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IMPACT OF AI ON CHINA'S LABOUR MARKET AND ECONOMIC GROWTH: HYBRID MODELLING

As the second largest economy in the world, China is at a critical stage of AI technology application. This study aims to explore the impact of AI on China's labour market and economic growth using a mixture of computational techniques and methodologies: correlation and regression analysis, production functions theory, linear programming, trends analysis, System Dynamics simulation concept. The main results show that AI technology diffusion is strongly correlated with the main labour market indicators and plays an important role in alleviating the impact of aging population and labour force shortages on economic growth on China. Two different macro production functions, which include robot installation as a separate parameter are built to be used in a System Dynamics model for comparative cause-and-effect simulation forecast of the robot installation, labour force, investments in fixed assets and GDP dynamics up to 2030.

Keywords: *AI, China's labour market, regression analysis, production function, simulation forecast.*

Tabl. 2. Fig. 9.

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ВПЛИВ ШІ НА РИНОК ПРАЦІ ТА ЕКОНОМІЧНЕ ЗРОСТАННЯ КИТАЮ: ГІБРИДНЕ МОДЕЛЮВАННЯ

Як друга за величиною економіка світу, Китай перебуває на критичному етапі застосування технологій штучного інтелекту. Це дослідження має на меті дослідити вплив штучного інтелекту на ринок праці Китаю та економічне зростання, використовуючи поєднання обчислювальних методів та технологій: кореляційного та регресійного аналізу, теорії виробничих функцій, лінійного програмування, аналізу трендів, системно-динамічної концепції імітації. Основні результати показують, що поширення технологій штучного інтелекту тісно корелює з основними показниками ринку праці та відіграє важливу роль у пом'якшенні впливу старіння населення та дефіциту робочої сили на економічне зростання Китаю. Побудовано дві різні динамізовані макроекономічні виробничі функції, які включають коефіцієнт роботизації як окремий аргумент. Їх використано у системно-динамічній моделі для прогнозування динаміки роботизації, робочої сили, інвестицій в основні засоби та динаміки ВВП Китаю до 2030 року.

Ключові слова: *ШІ, ринок праці Китаю, регресійний аналіз, виробнича функція, імітаційний прогноз.*

Problem articulation. According to the forecast of International Data Corporation (IDC), by 2025, AI was expected to drive global economic growth by more than $ 15 trillion and change the structure of the global industrial chain. The Chinese government's supportive policies and strategic layout for AI have promoted the widespread of its application in China, especially in the fields of manufacturing, financial services, and healthcare (China's "New Generation Artificial Intelligence Development Plan", 2017). In the first nine months of 2024, China's AI industry

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attracted over 80 billion yuan in investments (Statista, 2024). Nearly half of this funding was directed toward AI applications, highlighting a focus on practical implementations of AI technology. However, with the popularization of AI technology, the labour market faces severe challenges: on the one hand, the automation and AI may replace some traditional jobs; on the other hand, new technical positions and types of work are emerging and the skill requirements for workers are constantly increasing.

Main hypotheses and research objectives. In our research we try to test a number of the main hypotheses:

H1 – AI is strongly correlated with labour market indicators;

H2 – the impact of AI on China's job market is more substitutive, than complementary;

H3 – AI has positive impact on GDP dynamics, partly compensating the effect of aging population and shrinking labour force.

For quantitative analysis we needed statistics related to the spread of AI in China. The most accessible and directly related to our research is information about robotics dynamics. AI and robots are increasingly intertwined, with AI providing the intelligence that enables robots to perform complex tasks and adapt to their environments. As technology progresses, the collaboration between AI and robotics will open new opportunities and challenges across various fields, influencing how people live and work.

We introduced the concept of hybrid modelling as a technology for sequential operation with a complex of mathematical and computer models and methods when considering different aspects of a specific problem. It has long been known that in the framework of System-Thinking-Activity Methodology (Bouryak, A. et al., 2002) system thinking is seen as operating with ideal objects of a certain theory. For systems analysts and professionals in the field of modelling, such ideal objects are models of different classes. Thus, in our research there are two main objectives: testing the hypotheses put forward and demonstration of a mixture of calculational and modelling technologies while analyzing AI impact on China's labour market and economic growth.

The study is based on macroeconomic data, retrieved from China Statistical Yearbooks (2011–2024) and robot installation and robot density data from the International Federation of Robotics (IFR) – Annex 1.

Literature review. At present, empirical research on the impact of artificial intelligence on the labour market mainly focuses on the following aspects:

The relationship between artificial intelligence and employment structure.

Some studies suggest that the development of artificial intelligence (AI) not only boosts productivity but also changes the structure of the labour market, particularly in terms of replacing low-skill labour (Guangsu & Gaosi, 2020). In China, with the application of AI in the manufacturing and service industries, certain low-skill jobs are gradually being replaced by machines, while the demand for high-skill talent is increasing (Chui et al., 2016). "As AI technology continues to advance, China's employment structure will undergo profound changes, especially in traditional manufacturing and service sectors, where automation and intelligent systems will replace many repetitive, low-skill jobs" (Chengzhang & Min, 2023).

b) *AI impact on salary levels*

The impact of AI on wage levels varies across industries and intensify job market polarization. In technology-intensive sectors such as IT and finance, the proliferation of AI has led to higher wage levels, particularly for high-skill positions, where wages have risen significantly (Brynjolfsson & McAfee, 2014). The widespread use of automation technology may lead to lower wages for low-skilled jobs in manufacturing and basic services, while wages for high-skilled jobs will increase due to higher qualification and increased demand.

c) *Industry-level impact*

Many studies have explored the impact of AI on specific industries. For example, Bessen (2019) noted that the widespread adoption of AI and automation in the service sector has brought about changes, especially in customer service, healthcare and education, where new job roles and types are evolving. The forms of work and occupations in these industries have changed and AI applications are driving automation and digitalization. The widespread use of AI allows Chinese enterprises to participate more efficiently in the global value chain, promoting industrial upgrades, but it also leads to a shift in labour demand, particularly with a significant increase in the need for technical and managerial positions (2025).

d) *Regional Difference Analysis*

For China, the impact of AI varies significantly in different regions. The labour market in developed regions (such as Beijing and Shanghai) is greatly affected by AI, while in underdeveloped regions, the penetration of AI technology is relatively low, resulting in different responses in the labour market in different regions. Tambe et al. (2019) and Kong & Liu (2020) pointed out that the spread of robotic technologies has resulted in significant employment structure differences across regions the acceptance of technological progress varies in different regions and industries, especially in small and medium-sized cities and rural areas, where the application of AI is still in its early stages, so its impact on local employment is relatively limited. This is particularly prominent in China, where the eastern region and first-tier cities have a high degree of acceptance and application of AI technology, while the central and western regions face the problem of slow technology popularization, resulting in increased differences in regional labour markets.

Key results

a) *AI and labour market. Correlation between robot density and labour market indicators.*

Table 1. **Correlation matrix,** *author's results*

	Robot density (X1)	Number of high-level talents (10000 people) (X2)	Average salary (X3)	Number employed (10000) (X4)	Elderly support ratio (%) (X5)
X1	1.000				
X2	0.976	1.000			
X3	0.975	0.981	1.000		
X4	-0.928	-0.924	-0.908	1.000	
X5	0.975	0.986	0.996	-0.932	1.000

Let's start from our first hypothesis, i.e., test the correlation between robot density indicator and labour market indicators. As we see in table 1, all the indicators are strongly correlated between each other and with robot density, which has high positive correlation with all the indicators and strong negative correlation with a number of employed, which is quite understandable if the hypothesis of substitution is true. Two other negative correlation coefficients are between the average salary and the number of employed and between the number of employed and elderly support ratio. From mathematical point of view the more the number of employed the less will be average salary indicator, and elderly support ratio is also negatively correlated with the number of employed, because the less is the number of employed, the greater should be elderly (and unemployed) support ratio. Besides, negative correlation of the number of employed and the number of high-level talents can be explained by the fact that with the growth of robotics, the work of one highly qualified specialist replaces the work of several low-skilled workers. But the most important for us is confirmation of a significant relationship between spread of AI and labour market indicators.

Robot density (RD) – it's robot installation per 10000 employees. Two periods of rapid growth are clearly visible in China's robot density dynamics (fig. 1) – an exponential growth in 2011–2017 ($RD=0.1792e^{0.3288x}$, $R^2 = 0.98$) and a kind of a goal seeking trajectory starting from 2019 ($RD = 0.0219x^4 - 0.371x^3 + 1.9795x^2 - 3.2991x + 3.4412$, $R^2 = 1$).

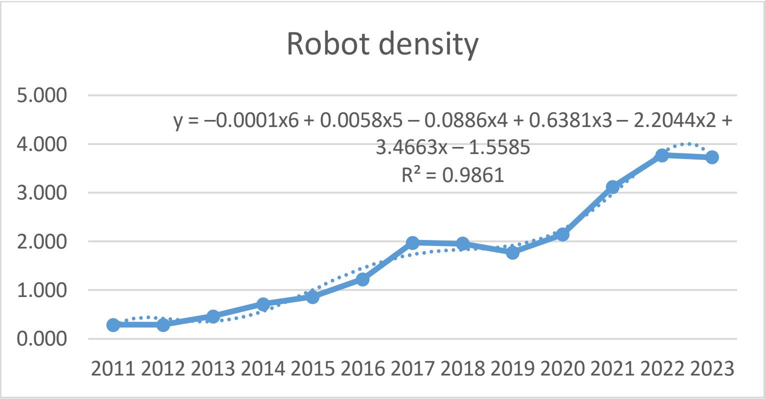

Fig. 1. **Robot density dynamics (2011–2023),**
author's visualization, https://ifr.org/wr-industrial-robots/

The new push to robot installation coincides with the onset of the coronavirus pandemics. In 2023 a relative decline of this indicator began, though China has overtaken Germany in the use of robots in industry and has moved up to the third place in the world rankings (Wiley..., 2024). China leads the world by a wide margin in terms of the number of industrial robots installed annually (276.3) by a sevenfold margin from Japan with 46.1(International Federation..., 2023).

From a labour market perspective, it is natural to assume that industrial robots are displacing people employed in production, especially low-skilled workers. We may check this hypothesis, analyzing correlation between China labour force and robot density indicators for different time horizons. For example, in 2011–2018 this correlation coefficient is –0.13, in 2014–2023 it equals already –0.97. The correlation between the number employed indicator and RD in 2014–2023 makes –0.94, which confirms our hypothesis, that AI has a substitution impact rather than a complementary one.

As for correlation between RD and unemployment rate, it's insignificant (0.31), which means that robot installation doesn't mean that displacement of employed will inevitably make them fall into the category of unemployed. They can improve their skills and take up new jobs, including those, arising from the spread of AI.

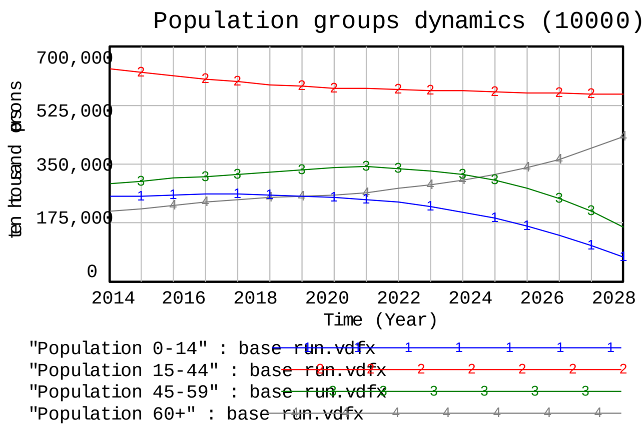

Fig. 2. **China's age groups dynamics and simulation forecast till 2030,** *(Bitkova & Xin, 2024)*

Of course, it's necessary to take into account the impact of demographic tendences in China on its labour force and the number employed dynamics. From the one hand, robots are substituting employed persons, but from another one – they help to offset the decline in the workforce due to the progressive aging of the nation and the decline in the working-age population in China.

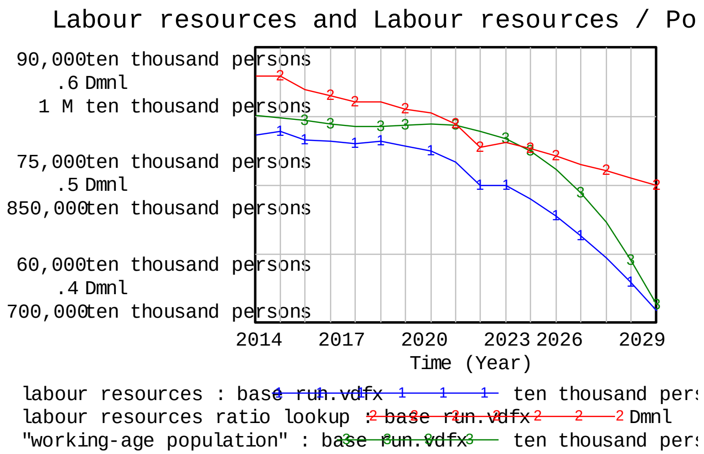

Fig. 3. **Labour resources and Labour resources/Population ratio,** *(Bitkova & Xin, 2024)*

A simulation model, presented in (Bitkova & Xin, 2024), gives the following forecasts for China's age groups and labour resources dynamics till 2030 (fig. 2, 3).

b) *Multiple linear regression model 1.* The next step in our quantitative analysis is the assessment of the impact of a number of factors on the working population (Labour force) with a special attention to the impact of Robot density indicator.

The model 1 we've got looks like:

$$Y = 85800.9 – 1320.76X_1 + 230525.8X_2 – 144780.9X_3 + 0.177X_4,$$

where Y is Working population, X_1 – Robot density, X_2 – Proportion of highly talents; X_3 – Elderly support rate; X_4 – Mean salary.

Regression model report shows that the model explains most of the variation in the dependent variable: $R^2 = 0.86$ and F-value = 10.8 are medium high, F-value is greater than Ftable ($k_1 = 4$, $k_2 = n-k-1 = 8$, $\alpha = 0.05$) = 3.84; both tStat and p-values show that model coefficients (except for $\beta_2 = 230525.8$) are also significant, and elderly support and robot density factors both have negative influence on the working population, which is quite understandable. The impact of mean salary is of course positive, but rather week ($\beta_4 = 0.177$). Though it may seem, that proportion of high-skill talents has strong influence on the dependent variable, in fact this coefficient is statistically insignificant.

c) *AI and economic growth.* Regression analysis. China's GDP and GDP per capita are steadily increasing, and in terms of GDP per capita, this can be only partially explained by the decline in the total population, while GDP is growing regardless of the decline in the working-age population and the number of employed. Thus, we may assume that AI creates a compensatory effect on economic growth in the context of unfavourable demographic situation.

Multiple linear regression model 2

Model 2 looks like:

$$Y = 23725.35 + 1814.522X_1 – 188781X_2 + 0.8422X_3,$$

where Y is GDP per capita; X_1 – Robot density; X_2 – Elderly support rate; X_3 – Mean salary.

High values of $R^2 = 0.999$ and F-value = 636.856 mean that the total variation of the outcome is well explained by the model and the model is a good fit for the data. All the coefficients are also statistically significant: |t Stat| > 2, p-values are all less than 0.05. Thus, the model confirms the hypothesis that investments in robotics have significant impact on GDP: one unit increase in RD gives 1814.522 units increase in GDP. If we compare linear coefficients of Robot density variable in both models, we'll see that its positive impact in GDP per capita is larger than its negative impact on the working people indicator.

d) *Construction of production functions.* To study the degree of participation of the main factors in the formation of GDP and their replacement rates, we've built a macro production function (PF), the arguments of which, in addition to Investments in fixed assets (K) and Labour force (L), include the indicator of Robot installation (R).

Production function 1. Let's consider a Cobb-Douglas production function (PF) with Hicks-neutral technical progress:

$$Y_t = ae^{\beta t} K_t^{\alpha_1} L_t^{\alpha_2} R_t^{\alpha_3}, \tag{1}$$

where:

Y_t – GDP in year t; a – proportionality coefficient; β – technical progress parameter; K_t – fixed assets investments in year t; L_t – labour force in year t; R_t – robot installation in year t; α_i – PF parameters

Investments in Robot installation are generally considered as a part of Investments in fixed assets. But in the framework of our research, it was important to single out the robot installation as a separate argument of the PF in order to quantitatively assess the characteristics of the interchangeability of labour resources and robots, and partial GDP elasticity due to the percentage change in the specified arguments.

In order to evaluate PF parameters, the normal procedure is its logarithmization, which allows to get the following multiple linear regression model:

$$Y_t = lna + \beta t + \alpha_1 lnK + \alpha_2 lnL + \alpha_3 lnR \tag{2}$$

Logarithmization may lead to a shift in parameters estimates, but in practice the magnitude of this shift can often be neglected.

Based on the fact that in most cases the least squares method allows to get a sufficiently good result for linear models approximation, we've conducted a number of experiments, using different PF arguments representing capital and labour, as well as robot installation/robot density indicators and varying time horizons. The only statistically acceptable regression model (based on 2011–2023 data) was the one for GDP (Y), as a dependent variable and Investments in fixed assets (K), Labour force (L) and Robot installation (R) – as independent variables, using the least square method in relation to the linearized model, proposed and substantiated in (Shults & Grebnev, 2015):

$$lnY = a + \alpha_1 \ln\left(\frac{K}{n}\right) + \alpha_2 ln^2\left(\frac{K}{n}\right) + \alpha_3 \ln\left(\frac{L}{n}\right) + \\ + \alpha_4 ln^2\left(\frac{L}{n}\right) + \alpha_5 \ln\left(\frac{R}{n}\right) + \alpha_6 ln^2\left(\frac{R}{n}\right) + \beta_1 t + \beta_2 t^2 \tag{3}$$

We've got the following approximation function for lnY:

$$lnY_{mod} = -9321.27+1.2\ln(K/n)-0.06\ln^2(K/n)+258.176\ln(L/n) - \\ -14.735\ln^2(L/n)-0.412\ln(R/n)+0.03\ln^2(R/n) +8.122t-0.002t^2 \tag{4}$$

The model on the whole is valid ($R^2 = 0.998$; Adjusted $R^2 = 0.994$; F-value = 246.25 (F_{table} for α = 0.01 equals 14.799); MAPE = 0.009, but judging by tStat and p-values its coefficients are unreliable. This may be due to multicollinearity, which as it is known does not affect the function's forecasting ability. We'll check it later using this function as an endogenous variable of a simulation model. Besides, though approximation function is significant, it's not easy to confirm fulfillment of the necessary requirements for the relevant production function.

Production function 2. Trying to get a reliable production function we've applied a least modules method of the linearized function approximation, which allows to get parameters' estimates as a result of the following linear programming problem solving:

$$Z = \sum_{i=1}^{n} (U_i + V_i) \rightarrow min$$
$$lnGDP_i = a_0 + a_1 lnK_i + a_2 lnL_i + a_3 lnR_i + a_4 t + U_i - V_i \quad (5)$$
$$V_i, U_i \geq 0, \mathrm{i} = 1 \div n$$

Using the same PF arguments and the same data as for PF1 we've got a statistically perfect result: $R^2 = 1$; F-value = 357.57; MAPE = 0.009; sum of (randomly scattered) residuals (a goal function) equals 0.174.

Estimates of the coefficients of a multiple linear regression model are the following:

$$a_0 = 126.97;\ a_1 = 0.021;\ a_2 = 0.49;\ a_3 = 0.08;\ a_4 = 0.066 \quad (6)$$

Thus, we have the following PF2:

$$Y_t = GDP_t = \mathrm{a}e^{\beta t} K^{\alpha_1} L^{\alpha_2} R^{\alpha_3} = e^{a_0} e^{0.066t} K_t^{0.021}\ L_t^{0.49}\ R_t^{0.078} \quad (7)$$

This production function meets all the requirements for this type of PF: $e^{a0}\,e^{0.066t}$ is positive and it's a growing function of *t*; all the exponents of the arguments are greater than zero, which means that elasticities of the output with respect to each of the resources are positive. That is, if we add a unit of a given resource, GDP will increase. Marginal rate of substitution for the arguments L and R makes –0.159L/R, which means that, the reduction in the workforce is compensated by robot installation in the amount of 0.159L/R at a fixed value of GDP. For Cobb-Douglas PF elasticities of the output with respect to its arguments coincide with their exponents. In our approximation function the highest coefficient of elasticity corresponds to the labour argument – one percent of change in the labour force will lead to 0.49 percent change in GDP.

Since we have managed to obtain a statistically reliable formula, which at the same time satisfies all the requirements for a PF, it can be used, for example, in the problems of maximizing output under constraints on investments in resources or minimizing the expenses of getting a given output, and of course for forecasting purposes taking into account trends in the dynamics of PF arguments.

e) *Trends analysis and simulation forecast.* Analysis of trends formulars, obtained in Excel for GDP, Population, Investments in fixed assets, Labour force, Robot installation and Robot density (for all of them R^2 lies between 0.95 and 1), upon closer examination has revealed that only those for GDP (y = 67439x+370909) and Population ($y = -52.694x^2 + 1341x+134180$) have turned to be statistically reliable.

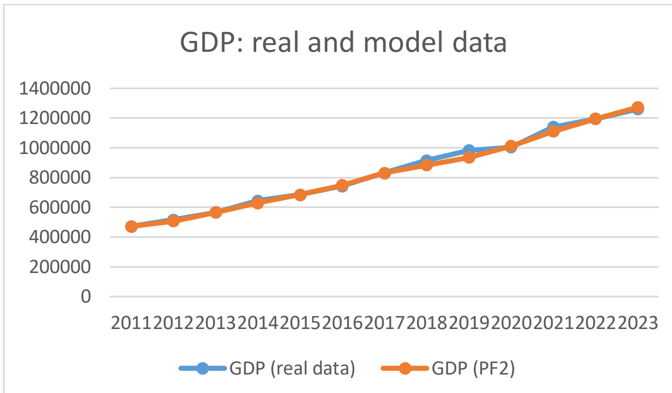

Fig. 4. **GDP dynamics (real and model data),** *authors' result*

That is why in our simulation model, developed using System Dynamics (SD) simulation concept, we've used a smoothing built-in function to get an appropriate result.

SD concept, proposed in mid-60s by J. Forrester is well known as an adequate instrument of macro processes display, analysis and forecasting, taking into account cause-and-effect relationships between the model variables and feedback loops effects. Our model is intended for forecasting, mainly based on causes trees instrument. PF1 and PF2 are used in the simulation model as endogenous variables with the corresponding formulars used in the model variables' operators.

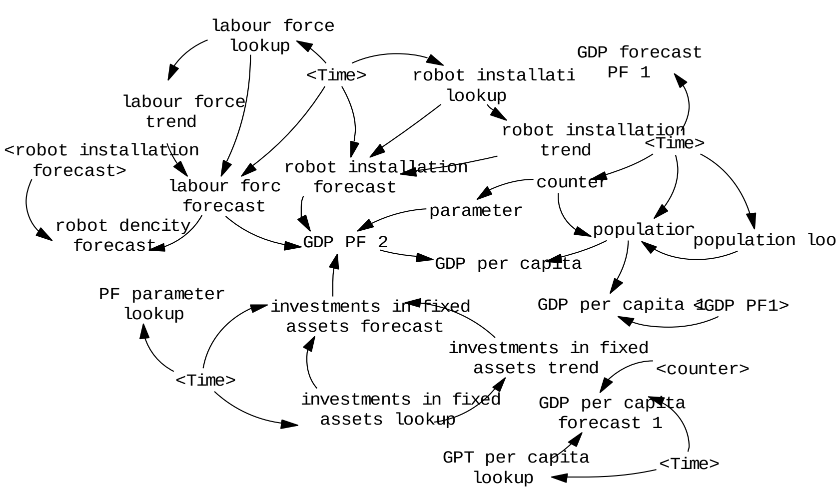

Fig. 5. **Structural System Dynamics model. View 1,** *authors' development*

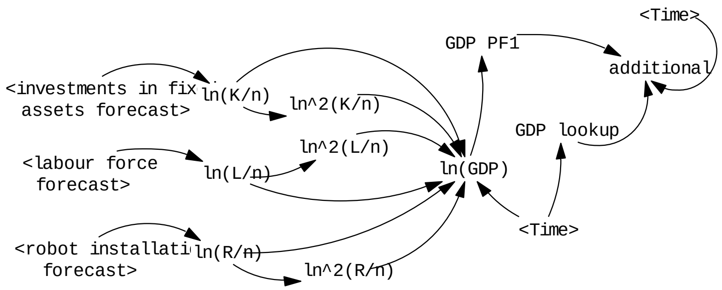

Fig. 6. **Structural System Dynamics model. View 2,** *authors' development*

The main results of the simulation forecast are presented in fig. 7—9.

Till 2023 the trajectories of Robot installation real dynamics and a forecast coincide (fig. 7), but then we see two tendences – either this indicator will stay on the value of 2023 or there will be damped oscillations, converging to Robot installation rate coinciding with that of 2023. That is, no radical changes in Robot installation are expected till 2030. From 2019 till 2030 the mixed (real + forecast) trajectory corresponds to an S-shaped type of dynamic behaviour with oscillations around the carrying capacity of about 280,000 units per year.

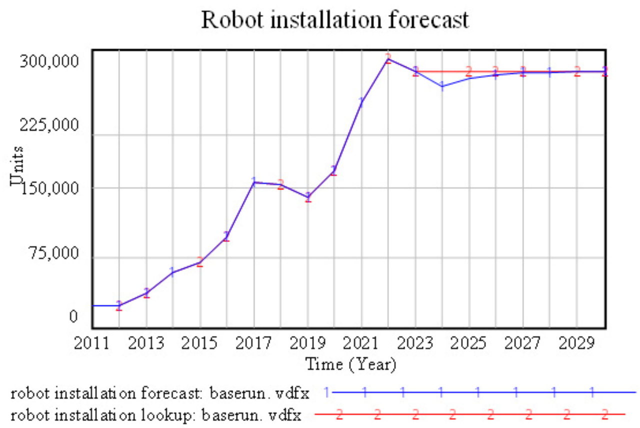

Fig. 7. **Simulation results. Robot installation forecast,** *authors' result*

The real limitations, influencing Robot installation rate in China are manufacturing overcapacity, skilled labour shortage, economic fluctuations and supply chain challenges.

Excess capacity in certain industries, particularly heavy manufacturing, has led to reduced demand for new robots. Companies with surplus production capabilities are less inclined to invest in automation technologies.

The adoption of industrial robots often requires a workforce with specialized skills for operation and maintenance. China faces a shortage of such professionals, which can hinder the effective deployment and utilization of robotic systems.

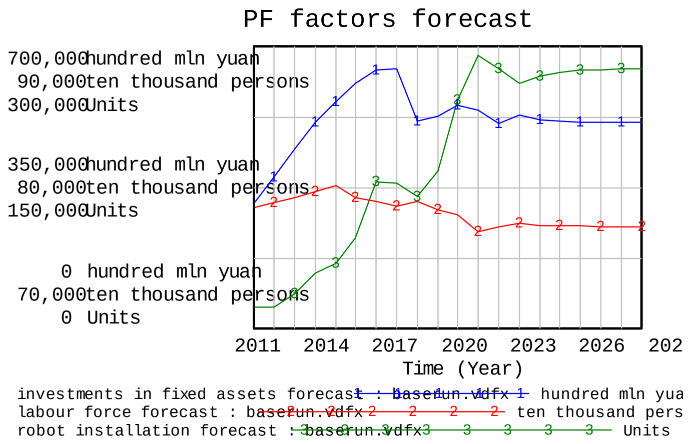

Fig. 8. **Simulation results. Forecast of PF's arguments dynamics,** *authors' result*

Economic slowdowns and uncertainties can lead companies to delay or scale back investments in automation, affecting the overall installation rate of robots.

The robotics industry relies on a complex supply chain for components like harmonic gear reducers and advanced sensors. Disruptions in this supply chain can delay production and installation timelines.

That is why our forecast seems to be plausible.

Our forecast of economic growth in China using PF1 and PF2 is based on the forecast of the arguments' dynamics (fig. 8). We have already discussed the Robot installation dynamics, thus let's look at the forecast of Investments in fixed assets and Labour force forecasts. Both indicators tend to decline slowly, but may stabilize in the future. As it was mentioned earlier the labour force dynamics strongly depends on demographic shifts in China, notably aging population and low birth rates. The most evident measures, which may counteract this trend and can promote labour force sustainability include raising the retirement age (from 60 to 63), encouraging higher birth rates (which are now lower than the death rates), promoting labour force participation and attracting foreign workers.

As for decline in China's fixed assets investments it's due to several interrelated factors, such as property sector significant downturn since 2021, geopolitical tensions and decline in FDI inflows, aging population and low productivity growth, deflationary pressure and weak household consumption.

If we assume our PF's arguments forecasts to be life-like then we'll get the following forecast of GDP dynamics (fig. 9).

PF1 formular gives us more moderate forecast compared to PF2, which gives a more optimistic one. However, forecast based on PF1 is closer to the IMF prediction, anticipating that China's GDP growth will decelerate to approximately 4.5% in 2025 and further to just over 3% by 2029. That is, our PF1 has proved its forecasting ability.

It's important to note that economic forecasts are inherently uncertain and subject to change based on evolving domestic and international circumstances.

Therefore, while these projections provide a general outlook, actual future growth rates may be different.

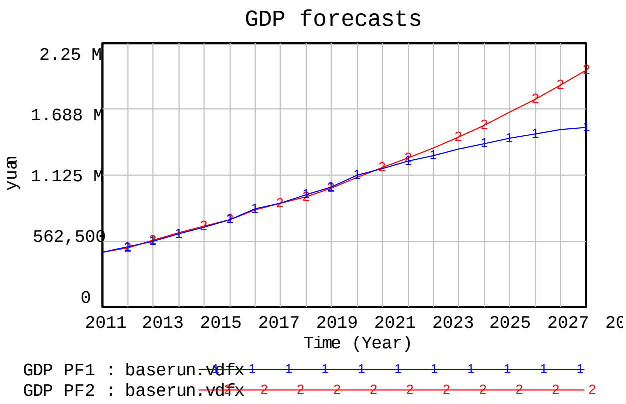

Fig. 9. **Simulation results. Forecast of GDP dynamics based on PF1 and PF2,** *authors' result*

Conclusions. From the point of view of the previously stated hypotheses we may say the following:

– All the main China's labour market indicators are strongly correlated between each other and with Robot density (RD) indicator, which has high positive correlation with all the indicators, except for the number of employed, which reflects the substitutive character of robotics in the labour market, especially in manufacturing and traditional service industries, where the tendency of robots to replace manual labour is more obvious;

– Strong positive relationship between the proportion of elderly population and robot density indicates that with the arrival of the aging society, the application of AI technology in the fields of elderly care and medical care may become an effective way to alleviate labour shortage and enhance productivity;

– Correlation between RD and unemployment rate, is insignificant, which means that robot installation doesn't mean that displacement of employed will inevitably make them fall into the category of unemployed. They can improve their skills and take up new jobs, including those, arising from the spread of AI;

– Multiple linear regression models 1 and 2 confirm the hypothesis that investment in robotics has significant impact on GDP, and if we compare linear coefficients of RD variable in both models, we'll see that its positive impact in GDP per capita is larger than its negative impact on the Labour force. Thus, AI is compensating the effect of aging population and shrinking labour force;

– Both Cobb-Douglas production functions (PF) with Hicks-neutral technical progress, built using different approximation techniques, demonstrate a high degree of their predictive ability, with a moderate forecast for PF1 and more optimistic one for PF2;

– System Dynamics simulation model allows to get forecasts based on both production functions' approximation formulars and provide a cause & effect analysis of the influence of the arguments' dynamics on PF's forecast. PF1 is closer to the IMF prediction, anticipating that China's GDP growth will decelerate by 2029.

– The combination of computational techniques has proven effective in analyzing complex multi-faceted problems and stimulating thinking for a reasonable explanation of the results and the formulation of recommendations for overcoming the undesirable development of the problem situation.

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Annex 1

Table 2. **Initial data for calculations,** *China Statistical Yearbook, 2011–2024; International Federation of Robotics*

Year	Robot installation (units)	Robot density (ratio)	Number of high-level talents (10000 people)	Average salary (yuan)	Elderly support ratio (%)	Unemp loyment rate. (%)	Urbani-zation (ratio)
2011	23000	0.293	12629	41799	0.123	4.55	0.516
2012	23000	0.292	13356	46769	0.127	4.58	0.531
2013	36967	0.467	14346	51483	0.131	4.6	0.544
2014	58294	0.715	14683	56360	0.137	4.63	0.558
2015	69375	0.862	17055	62029	0.143	4.65	0.573
2016	96555	1.223	17443	67569	0.15	4.56	0.588
2017	156317	1.974	17912	74318	0.159	4.47	0.602
2018	154049	1.958	18183	82413	0.168	4.31	0.615
2019	140000	1.772	18996	90501	0.178	4.56	0.627
2020	168000	2.143	21722	97379	0.197	5	0.639
2021	243000	3.114	24997	106837	0.208	4.55	0.647
2022	290000	3.773	25945	114029	0.218	4.98	0.652
2023	276288	3.730	25868	120698	0.223	4.67	0.662

Year	GDP (100 mln yuan)	GDP per capita (yuan)	Popula-tion (10000)	Investments in fixed assets (100 mln yuan)	Labour force (10000)	Number employed (10000)
2011	472115	36277	135710	311485.1	78579	76196
2012	516282.1	39771	136656	374694.7	78894	76254
2013	566130.2	43497	137610	446294.1	79300	76301
2014	644380.2	46912	138519	512020.7	79690	76349
2015	685571.2	49922	139372	562000	80091	76320
2016	742694.1	53783	140189	606466	79282	2011
2017	830945.7	59592	141028	641238.4	79042	76058
2018	915243.5	65534	141707	645675	78653	75782
2019	983751.2	70078	142186	513608.3	78985	75447
2020	1005451	71828	142493	527270.3	78392	75064
2021	1141231	81370	142589	552884.2	78024	74652
2022	1194401	85310	142589	542365.7	76863	73351
2023	1260582	89358	142567	509707.9	77216	74041