered particular attention. This skill set is built on the foundation of computers replacing humans in tasks with clear and repetitive rules, making it more crucial for the accounts. The influence of AI on human social skills is deemed to be less significant compared to technology skills, as studies suggest that due to the limitations of AI technologies, replacing social skills is more challenging (Huang, 2018). However, social skills can enhance communication efficiency across various roles, allowing employees with higher social skills to gain a competitive advantage through information exchange (Deming, 2017). Whether the evolution of AI technology has altered these conclusions is a worthy topic for discussion.

The literature review allowed to determine the following research hypotheses:

Hypothesis 1. The importance of technology skills for accountants exhibits a fluctuating pattern. Specifically, with the rise of deep learning in 2012, the importance of technology skills increased initially and then declined, until the emergence of GPT-3 in 2020, marking a renewed ascent in the importance of technology skills.

Hypothesis 2. The importance of technology skills fluctuates more among low-educated employees compared to highly educated ones.

3 DATA AND METHODS

3.1 Data Preparation and Methods of Calculation

This study utilizes data from recruitment advertisements on Sina Weibo. The specific steps for data acquisition and processing are as follows: Firstly, a Python web crawler is employed to collect textual content from online job advertisements for accountants posted between 2012 and 2022. Texts with lengths less than 50 characters or lacking city data are filtered out. Subsequently, based on job task information for accountant and financial advisor positions from the O*NET database, a keyword library for job tasks is generated. Additionally, a keyword library for skill requirements is created using skill requirement information from the O*NET database. Next, a blank dataset is constructed with fields named job task frequency, skill requirement frequency, educational requirements for applicants, and city of employment. Using natural language processing programs, the frequency of job task keywords is extracted from each job advertisement to generate the dependent variable $Task_{it.}$ Skill requirement keyword frequencies, educational requirements, and city data are also obtained to create the explanatory variables TS_i, SS_i, and the Controls. The generated data is then inserted into the blank dataset, resulting in a balanced panel dataset of online recruitment for 42 cities from 2012 to 2022 to estimate Equation 1.

3.2 Model and Variables

To test the hypotheses in the second part of the study, we establish the following Equation 1:

$$Task_{it} = \beta_0 + \beta_1 TS_i + \beta_2 SS_i + \beta_2 Controls_{it} + \varepsilon_{it}$$

where the dependent variable $Task_{it}$ represents the job tasks of accountants and financial advisors in different companies across various years. The explanatory variable gauge the technology skill requirements of different companies, while SS_i measure the social skill requirements. Controls include variables that may influence job task content, and ε_{it} is the disturbance term.

3.3 Methodology

The first goal of the empirical analysis is to ascertain the impact of changes in the importance of skills on the job requirements for Chinese accountants from 2012 to 2022. The research process involves two stages. First, we conduct Ordinary Least Squares (OLS) tests to empirically examine the relationship between the changes in technology skills and social skills importance and job requirements. Second, we employ Generalized Method of Moments (GMM) with work experience dummy variables as instruments to address potential endogeneity issues (Ye et al., 2015).

The second goal of the empirical analysis is to identify the relative changes in importance between technology skills and social skills from 2012 to 2022. To achieve this objective, we employ the Relative Importance (RI) analysis method (Krasikova et al., 2011). The fundamental idea of RI is to compare the relative importance of different explanatory variables after the model has been formed.

4 EMPIRICAL RESULTS

4.1 Ols Results

The OLS regression results are presented in Table 1. It is shown that technology skills are significantly and positively correlated with the job tasks of accountants, with a substantial coefficient. Although social skills also exhibit a significant positive correlation with the tasks of accountants, the coefficient is smaller. This suggests that, in the Chinese labour market from 2012 to 2022, relative to social skills, technology skills are more critical for the tasks of accountants. Technology skills have previously replaced manual skills, and now they may face potential substitution by AI.

Table 1: OLS regression.

	Accountant's tasks
TS	0.794*** [0.063]
SS	0.078*** [0.019]
Constant	8.134*** [0.696]
Control	Yes
City dummies	Yes
Year dummies	Yes
N	7515
R^2	0.298

4.2 Relative Importance Analysis

In contrast to examining the impacts of different skills on accountant's tasks, our primary concern is the relative importance of technology skills. This can be achieved through the Relative Importance (RI) analysis method.

RI primarily focuses on ranking predictor variables according to their relative importance by comparing the additional contribution of these variables to the variance across all possible sub-models. The additional contribution of a predictor variable refers to the increase in explained variance when that variable is added to a given sub-model. For ease of analysis, we adopt the method by Krasikova to standardize the reported RI values below (Krasikova et al., 2011). Specifically, the RI for all variables is consolidated into RI total. Subsequently, the ratio of RI for each variable to RI total is calculated to obtain standardized contributions. This standardization advantageously ensures that the sum of the standardized contributions for all explanatory variables equals 1, facilitating a more straightforward comparison of the relative importance of each variable with others.

Table 2 presents the results of the Relative Importance (RI) analysis.

Table 2: Relative importance (RI) analysis.

Year	Overall		High education		Low education	
	SS	TS	SS	TS	SS	TS
2012	33%	67%	5%	95%	36%	64%
2013	15%	85%	1	0%	18%	82%
2014	0%	1	15%	85%	1%	99%
2015	9%	91%	60%	40%	10%	90%
2016	20%	80%	28%	72%	18%	82%
2017	6%	94%	6%	94%	6%	94%
2018	29%	72%	53%	47%	20%	80%
2019	36%	64%	12%	88%	35%	65%
2020	57%	43%	24%	76%	60%	40%
2021	44%	56%	36%	64%	44%	56%
2022	39%	61%	36%	64%	36%	64%
All	46%	54%	35%	65%	45%	55%

4.2.1 The Overall Characteristics of Accountant Positions

Technology skills are relatively more important than social skills for accountants, with a relative importance of 54% for technology skills and 46% for social skills. This overall characteristic is more pronounced in high-education samples (65%) compared to low-education samples (55%).

China's higher education system is divided into undergraduate education and vocational education through the National College Entrance Examination (Gaokao). Those with higher Gaokao scores are identified as having higher intellectual abilities and enter the undergraduate education level (High education), while those with lower scores enter the vocational education level (Low education). It is generally believed that undergraduate education focuses more on theoretical learning, while vocational education emphasizes skill development, as skills learning is considered to have lower difficulty compared to theoretical learning. However, Table 2 reflects that with the evolution of AI technology, employers set higher requirements for technology skills for individuals with higher educational qualifications.

4.2.2 Trend Characteristics of Accountant Positions

The relative importance of technology skills experienced a brief increase from 2012 to 2014, but it steadily declined from 2014 onwards, while the importance of social skills increased annually. This trend reversed in 2020(Figure 1).

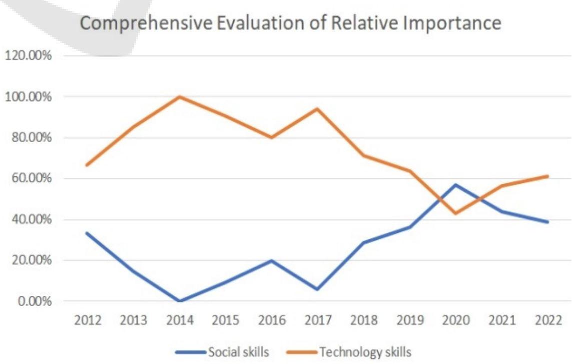

Figure 1: Comprehensive Evaluation of Relative Importance.

One possible explanation is that as the automation level of accountant tasks deepened, employers began to place increasing emphasis on the technology skills of accountants, with the rise of deep learning in 2012 intensifying this focus. However, as AI gradually infiltrated software-assisted business processes in accountant positions, the importance of technology skills gradually diminished. In the process of integrating AI tools with accountant tasks, employers gradually realized that traditional accountant staff, familiar with the nature and processes of the business, were sufficient for making judgments, while the rest could be delegated to AI. In a complex organizational environment, employees with higher social skills undoubtedly had a greater advantage in achieving the goal of obtaining business information from other departments (Deming, 2017). During this phase, AI tools exhibited a decentralized characteristic.

The introduction of GPT-3 in commercial use in 2020 changed the decentralized nature of AI tools. GPT-3, a powerful tool encompassing various capabilities such as judgment, analysis, and processing, rendered the importance of employees being familiar with business gradually less significant. However, using this powerful tool to meet personalized demands requires a certain level of technology skills, leading to an increase in the relative importance of technology skills over social skills. Furthermore, like the rise of deep learning in 2012, the appearance of GPT-3 sparked another wave of public enthusiasm for AI, inadvertently heightening the importance that employers placed on technology skills.

This trend feature is even more pronounced in the low education sample compared to the high education sample (Figure 2). If the impact of breakthrough events in AI technology (the rise of deep learning and the commercialization of GPT-3) heightened people's attention to technology skills, the gradual decline in the emphasis on technology skills reflects the actual demand for technology skills in accounting. Thus, the demand for highly educated talent in accountant positions becomes more stable, while the demand for lower-educated talent exhibits greater volatility.

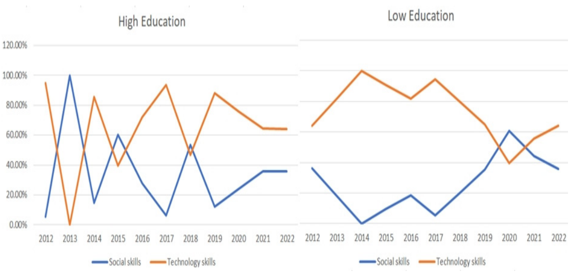

Figure 2: Comparison of Relative Importance across varied educational backgrounds.

4.3 Endogeneity Issues

There may be endogeneity issues between task requirements and skill demands, such as changes in job task requirements leading to changes in skill requirements. Although the work content and task requirements for accountants have seen minimal long-term changes. To address this potential endogeneity issue, we conducted Generalized Method of Moments (GMM) tests on job requirements and occupational skills.

We chose work experience dummy variables as instrumental variables. Work experience dummy variables are significantly correlated with skill requirements, while the relationship between work experience and job task requirements is less clear. Employers have higher skill requirements for experienced job seekers, but we cannot conclude that employers will lower skill requirements due to a lack of experience in job seekers. So, we consider work experience dummy variables as fine instrumental variables for skill requirements. The results of the GMM regression are shown in Table 3. We find that the results of the GMM tests are generally consistent with the benchmark OLS tests.

Table 3: GMM estimation.

	Accounting tasks
TS	0.819*** [0.075]
SS	0.067*** [0.025]
Control	Yes
Constant	13.256 [8.326]
N	7515
R^2	0.288

*This table reports the results of the GMM regressions of the accountant tasks on technology skills, social skill and some control variables. The robust t statistics are in parentheses. ***, **, * Significance at 1,5, and 10%, respectively.*

4.4 Robustness Test

The focus of this paper is the relationship between task requirements and skill demands. In practice, there may be different measurement methods for skill demands, leading to potential measurement errors. This paper primarily defines technology skills and social skills based on O*NET Online requirements, while DEMING provides different definitions for information usage skills and social skills. In robustness tests, we combine DEMING (2017)'s social skills and O*NET on line's social skills as a new social skills variable and integrate DEMING

(2017)'s information usage skills and O*NET on line's technology skills as new technology skills variables (Deming, 2017).

Table 4 reports the results of regressions using the new variables. We employed both OLS and GMM, and the results of the two tests are generally consistent. These results are generally consistent with Table 1 and Table 3. The results of the Relative Importance (RI) analysis using new variables are generally consistent with the results in Table 2. These results are not reported here to save space.

Table 4: Robustness Test.

	OLS	GMM
TS	0.663*** [0.035]	0.848*** [0.040]
SS	0.072*** [0.017]	0.175*** [0.039]
Control	Yes	Yes
Constant	7.966*** [0.704]	6.435 [8.273]
City dummies	Yes	Yes
Year dummies	Yes	Yes
N	7515	7515
R^2	0.316	0.287

*The robust t statistics are in parentheses. ***, **, * Significance at 1,5, and 10%, respectively.*

5 CONCLUSIONS

The theme of discussing the impact of AI on the labour market is highly popular in the academic community, inspiring researchers to explore more research directions and contribute to the development of this topic. The analysis of this research field involves both quantitative and qualitative studies. However, at both the theoretical and empirical levels, the evolution of AI itself on the labour market has been overlooked. Simultaneously, the impact of AI has been exaggerated due to the neglect of different educational backgrounds. The empirical evidence obtained from the East Asian countries' employment market from 2012 to 2022 will help address these shortcomings.

However, like any research, this study also has certain limitations. One of them is the limited availability of data. Despite obtaining online recruitment data from Sina Weibo for the years 2012-2022 through web scraping, many data points were not acquired due to flaws in web scraping technology and time limitations in Sina Weibo's data storage. Another limitation is the subjectivity of data cleaning rules, resulting in the exclusion of valuable data from the scope of the study.

The research findings indicate that the evolution of AI has led to changes in the relative importance of skills, affecting the task requirements for accounts. Overall, technology skills are crucial for accounting practitioners, especially for highly educated employees.

From the trend perspective, the importance of technology skills exhibits fluctuating characteristics, rising with breakthroughs in AI and gradually falling until another technological breakthrough occurs. This feature is more pronounced among low-educated employees, indicating that the evolution of AI technology has a greater impact on them.

The findings of this study provide inspiration for decision-making among relevant stakeholders.

Maintaining economic growth and promoting employment are important economic goals for policymakers. Encouraging the application of AI across various industries can reduce business costs, improve work efficiency, and thus contribute to economic growth. However, for the highly automated accounting industry, there is a potential conflict between cost reduction and social responsibility that policymakers should consider when formulating policies. The impact of AI on employment, especially for low-educated populations, poses a challenge for policymakers. Common policies including skills training tailored to low-educated populations can solve short-term labour shortages during peak industry demand, while it leads to the waste of human resources during off-peak seasons. Furthermore, the use of most AI tools does not require complex skills, further reducing the necessity of skills training. The policymakers could consider implementing flexible policies to address the impact of AI on accountants. For instance, establishing subsidies or incentive programs tailored to various skill levels could support the transition of lower-educated accountants amid technological changes. Additionally, enhancing technical training for lower-educated accountants and encouraging collaboration between businesses and educational institutions to provide practical skills training can help mitigate employment disparities caused by technological shifts.

As a highly digitized industry, continuously updating technological skills often leaves accounting practitioners, especially those with lower educational backgrounds, in a state of anxiety. The typical response is to participate in various technology skills training programs. Meanwhile, training in skills that appear unrelated to AI is often overlooked, yet these may be precisely the skills that cannot be replaced by AI. This study also found that employers have a more stable demand for employees with higher academic background, which may suggest that improving academic qualifications is more important than skills training for accounting practitioners. When adopting

AI, employers should carefully balance cost savings with employee welfare, considering ways to enhance efficiency through technology without entirely relying on technology to replace human labour. Employees should stay informed about industry trends and actively pursue new skills and career adjustments to navigate the challenges and opportunities presented by AI.

The rise of deep learning and the emergence of ChatGPT have increased people's attention to AI and directly expanded society's demand for training in technological skills. Employers are even willing to hire low-educated employees who were previously ignored to meet recruitment needs. However, if the actual impact of AI on the accounting industry is lower than expectation, employees with lower academic background will be affected even more. Thus, schools should update educational programs in response to industry demands, emphasizing training in non-technical skills such as critical thinking and problem-solving, which are less susceptible to automation.

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