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SUBSTITUTION OR CREATION? IDENTIFYING THE ROLE OF ARTIFICIAL INTELLIGENCE IN EMPLOYMENT

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Abstract. Recognising the significant role of artificial intelligence in the labour market is essential for China to develop sustainably. The research utilises the mixed frequency vector auto-regression (MF-VAR) technique, which would innovatively incorporate data at different frequencies into one model to identify the intricate correlation between the monthly artificial intelligence index (AII) and the quarterly unemployment rate (UR) in China. Through comparison, the MF-VAR method has a more substantial explanatory power than the low-frequency VAR (LF-VAR) model, the impulse responses of the former reveal that AII exerts favourable and adverse influences on UR. Among them, the positive effect occurs on the AII in the first and second months. In contrast, the negative one appears on the AII in the third month, highlighting that artificial intelligence has both stimulating and inhibiting effects on the labour market in China. By analysing UR's predictive error variance decomposition, the total impact of China's artificial intelligence technology on employment is a substitution; this outcome is accordant with the theoretical discussion. In the new round of scientific and technological revolution and industrial transformation, meaningful recommendations for China would be put forward to avert the wave of unemployment brought by the development of artificial intelligence technology.

Keywords: artificial intelligence, employment, mixed frequency data, China.

JEL Classification: C32, J21, O33.

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1. Introduction

The research purposes to seize the conduction mechanism between artificial intelligence and employment, also we probe if the former replaces or creates the latter. Artificial intelligence is a computer technology that aims to simulate human intelligence, where machine learning, natural language processing and image recognition are essential components of this digital technology (Amagasa & Moriya, 2022; Hang & Chen, 2022; Mo et al., 2023; Tian et al., 2023; Zeba et al., 2021). As artificial intelligence develops its potential and value in daily life, work and socio-economic fabric (Ali et al., 2023; Yu et al., 2022), it will pose a threat to the labour market (Nguyen & Vo, 2022; Rampersad, 2020; Wang et al., 2023a). According to the

Economic Potential of Generative Artificial Intelligence released by McKinsey, artificial intelligence will replace more than half of the occupations between 2030 and 2060 (Chui et al., 2023). However, this digital technology might also create more jobs due to the demand in emerging fields, the supporting role of artificial intelligence and the increased opportunities for entrepreneurship (Guliyev et al., 2023; Li & Qi, 2022; Said et al., 2023; Zhang et al., 2021; Wang et al., 2023a). According to Chui et al. (2023), artificial intelligence will create 230 million new jobs, focusing primarily on innovation. Thereupon, artificial intelligence technology plays an essential role in the labour market, which is a vital study but has not been dissected systematically. By discussing this topic, we would help countries or regions to prevent the wave of unemployment brought about by the progress of artificial intelligence technology.

With China's increasing policy support for artificial intelligence, its market shows a vigorous development trend (Qin et al., 2023c). Following the Sullivan report, the size of China's artificial intelligence market increased from 33 billion yuan in 2016 to 370.5 billion yuan in 2022, with a year-on-year increase of 42.34%, which is far higher than the global average (26.69%). China remains the leading position in artificial intelligence-related publications (nearly 40% of the world's total) and patent applications (about 80% more than the U.S.). Also, the Tortoise Global Artificial Intelligence Index, which evaluates and compares the artificial intelligence capabilities of various countries from investment, innovation and practice, presents that China remains second with a score of 62 points. As the world's largest labour force (Feng et al., 2017; Li et al., 2023b), the fast progress of China's artificial intelligence might exert significant influences on employment (Wang et al., 2023a). On the one hand, according to World Bank Group (2016), 77% of the occupations in China would be affected by artificial intelligence technology. On the other hand, according to Chui et al. (2023), China would face the most significant shift in employment, with 12 million to 102 million workers expected to be reemployed by 2030. Consequently, we can see that artificial intelligence technology will be closely related to the labour market in China, but no investigation has explored this connection comprehensively. Additionally, the previous research neglected the complex mutual influences based on mixed frequency data, and the exploration tries to fill them.

The article possesses three contributions: First, the existing researches mainly focus on the theoretical discussions of the specific role of artificial intelligence in the labour market (Rampersad, 2020; Rebelo et al., 2023), which might not obtain the bidirectional effects between them. Besides, few explorations apply a country-specific study, which makes it challenging to put forward targeted countermeasures and recommendations. The article is a ground-breaking effort to quantify the transmission mechanism between artificial intelligence and employment in China. Second, the previous researches on artificial intelligence primarily employ the number of patents (Mutascu, 2021; Nguyen & Vo, 2022), search keywords in Google (Guliyev, 2023; Guliyev et al., 2023), questionnaires (Li & Qi, 2022) or robots (Gravina & Pappalardo, 2022; Javed, 2023; Jung & Lim, 2020; Ni & Obashi, 2021) to reflect, and these measurements are not comprehensive. In order to resolve this difficulty, we choose the Artificial Intelligence Concept Index (AII) to measure the development in the artificial intelligence market, which is an innovation in the extant literature. The quantitative result suggests favourable and adverse influences from AII to the unemployment rate (UR), where the positive one reveals that artificial intelligence technology would replace employment, whereas the negative one suggests that digital technology may create more employment opportunities. This outcome is consistent with the theoretical analysis, highlighting that AII has a specific effect on UR, but its direction is not determined. In light of UR's predictive error variance decomposition, artificial intelligence technology's total effect on employment in China is substitution. This conclusion would put forward meaningful suggestions for the relevant authorities, enterprises, and workers in China to avoid the unemployment wave brought about by the development of artificial intelligence technology. Third, since AII is monthly data and UR is quarterly data, the extent studies generally average or aggregate the high-frequency variable to the low one, for example, the low-frequency vector auto-regression (LF-VAR) technique, making the estimated results and discussions unreliable. The research fully considers the mixed-frequency data and constructs the mixed-frequency vector auto-regression (MF-VAR) system to acquire more information (Hu et al., 2022; Su et al., 2023a). After that, the research would recognise the intricate and non-linear interrelation between AII and UR.

The article is organised as Section 2 reviews the extant studies. The theoretical and quantitative methodologies are introduced in Section 3. Section 4 presents the data. The quantitative results are discussed in Section 5. Section 6 elaborates on the conclusions and policy recommendations.

2. Literature review

2.1. Theoretical discussions of artificial intelligence in labor market

The extant researchers have discussed the concrete role of artificial intelligence in the labour market but have not reached a consensus. Some scholars believe that applying artificial intelligence technology would substitute for employment. Acemoglu and Restrepo (2020) prove that one more robot per thousand workers would decrease the employment-to-population ratio by 0.2 points, highlighting the adverse effect of artificial intelligence on the labour market. Jung and Lim (2020) suggest that the extensive use of artificial intelligence and industrial robots would impede employment growth, ascertaining the substitution effect of this digital technology. Goyal and Aneja (2020) find artificial intelligence would decrease low- and medium-skill jobs, causing unemployment to increase. Rampersad (2020) confirms that fear is growing that artificial intelligence would substitute many occupations, and workers must be more innovative and able to catch the opportunities of industrial transformation and put forward creative solutions to global challenges. Ni and Obashi (2021) state that since the magnitude of the effect is larger for job destruction than creation, the application of robots exerts a total adverse influence on the enterprises' net employment growth. Gravina and Pappalardo (2022) underline that robotisation in European countries (EU15) is related to decreased sectoral employment in emerging economies, particularly in Asia, tradable and more robotised industries. Nguyen and Vo (2022) indicate that artificial intelligence would generally increase unemployment until a certain inflation threshold is reached, after that, this decreasing effect will be weakened. Javed (2023) highlights that one more robot per thousand workers will reduce the employment-to-population ratio of immigrants and natives by 0.67 and 0.38 percentage points, respectively. Wang et al. (2023a) use the LightGBM-based prediction model to predict that 54% of jobs in China will be replaced by artificial intelligence in the following decades.

Some scholars refute the above opinion. Mutascu (2021) discovers that artificial intelligence will decrease unemployment only during periods with low inflation, and this digital technology's contribution to unemployment is fairly neutral. Sequeira et al. (2021) point out that the adverse displacement effect of robotisation may be surpassed by the effects of productivity and reallocation, causing a positive impact on the labour market. Li and Qi (2022) point out that artificial intelligence positively affects youth employment in Australia during the post-epidemic era. Ma et al. (2022) highlight that the impact of artificial intelligence on middle-skill employment is weakened gradually, and the effect on high-skilled employment presents a U-shaped change in China. Guliyev (2023) suggests that artificial intelligence reduces the level of unemployment, highlighting the displacement effect of artificial intelligence in 24 high-tech developed countries. Guliyev et al. (2023) reveal that artificial intelligence would improve productivity, which causes increasing capital accumulation and the creation of new jobs, further confirming the displacement effect of artificial intelligence in Group 7 (G7) countries. Rebelo et al. (2023) ascertain that artificial intelligence influences the tasks of mental healthcare workers by offering support and enabling more profound insights; thereupon, this digital technology aims to help mental healthcare workers instead of substituting them. Sun et al. (2023) confirm a U-shaped interrelationship between robot usage and overall employment, but the effects of artificial intelligence on the labour market are different in various sectors (e.g., agriculture, industry and services sectors).

2.2. Measure of artificial intelligence

There are various methods to measure artificial intelligence. Mutascu (2021) chooses the number of artificial intelligence patents by inventor residence or applicant, which not only reflects the artificial intelligence use but also represents the interest in this field from the perspective of research and development. Nguyen and Vo (2022) also use artificial intelligence patent data to measure the development of this digital technology, which contains all recorded patent documents across the globe. Regarding search keywords in Google, Guliyev (2023) captures the volume of the Google Trend Index related to artificial intelligence, data science and machine learning to measure artificial intelligence. Guliyev et al. (2023) further searched for terms considered for artificial intelligence from four aspects, including artificial intelligence, machine learning, data science, and big data. In terms of the questionnaire, Li and Qi (2022), based on the online recruitment data, chose the positions that cover three categories: programmed operation, on-programmed interaction, and artificial intelligence posts. Regarding robots, Jung and Lim (2020) measure artificial intelligence by adopting industrial robots, which is counted by annual shipments of industrial robots per 10000 manufacturing workers. Ni and Obashi (2021) use industrial robots to measure, which involves data on the number of industrial robots delivered and operated by country and industry (also Gravina & Pappalardo, 2022; Javed, 2023).

2.3. MF-VAR model

The MF-VAR model has been effectively applied in a wide range of fields. Kuzin et al. (2011) ascertain that the MF-VAR model could explain indicators and target series without imposing functional prior constraints on dynamics, which is an advantage in the case where few sequences are adopted thus providing a better approximation to data generating process. Hu et al. (2022) employ the MF-VAR method to resolve the problem of data frequency inconsistency, which overcomes the defect of traditional techniques that high-frequency sequences are usually forced to aggregate to match low-frequency ones. Chang et al. (2023) ascertain that high-frequency data (e.g., quarterly GDP) is aggregated as a proxy sequence to reflect economic growth, causing the information from the original data to miss, and the MF-VAR model could solve this problem by allowing to recognise the heterogeneous effect on low-frequency variable that occurs throughout the high-frequency timescale in every low-frequency period. Jiang and Yu (2023) believe that the MF-VAR model allows for exploring the influence of high-frequency sequences on low-frequency ones and also obviates the demand for any filtering process, thus improving the estimated accuracy. Su et al. (2023) confirm that the temporal aggregation of high-frequency variables might adversely impact statistical inferences and lead to incorrect results. In contrast, the MF-VAR method would consider the heterogeneous effects among various frequency sequences.

3. Theoretical and empirical models

The significant symbols in theoretical and empirical models are listed in Table 1.

Table 1. Major symbols and abbreviations in theoretical and empirical models

Theoretical analysis	
Symbols	Meanings
P_i	production of the i-th industry
K_i	capital of the i-th industry
L_i	labor of the i-th industry
α_i (β_i)	factor input coefficients in different industries
T_i	non-artificial intelligence technology development
AII	Artificial Intelligence Concept Index
UR	unemployment rate
γ_i	influencing coefficient of artificial intelligence technology
ω_{i}	i-th industry's wage rate
Empirical analysis	
Symbols	Meanings
k	lag length
$\beta_{ij,k}$	corresponding parameter
$\mathrm{AII}_{a,t}$	quarterly series calculated through averaging monthly AII
AII_{it}	AII at the i-th month of quarter t
υ_{it}	disturbance term
Abbreviations	Full names
MF-VAR	mixed frequency vector auto-regression
LF-VAR	low frequency vector auto-regression
GDP	gross domestic product

3.1. Theoretical analysis

First, we assume that the production of representative producers among different industries obeys the Cobb-Douglas function, which could be denoted as Equation (1):

$$P_i = T(\mathrm{AII}_i)K_i^{\alpha_i}L_i^{\beta_i}, \quad i = 1, \ldots, n, \tag{1}$$

where P_i, K_i and L_i refer to production, capital and labour of the i-th industry. α_i and β_i refer to the factor input coefficients in different industries ($0 < \alpha_i, \beta_i < 1$). Technical development (T) is supposed to be a function of AII_i, that is $T(\mathrm{AII}_i)$, where AII_i is the artificial intelligence technology inputs of the i-th industry. In light of Donglin et al. (2012), we propose a hypothesis that $T(\mathrm{AII}_i) = T_i \mathrm{AII}_i^{\gamma_i}$, where γ_i ($0 < \gamma_i < 1$) is the influencing coefficient of artificial intelligence technology. Since the progress of artificial intelligence is unbalanced among various industries, we should address the industry heterogeneity of these technology inputs (Wang et al., 2020). T_i reflects the non-artificial intelligence technology development. Then, Equation (1) could be rewritten as the following formula:

$$P_i = T_i \mathrm{AII}_i^{\gamma_i} K_i^{\alpha_i} L_i^{\beta_i}, \quad i = 1, \ldots, n. \tag{2}$$

Then, we suppose that there is a perfectly competitive situation, profit maximisation happens when $L_i^{1-\beta_i} = \dfrac{\beta_i T_i \mathrm{AII}_i^{\gamma_i} K_i^{\alpha_i}}{\omega_i}$, where ω_i refers to the i-th industry's wage rate. After that, we take the natural logarithm as Equation (3):

$$\ln L_i = \frac{1}{1-\beta_i}(\ln\beta_i + \ln T_i + \gamma_i \ln \mathrm{AII}_i + \alpha_i \ln K_i - \ln\omega_i). \tag{3}$$

From this formula, it could be obviously observed that employment is affected by artificial intelligence technology, and its influencing coefficient is $\dfrac{\gamma_i}{1-\beta_i}$ ($0 < \beta_i, \gamma_i < 1$). Thereupon, we can hypothesise as follows:

H1: *Artificial intelligence exerts an essential effect on the labour market, but the direction of influence (positive or negative) from AII to UR could not be confirmed.*

3.2. Methodology

3.2.1. Low frequency vector auto-regression technique

According to Motegi and Sadahiro (2018) and Qin et al. (2023a; 2023b), we build a traditional low-frequency vector auto-regression (LF-VAR) system as Equation (4):

$$\begin{bmatrix} \mathrm{AII}_{a,t} \\ \mathrm{UR}_t \end{bmatrix} = \sum_{k=1}^{3} \begin{bmatrix} \beta_{11,k} & \beta_{12,k} \\ \beta_{21,k} & \beta_{22,k} \end{bmatrix} \begin{bmatrix} \mathrm{AII}_{a,t-k} \\ \mathrm{UR}_{t-k} \end{bmatrix} + \begin{bmatrix} \upsilon_{1t} \\ \upsilon_{2t} \end{bmatrix}, \tag{4}$$

where $\mathrm{AII}_{a,t}$ and UR_t point out the quarterly artificial intelligence index and unemployment rate. As the economic growth has close relationships with artificial intelligence and employment, which may affect the correlation between AII and UR (Boubtane et al., 2013; Deng et al., 2023; Hang & Chen, 2022; Kelishomi & Nisticò, 2022; Soler et al., 2018). After that, the research takes gross domestic product (GDP) as the control sequence, and the above formula would be re-expressed as Equation (5):

$$\begin{bmatrix} AII_{a,t} \\ UR_t \\ GDP_t \end{bmatrix} = \sum_{k=1}^{3} \begin{bmatrix} \beta_{11,k} & \beta_{12,k} & \beta_{13,k} \\ \beta_{21,k} & \beta_{22,k} & \beta_{23,k} \\ \beta_{31,k} & \beta_{32,k} & \beta_{33,k} \end{bmatrix} \begin{bmatrix} AII_{a,t-k} \\ UR_{t-k} \\ GDP_{t-k} \end{bmatrix} + \begin{bmatrix} \upsilon_{1t} \\ \upsilon_{2t} \\ \upsilon_{3t} \end{bmatrix}. \tag{5}$$

We assume that each series is evident enough to follow covariance stationarity (Su et al., 2023). Additionally, the research makes the lag length as 3, that is $k = 3$. Furthermore, $\beta_{ij,k}$ points out the corresponding parameter, where $i, j, k = 1$, 2 and 3. By Equation (5), UR_t would be denoted as the following formula:

$$UR_t = \sum_{k=1}^{3} \left[\beta_{21,k} AII_{a,t-k} + \beta_{22,k} UR_{t-k} + \beta_{23,k} GDP_{t-k} \right] + \upsilon_{2t}, \tag{6}$$

where $AII_{a,t}$ reveals a quarterly series calculated through averaging monthly AII, which can be re-expressed as $AII_{a,t} = (AII_{1t} + AII_{2t} + AII_{3t})/3$. AII_{it} (i = 1, 2 and 3) points out the AII at the i-th month of quarter t, and the above formula would be expanded to Equation (7). The following formula, $\frac{\beta_{21,k}}{3}$ shows the homogeneous effects of $AII_{i,t-k}$ (i, k = 1, 2 and 3) on UR_t:

$$UR_t = \sum_{k=1}^{3} \left[\beta_{21,k} \left(\frac{1}{3} \sum_{i=1}^{3} AII_{i,t-k} \right) + \beta_{22,k} UR_{t-k} + \beta_{23,k} GDP_{t-k} \right] + \upsilon_{2t}. \tag{7}$$

3.2.2. Mixed frequency vector auto-regression technique

Since the LF-VAR model must collect all series into the least frequency sampling, converting mixed frequency data into the same one by means of average, substitution or interpolation, such as averaging monthly AII. However, this model may cause information loss or exaggeration, resulting in inaccurate analysis and estimated results. To resolve the limitations of the LF-VAR model, the mixed frequency vector auto-regression (MF-VAR) technique is proposed that could be modelled in line with mixed frequency data without processing the original data (Ghysels et al., 2004; Götz et al., 2016), which possesses more effectual estimated capacity (Chang et al., 2023; Hu et al., 2022; Jiang & Yu, 2023; Kuzin et al., 2011; Su et al., 2023). More importantly, this technique is primarily put forward to be employed in small proportions of sampling frequency (Ghysels et al., 2016). Thus, the MF-VAR process constructed by monthly AII, as well as quarterly UR and GDP, would be written as the following formula:

$$\begin{bmatrix} AII_{1t} \\ AII_{2t} \\ AII_{3t} \\ UR_t \\ GDP_t \end{bmatrix} = \sum_{k=1}^{3} \begin{bmatrix} \beta_{11,k} & \beta_{12,k} & \beta_{13,k} & \beta_{14,k} & \beta_{15,k} \\ \beta_{21,k} & \beta_{22,k} & \beta_{23,k} & \beta_{24,k} & \beta_{25,k} \\ \beta_{31,k} & \beta_{32,k} & \beta_{33,k} & \beta_{34,k} & \beta_{35,k} \\ \beta_{41,k} & \beta_{42,k} & \beta_{43,k} & \beta_{44,k} & \beta_{45,k} \\ \beta_{51,k} & \beta_{52,k} & \beta_{53,k} & \beta_{54,k} & \beta_{55,k} \end{bmatrix} \begin{bmatrix} AII_{1,t\text{-}k} \\ AII_{2,t-k} \\ AII_{3,t-k} \\ UR_{t-k} \\ GDP_{t\text{-}k} \end{bmatrix} + \begin{bmatrix} \upsilon_{1t} \\ \upsilon_{2t} \\ \upsilon_{3t} \\ \upsilon_{5t} \\ \upsilon_{6t} \end{bmatrix}, \tag{8}$$

where $\beta_{ij,k}$ (i, j = 1, 2, 3, 4 and 5, k = 1, 2 and 3) is the matrix of parameters, and υ_{it} (i = 1, 2, 3, 4 and 5) is the disturbance term. The MF-VAR technique would reduce the coefficients' number by fitting a function to a coefficient of high-frequency variable (Wang et al., 2020). It can be seen from Equation (8), AII_{1t}, AII_{2t} and AII_{3t} are piled up as one vector. Hence, in order to reflect the interrelation between artificial intelligence and employment in China, the above formula would be further denoted as Equation (9):

$$\mathrm{UR}_t = \sum_{k=1}^{3}\left[\sum_{j=1}^{3}\beta_{5j,k}\mathrm{AII}_{j,t-k} + \beta_{55,k}\mathrm{UR}_{t-k} + \beta_{56,k}\mathrm{GDP}_{t-k}\right] + \upsilon_{5t}, \tag{9}$$

where $\alpha_{5j,k}$ (j = 1, 2, 3, 4 and 5, k = 1, 2 and 3) would take various values of each other; thereby, $\mathrm{AII}_{1,t-k}$, $\mathrm{AII}_{2,t-k}$ and $\mathrm{AII}_{3,t-k}$ are considered to have heterogeneous effects on UR_t. In light of Hu et al. (2022) and Su et al. (2023), we specifically set up the Cholesky order, that is $\mathrm{AII}_t \rightarrow \mathrm{UR}_t \rightarrow \mathrm{GDP}_t$ in the LF-VAR system and $\mathrm{AII}_{1t} \rightarrow \mathrm{AII}_{2t} \rightarrow \mathrm{AII}_{3t} \rightarrow \mathrm{UR}_t \rightarrow \mathrm{GDP}_t$ in the MF-VAR process.

Generally, in order to cope with the various frequency data, the LF-VAR technique uses time-dependent summation. However, Silvestrini and Veredas (2008) prove that the statistical inferences might be incorrect if high-frequency sequences are forced to aggregate or average, such as in the LF-VAR technique, since information is missing. On the contrary, the MF-VAR process has a unique property in that it takes full advantage of mixed-frequency data (Miller, 2014), and it is conducive to capturing the heterogeneous effect of high-frequency series on the low ones (Motegi & Sahahiro, 2018). Performing the MF-VAR methodology, which requires no filtering procedure, would recognise the effects of monthly AII on quarterly UR under the control of quarterly GDP.

4. Data

We take the monthly (129 months) series from January 2013 to September 2023, and quarterly (43 quarters) sequence of the first quarter of 2013 to the third quarter of 2023 to identify whether artificial intelligence replaces or creates employment. 2013 is considered the first year of maturity of deep learning, an essential artificial intelligence technology. Since then, artificial intelligence technology has ushered in an era of explosion. Under this background, China has actively promoted the development of artificial intelligence: From 2013 to 2015, China primordially recognised the significant role of artificial intelligence and prepared to introduce relevant policies; from 2015–2017, artificial intelligence rises to the national development strategy (e.g., it is written into the Five-Year Plan), and plenty of the related policies are implemented to encourage industrial development; since 2017, these policies have been more targeted, focusing on the combined value of artificial intelligence technology and social and economic industries. Based on these, China has become one of the leading economies in artificial intelligence. However, the existing researches employ various approaches to measure artificial intelligence: First, according to Mutascu (2021) and Nguyen and Vo (2022), they employ the number of patents to measure, whereas relying solely on patent rights may ignore the actual application of this digital technology. Second, in accordance with Guliyev (2023) and Guliyev et al. (2023), they search keywords in Google to construct, while Google search data may not be fully representative of the market as a whole, such as China may be more likely to use other search engines. Third, in light of Li and Qi (2022), they use questionnaires and online data to analyse, but it has intense subjectivity. Fourth, in line with Jung and Lim (2020), Ni and Obashi (2021), Gravina and Pappalardo (2022) and Javed (2023), they choose robots to represent; however, they cannot reflect the full capabilities and potential of artificial intelligence since robots are only one of the important applications of this digital technology.

Thereupon, we select the monthly Wind Artificial Intelligence Concept Index (AII) to reflect the development of the artificial intelligence market in China (Qin et al., 2023a, 2023c), which could be obtained from the Wind Database. This index's code is 866095. WI is formed by assigning the free float market value weight to 50 constituent stocks. These stocks mainly contain enterprises engaged in three areas, including information technology (accounts for 84.11%), alternative consumption (accounts for 10.51%) and industry (accounts for 5.38%). An increase in AII highlights that there is faster progress in the artificial intelligence market and vice versa. Further, we set AII_1, AII_2 and AII_3 as AII at the first, second and third month in each quarter respectively, and AII_a is the average of AII_1, AII_2 and AII_3. To prevent the adverse impacts of excessive and unusual fluctuation, the research transforms AII, AII_1, AII_2, AII_3 and AII_a by making the natural logarithm.

As an emerging digital technology, artificial intelligence exerts an essential effect on the economic field, especially on the labour market. In order to identify this effect, we choose the quarterly urban registered unemployment rate in China (UR) to represent the development of the labour market (Feng et al., 2017; Li et al., 2023b; Zhang & Liu, 2020), which can be acquired from the National Bureau of Statistics of the People's Republic of China. This index is calculated by the human resources and social security department based on the administrative records of unemployed persons registered with employment service agencies. The higher UR means that there is a stunted development of the labour market and vice versa. Besides, since the registered unemployment rate is only published until 2021, the urban survey unemployment rate for 2022–2023 is used to represent UR, which is to obtain employment information by means of household visits. Additionally, economic growth is closely related to the labour market and digital technology (Boubtane et al., 2013; Deng et al., 2023; Hang & Chen, 2022; Kelishomi & Nisticò, 2022; Soler et al., 2018), which exerts certain impacts on the connection between AII and UR. After that, the research selects the quarter-on-quarter gross domestic production growth in China (GDP) to reflect economic growth (Wang et al., 2023c), which could be acquired from the National Bureau of Statistics of the People's Republic of China. In accordance with the above analyses, the data frequencies of UR, GDP and AII are different, indicating that the interrelationship between artificial intelligence and employment is non-linear and complicated, as well as impacted by economic growth. The conventional LF-VAR technique cannot identify this complex connection; thus, the research performs the MF-VAR technique to more comprehensively analyse the transmission mechanism between AII and UR.

The descriptive statistics of the above sequences are shown in Table 2. It could be seen that the mean values of AII_1, AII_2, AII_3, AII_a, AII, UR and GDP are 8.388, 8.408, 8.431, 8.409, 8.409, 4.193 and 1.514, suggesting that these chosen sequences are concentrated on above levels. AII_1, AII_2, AII_3, AII_a, AII and GDP have negative skewness, suggesting they obey the left-skewed distributions, while UR conforms to the right one because of its positive value. Their kurtosis proves that AII_1, AII_2, AII_3, AII_a, AII, UR and GDP follow the leptokurtic distributions with the properties of high peaks and fat tails. Moreover, the Jarque-Bera test ascertains that the initial supposition that the variable follows the standard normal distribution will be refuted in AII_1, AII_2, AII_3, AII_a, AII, UR and GDP at a 1% level.

Table 2. Descriptive statistics for AII_1, AII_2, AII_3, AII_a, AII, UR and GDP

Variables	AII_1	AII_2	AII_3	AII_a	AII	UR	GDP
Observations	43	43	43	43	129	43	43
Mean	8.388	8.408	8.431	8.409	8.409	4.193	1.514
Median	8.602	8.578	8.584	8.573	8.584	4.040	1.600
Maximum	8.975	8.919	9.017	8.960	9.017	5.833	11.500
Minimum	6.955	6.997	7.031	6.994	6.955	3.610	–10.400
Standard Deviation	0.509	0.487	0.478	0.488	0.488	0.587	2.544
Skewness	–1.562	–1.535	–1.569	–1.596	–1.560	1.646	–1.075
Kurtosis	4.316	4.335	4.572	4.480	4.424	4.362	17.668
Jarque-Bera	20.600***	20.083***	22.063***	22.186***	63.197***	22.744***	393.773***
p-values	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: AII is monthly data, whereas other sequences are quarterly data. AII_a is the total average of AII_1, AII_2 and AII_3. *** points out the significance at a 1% level.

5. Quantitative analyses and discussions

Through employing the parameter bootstrapping of 10000 iterations in various horizons (h = 0, 1, ..., 12), the research builds the LF-VAR system based on AII_a, UR and GDP. Figure 1 reports the low-frequency impulse responses with 95% confidence intervals, shown in solid red lines. We can observe that AII_a exerts a favourable effect on UR, revealing that the development of artificial intelligence technology may raise unemployment and disrupt China's labour market. Conversely, UR has an adverse effect on AII_a in the first two periods and a positive effect in the fourth period. In addition, the influences of AII_a and UR on GDP tend to 0 after alternating positive and negative; GDP exerts a positive effect on AII_a in the short term and an adverse impact in the medium and long runs; UR is negatively affected by GDP.

The results of the predictive error variance decomposition of the LF-VAR technique are stated in Table 3. In the short-run situation (h = 4), the predictive error variance of UR would be interpreted as 4.5% by AII_a, 3.9% by GDP and 91.6% by itself; AII_a contributes 0.6% of the prediction error variance of GDP, UR and GDP account for 1.9% and 97.5% respectively; the predictive error variance of AII_a can be explained 1.9% by UR, 0.4% by GDP and 97.7% by itself. In the medium-run situation (h = 8), AII_a and GDP contribute more to the predictive error variance of UR, the proportions are 7.1% (with an increase of 2.6 percentage points) and 4.4% (with a rise of 0.5 percentage points); AII_a is explained more by UR, the proportion is 3.3% (with an increase of 1.4 percentage points), and AII_a and GDP account for 96.2% and 0.5% respectively; the predictive error variance of GDP is similar to the short term. In the long-run situation (h = 12), the contribution of AII_a to the predictive error variance of UR is further increased, which grows 2.7 percentage points to 8.9%, and UR and GDP account for 86.5% and 4.6% respectively; the prediction error variance of AII_a would be interpreted 8.5% by UR, 0.8% by GDP and 90.7% by itself; the prediction error variance of GDP is similar to the short and medium terms.

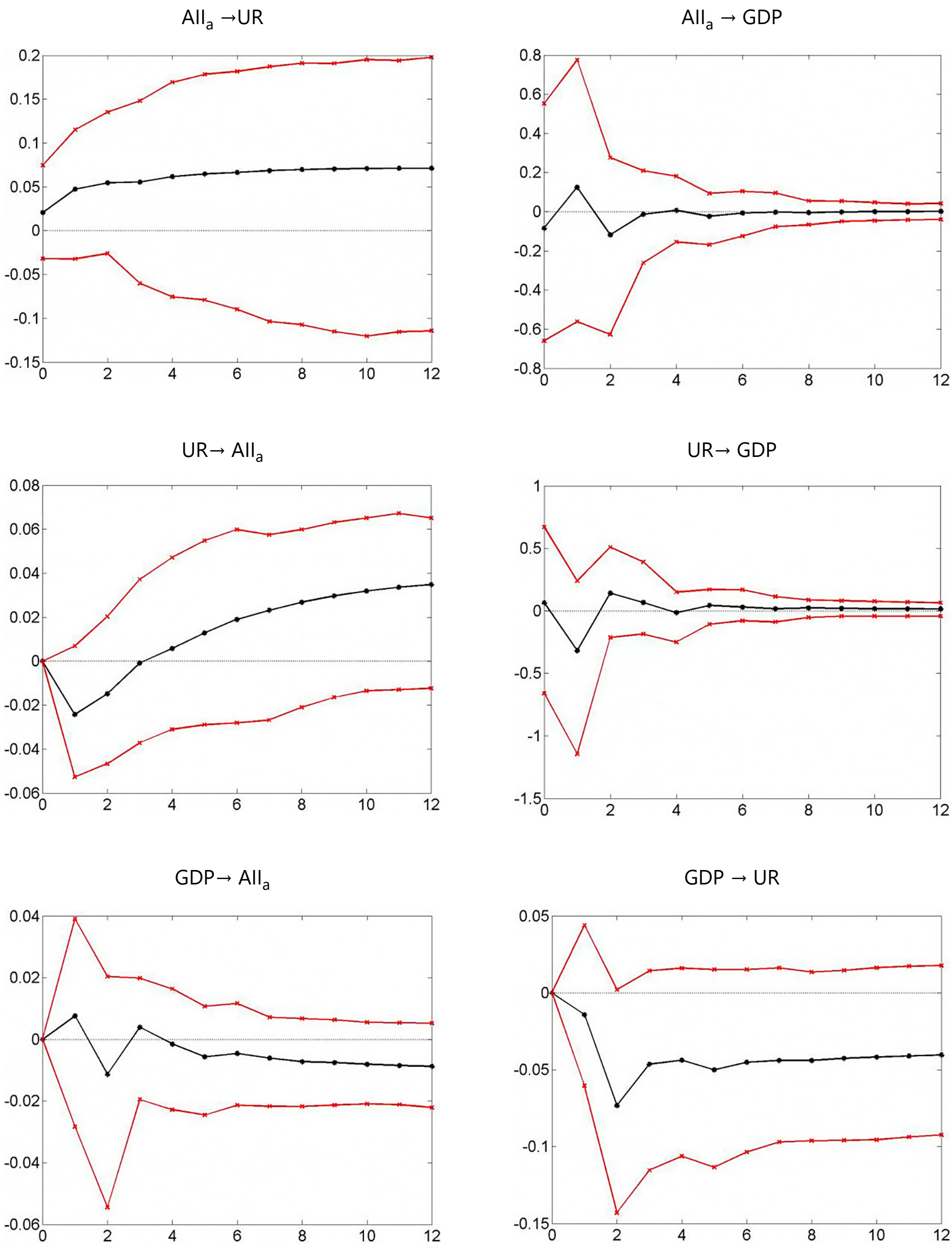

Figure 1. Impulse responses of the LF-VAR system

Table 3. Predictive error variance decomposition of the LF-VAR system

Decomposition of AII_a			
	AII_a	UR	GDP
h = 4	0.977	0.019	0.004
h = 8	0.962	0.033	0.005
h = 12	0.907	0.085	0.008
Decomposition of UR			
	AII_a	UR	GDP
h = 4	0.045	0.916	0.039
h = 8	0.071	0.885	0.044
h = 12	0.089	0.865	0.046
Decomposition of GDP			
	AII_a	UR	GDP
h = 4	0.006	0.019	0.975
h = 8	0.005	0.020	0.975
h = 12	0.005	0.020	0.975

Notes: The LF-VAR system employs quarterly AII_a, UR, and GDP, and the research uses predictive error variance decomposition at horizons of 4, 8, and 12 quarters, respectively.

However, if the monthly data (AII) is averaged into the quarterly series (AII_a) in the LF-VAR system, some information is lacking. Then, using the LF-VAR technique might lead to relatively weak explanatory powers and even incorrect statistical inferences (Ghysels et al., 2004; Ghysels et al., 2016; Su et al., 2023). To resolve this challenge, the research constructs an MF-VAR process to comprehensively recognise the non-linear interrelationship among AII, UR and GDP. Table 4 states the results of the predictive error variance decomposition of the MF-VAR technique. It could be observed that AII (AII_1 + AII_2 + AII_3) would contribute about 10% of the prediction error variance of UR, that is, 10.9% in the short run, 10.0 in the medium run and 10.5 in the long run. This outcome indicates that the MF-VAR system has more explanatory power than the LF-VAR one since the former can fully use mixed-frequency data information. A similar phenomenon is also perceived in other series; for example, AII accounts for about 5% of the prediction error variance of GDP, which further evidences that the MF-VAR process would draw a more accurate conclusion than the LF-VAR one. Thereupon, it is reliable to utilise the MF-VAR method to recognise the complex interrelationship between AII (monthly frequency) and UR (quarterly frequency) under the control of GDP (quarterly frequency).

The research discusses explicitly the mixed frequency impulse response results, and we depict these outcomes in Figure 2. It could be observed that AII_1 and AII_2 exert a favourable impact on UR, and AII_3 has an adverse effect on UR. The favourable influence indicates that artificial intelligence technology would substitute employment, and we interpret this positive effect from three sides. Firstly, high AII causes automation to replace manpower. Artificial intelligence technology would automate many repetitive and standardised works, which were originally done by humans (Rampersad, 2020; Wang et al., 2023a). For instance, artificial intelligence could control lines, automate production, as well as improve production efficiency

Table 4. Predictive error variance decomposition of the MF-VAR system

Decomposition of AII_1						
	AII_1	AII_2	AII_3	Sum (AII_i)	UR	GDP
h = 4	0.436	0.222	0.331	0.989	0.005	0.006
h = 8	0.416	0.232	0.317	0.965	0.029	0.006
h = 12	0.405	0.225	0.296	0.926	0.066	0.008
Decomposition of AII_2						
	AII_1	AII_2	AII_3	Sum (AII_i)	UR	GDP
h = 4	0.453	0.276	0.257	0.986	0.008	0.006
h = 8	0.431	0.268	0.253	0.952	0.040	0.008
h = 12	0.416	0.255	0.236	0.907	0.083	0.010
Decomposition of AII_3						
	AII_1	AII_2	AII_3	Sum (AII_i)	UR	GDP
h = 4	0.425	0.264	0.304	0.993	0.005	0.002
h = 8	0.412	0.260	0.292	0.964	0.032	0.004
h = 12	0.401	0.250	0.275	0.926	0.067	0.007
Decomposition of UR						
	AII_1	AII_2	AII_3	Sum (AII_i)	UR	GDP
h = 4	0.062	0.014	0.033	0.109	0.851	0.040
h = 8	0.070	0.010	0.020	0.100	0.853	0.047
h = 12	0.079	0.011	0.015	0.105	0.846	0.049
Decomposition of GDP						
	AII_1	AII_2	AII_3	Sum (AII_i)	UR	GDP
h = 4	0.013	0.007	0.030	0.050	0.024	0.926
h = 8	0.014	0.007	0.033	0.054	0.024	0.922
h = 12	0.014	0.007	0.033	0.054	0.025	0.921

Notes: The MF-VAR system employs monthly AII_i (i = 1, 2, 3), as well as quarterly UR and GDP. Besides, the research uses the predictive error variance decomposition at horizons are 4, 8 and 12 quarters respectively.

and product quality in the manufacturing field (Mo et al., 2023; Tian et al., 2023; Zeba et al., 2021). Also, automated customer service systems would replace manual telephone answering and other related jobs (Amagasa & Moriya, 2022). The advancement of artificial intelligence makes it possible for many traditional works (especially highly repetitive and regular jobs) to be replaced by robots or automated systems, which leads to fewer jobs in related industries, increasing UR. Secondly, high AII replaces knowledge works. Artificial intelligence technology offers strong intelligence and learning ability in some fields, and using this digital technology could carry out large-scale data analysis, pattern recognition and decision-making (Cai et al., 2023; Li et al., 2023a; Schramm et al., 2023). The application of artificial intelligence not only makes some traditional skills obsolete (e.g., handicrafts and other low-skilled jobs) but also replaces some jobs that require highly specialised knowledge and skills (e.g., accounting and legal consulting). For example, artificial intelligence could help doctors make disease diagnoses and treatment plans in the medical field, providing more accurate and timely medical services (Ali et al., 2023; Huang et al., 2023b; Qin et al., 2024). Hence, the development of artificial intelligence might replace knowledge-based positions, making relevant workers face employment difficulties, which causes UR to rise accordingly. Thirdly, high AII makes changes in career structure. The utilisation of artificial intelligence technology may lead to the reduction or disappearance of some traditional jobs. With the changes in job functions and career structure, UR would be further pushed up.

The adverse effect suggests that artificial intelligence technology would create employment, and we explain this negative influence from the following aspects. First, the development of infrastructure promotes the construction of intelligent information infrastructure and the improvement of the intelligence level of traditional infrastructure (McMillan & Varga, 2022; Wu et al., 2022), creating more new jobs in this process, which causes a decline in UR. Second, artificial intelligence not only facilitates the formation of artificial intelligence industrial clusters and innovation highlands (Alenizi et al., 2023; Schmitt, 2023) but also promotes the intelligent upgrading of enterprises through deep integration with industries in various fields (Lei et al., 2023; Thapa et al., 2023). Then, there are more employment opportunities in the market, leading UR to fall correspondingly. Third, the wide application of artificial intelligence in education, medical care, elderly care, environmental protection, urban governance, judicial services and other fields (Ali et al., 2023; Chiu et al., 2023; Ma et al., 2023; Qin et al., 2023a), as well as the deep application in accurate perception, prediction, early warning and other aspects would also raise new job opportunities (Said et al., 2023; Wang et al., 2023b; Zhang et al., 2021). Fourth, the development of artificial intelligence might drive the progress of other industries, not only directly creating more new jobs (Guliyev et al., 2023) but also indirectly decreasing UR by promoting economic growth (Boubtane et al., 2013; Soler et al., 2018). Fifth, developing and applying artificial intelligence could provide more high-quality jobs for workers and enhance their creativity and sense of achievement (Prentice et al., 2023). Then, it empowers workers to complete work in various forms according to their wishes and helps workers learn new professional skills most suitable for their characteristics, enhancing the quality of employment and reducing UR. Through analysing the predictive error variance decomposition of UR, the sums of contributions of AII_1 and AII_2 to UR is 7.6% in the short run, 8.0% in the medium run and 9.0% in the long run, which are larger than the contributions of AII_3 (3.3%, 2.0% and 1.5% in short-, medium- and long-term situations). Therefore, we can conclude that China's artificial intelligence technology positively and negatively impacts unemployment, but the total effect is substitution. The above discussions are consistent with the theoretical analysis that there are certain influences from AII to UR.

Then, we consider other impulse responses. To begin with, AII_1, AII_2 and AII_3 are positively affected by UR after the first period, which further confirms the result we discussed above; that is, the total interrelationship between AII and UR shows positive. Secondly, GDP exerts an adverse effect on UR, and UR negatively influences GDP; this phenomenon is consistent with Okun's Law. This theory reveals that when the actual GDP growth relative to potential GDP growth falls by 2%, the unemployment rate rises by about 1% (Attfield & Silverstone, 1998; Benos & Stavrakoudis, 2022; Elhorst & Emili, 2022). Hence, the negative connection between GDP and UR corresponds with reality, and it is reasonable to choose GDP as the control sequence in this research. Thirdly, AII exerts positive and negative effects on GDP.

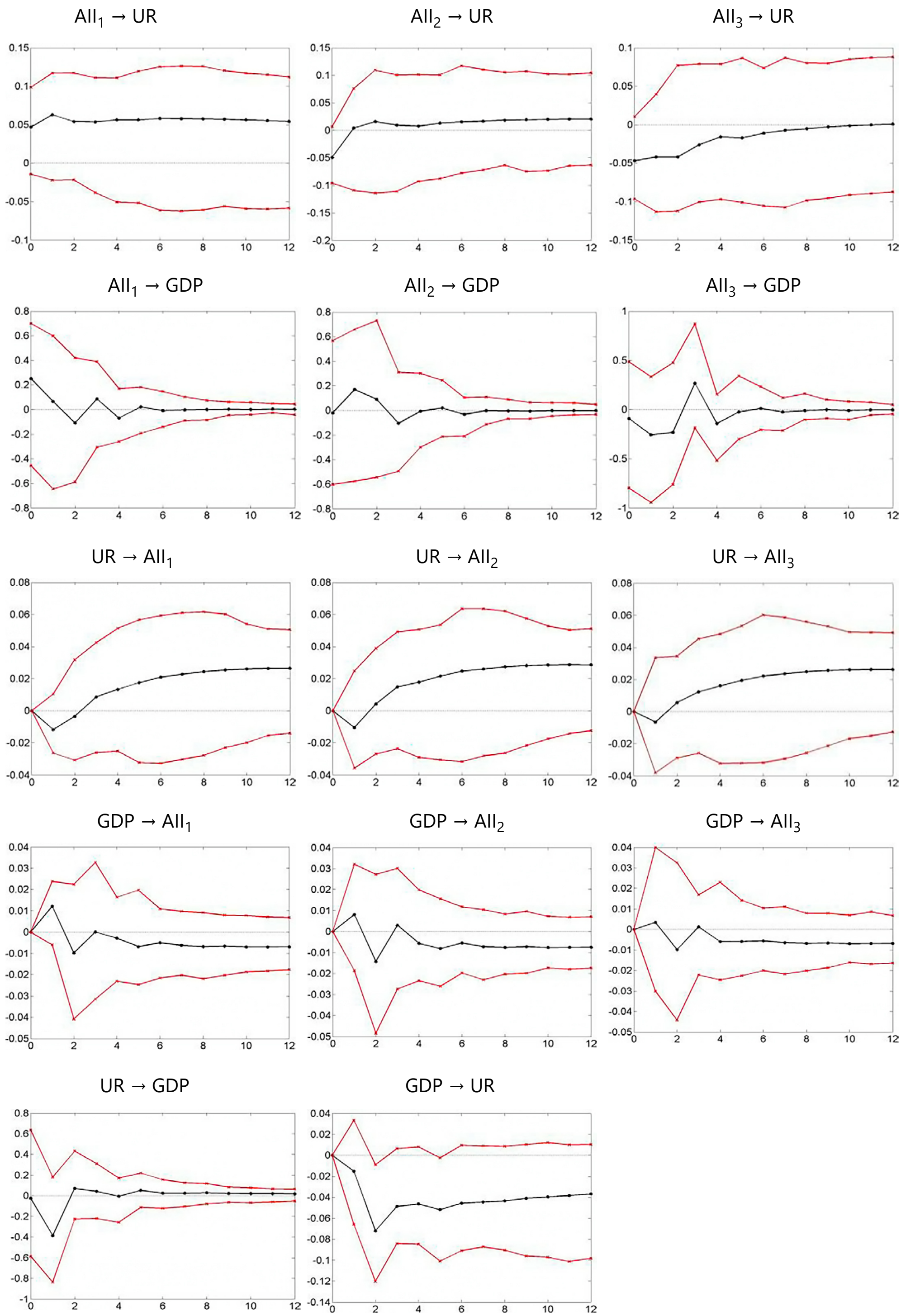

Figure 2. Impulse responses of the MF-VAR system

On the one hand, artificial intelligence technology can not only realise automated production that increases productivity (Czarnitzki et al., 2023; Parteka & Kordalska, 2023; Yang, 2022; Zhai & Liu, 2023) but also drives emerging industries that promote industrial transformation and upgrading (Lei et al., 2023; Su et al., 2024), causing GDP to grow accordingly. On the other hand, artificial intelligence might also be a hindrance to economic growth, such as this digital technology may decrease employment, cause privacy violations and data misuse, increase cyberattacks and criminal activity, widen the gap of wealth, have a high threshold for application and so on (Amagasa & Moriya, 2022; Huang et al., 2023a; Khalid et al., 2023; Rampersad, 2020; Saura et al., 2022; Wang et al., 2023b). Also, it can be perceived that GDP plays an intermediary role, that is AII influences UR via GDP. Fourthly, GDP has a favourable influence on AII in the short-run situation and an adverse effect in the medium- and long-run situations, which coincides with AII's positive and negative impacts on GDP.

To sum up, the extant literature theoretically analyses the concrete role of artificial intelligence in the labour market and draws various conclusions that the utilisation of artificial intelligence technology would substitute employment (e.g., Gravina & Pappalardo, 2022; Jung & Lim, 2020; Nguyen & Vo, 2022) and the reverse one (e.g., Guliyev et al., 2023; Li & Qi, 2022; Mutascu, 2021; Sequeira et al., 2021). However, no research provides quantitative evidence about the mutual influences between them. Additionally, few scholars probe it from the perspective of China (Ma et al., 2022; Wang et al., 2020). Furthermore, the complicated interrelationship between AII and UR based on mixed frequency data has been neglected by the previous research (Acemoglu & Restrepo, 2020; Javed, 2023; Ni & Obashi, 2021; Rampersad, 2020; Rebelo et al., 2023; Wang et al., 2023a). Hence, this article compares the predictive error variance decomposition between the LF-VAR technique and the MF-VAR methodology, it could be discovered that the latter has a better explanatory power than the former. Thereupon, it is reliable to utilise the MF-VAR technique to recognise the non-linear and complex interrelationship among the mixed frequency variables (monthly AII and quarterly UR), which offers quantitative proof as to whether artificial intelligence replaces or creates employment in China. In addition, the research takes quarterly GDP as the control series to enhance the accuracy and robustness of quantitative analyses. The impulse responses of the MF-VAR technique point out that AII exerts favourable and adverse impacts on UR, which is consistent with the theoretical analysis. Among them, the positive one is primarily due to the replacement of manpower and knowledge works by automation, as well as the reduction or disappearance of some traditional jobs caused by the changes in career structure. However, the negative one indicates that artificial intelligence would create more employment opportunities by developing and enhancing the infrastructure, forming the artificial intelligence industry, applying on a larger scale and fields, facilitating the progress of other industries, and improving workers' creativity. More importantly, according to UR's predictive error variance decomposition, the total effect of China's artificial intelligence technology on employment is substitution. In turn, UR positively impacts AII, further ascertaining the above results. Besides, UR has a negative connection with GDP, confirming the rationality of choosing GDP as the control sequence. Additionally, the interaction between GDP and AII is both positive and negative, and AII could influence UR through GDP.

6. Conclusions and policy recommendations

6.1. Conclusions

This article identifies the transmission mechanism between artificial intelligence and the unemployment rate in China and further confirms whether artificial intelligence exerts a creation or substitution effect on employment. We utilise the LF-VAR technique and the MF-VAR methodology to recognise the intricate interrelation between AII and UR, and the research also selects GDP as the control series to guarantee rationality and robustness. By comparing these two models, we find that the MF-VAR method will fully use mixed frequency data, which is more appropriate than the LF-VAR technique. The quantitative outcomes reveal favourable and adverse impacts of AII on UR, where the positive one points out that artificial intelligence technology would replace employment, whereas the negative one indicates that digital technology might create more employment opportunities. This result coincides with the theoretical analysis, highlighting that AII exerts certain influences on UR, but the influencing direction is not confirmed. Based on UR's predictive error variance decomposition, artificial intelligence technology's total effect on employment in China is substitution. In addition, AII is positively affected by UR, UR has a negative interaction with GDP, and there is a positive and negative connection between GDP and AII. Through probing the complex interrelation between AII and UR, we perceive that artificial intelligence has both stimulating and inhibiting impacts on the labour market in China, and its overall effect on employment is a substitution, which is novel evidence of the relationship between artificial intelligence and employment.

6.2. Policy implications

The current policy shortcomings regarding the impact of artificial intelligence technology on employment in China are mainly reflected in the following aspects: First, the existing policies focus more on current employment issues and fail to anticipate and plan for the long-term challenges adequately. Second, the existing policies usually fail to provide adequate training and re-education opportunities to help workers adapt to new employment environments. Third, the existing policies often fail to provide adequate protection for flexible employment, such as identifying labour relations, social security contributions and other issues that have not been resolved. Under this backdrop, the relevant authorities, enterprises and workers in China must formulate and adopt new policies to avoid the unemployment wave of artificial intelligence technology's development. On the one hand, the relevant authorities should adopt proactive policies to address the risks posed to employment by artificial intelligence. The related authorities could ensure workers' employment status and income by adjusting tax policies, establishing employment opportunities, providing skills training, etc. On the other hand, the relevant authorities should pay attention to developing policies and social welfare systems and strengthen the forecasting and planning of long-term trends. Precisely, they ought to predict new occupations and industries that are likely to emerge, assess the impact of these changes on employment, and then formulate relevant policies to protect the rights and interests of the unemployed and provide vocational training and re-employment support. The enterprises should offer more training and education opportunities to ensure workers and employees have the necessary skills and knowledge to secure their employment and potential. The workers must strengthen their learning and improve their skill levels, engage with and understand how artificial intelligence works and where it is applied, adapt to the needs and development trends of emerging professions and adjust their career planning and employment direction promptly. Above all, the whole society should actively respond to the impacts and changes of artificial intelligence on the labour market, such as changing the traditional concept of employment, encouraging people to accept new ideas and skills, adapting quickly to the new work environment, etc.

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