# Inhibition or promotion? --A study on the impact of artificial intelligence on consumption upgrading based on the perspective of industrial structure and market upgrading

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**Abstract.** Artificial intelligence (AI) is essential in driving industrial transformation, upgrading value chains, and promoting global cooperation, and is also an important engine for promoting economic growth and technological innovation. Studying the relationship between AI and consumption upgrading helps drive the deepening development of the AI industry, while stimulating consumption vitality, improving consumption levels, and achieving consumption upgrading. This article utilizes data spanning from 2013 to 2022 across 30 provinces to empirically test the impact of artificial intelligence on household consumption upgrading through a bidirectional fixed effects model. The examination of its influence mechanism and spatial spillover effects is deepened through the utilization of the Bootstrap-based mediation effect model, threshold effect model, and spatial Durbin model. Research has found that the improvement of artificial intelligence level can significantly promote the upgrading of household consumption. The development of AI level will promote the upgrading of consumption and economic growth within the province, while also producing a "demonstration effect" on neighboring areas. After robustness testing, the conclusion is still valid. In-depth analysis indicates that industrial structure upgrading and market upgrading serve as two significant intermediary pathways, with the presence of a single threshold effect. This article provides decision-making references for China to better promote consumption expenditure upgrading in the artificial intelligence industry from the perspective of supply and demand integration.

**Keywords:** Artificial intelligence, consumption upgrading, intermediary effect, threshold effect, spatial Durbin model.

## 1. Introduction

Artificial intelligence (AI) represents the cutting-edge development in the field of information technology, playing a crucial role in promoting technological innovation and industrial transformation. According to data from the China Academy of Information and Communications Technology and CCID Research Institute, in 2023, the scale of China's core AI industry reached 578.7 billion yuan, with the number of related enterprises amounting to 4,482 and the market scale approximately 14.4 trillion yuan. Since the "14th Five-Year Plan," the State Council and various provinces and cities have successively issued policy documents aimed at promoting the deep integration and development of AI with the real economy and various industries. Exploring the impact and mechanism of the development level of artificial intelligence on consumption upgrading in the transition of China's consumer demand from survival-oriented to development-oriented has significant practical significance and far-reaching impact on the future development of the AI industry and driving consumption upgrading.

In recent years, research on the impact of AI has expanded to cover aspects such as employment, labor remuneration, and industrial development. Studies on employment and labor remuneration are plentiful, with Acemoglu & Restrepo [1] exploring the substitution and creation effects of AI on employment. Huang Haoquan et al. [2] considered labor skill heterogeneity and the on-the-job

learning effect of low-skilled labor within the aforementioned framework. Yang Fei [3] integrated Acemoglu's [1] framework into Acemoglu et al.'s [4] industrial linkage model to explore how industrial intelligence impacts labor compensation shares. Yin Zhifeng et al. [5] discovered from patent data that AI enhances corporate market share, thereby improving employment levels. Regarding industrial structure, Wang Wen et al. [6] empirically stated that the intensive application of industrial robots contributes to the upgrading of China's service industry structure. Guo Kaiming's [7] research found that the advancement of artificial intelligence could promote the dynamic flow of production factors. Liu et al. [8] analyzed that AI accelerates knowledge creation and technological spillover to promote technological innovation. Zhao et al. [9] indicated that high-level AI promotes green technological progress and improves green efficiency.

Consumer upgrading is a hot topic in the academic community, with existing literature mainly exploring its connection with the digital economy, inclusive finance, and industrial upgrading. Zhou et al. [10] proposed an analytical framework based on eXplainable Artificial Intelligence (XAI) to explore the relationship between consumption upgrading and digital finance. Tan Sijin et al. [11] analyzed the impact of digital inclusive finance on residential consumption through the System GMM model. Yang Biyun et al. [12] discovered through the CHFS data that the digital economy can enhance residents' consumption levels. Jiang Qiping [13] empirically stated that industrial digitalization could promote the advancement of consumption structure. Sun Zao et al. [14] indicated that innovation in high-tech industries is key to consumption growth and structural improvement in developing countries. Regarding the relationship between AI and consumer upgrading, Shi Bo [15] theoretically analyzed how AI fosters green consumption and intelligent consumption, guiding industrial upgrading and driving consumer upgrading. Lin Chen et al. [16] constructed a DSGE model and found that AI promotes residential consumption and economic growth by optimizing capital structure. Though theoretical studies have discussed the connection between AI and consumer upgrading, empirical research on their impact and mechanisms remains limited.

This study uses panel data from 30 provinces between 2013 and 2022 to measure the level of AI development and consumption upgrading through a comprehensive indicator system, verifying that the improvement of AI development level can significantly promote consumer upgrading and exploring its impact mechanism. Compared to existing research, this paper's marginal contributions are as follows: firstly, it employs an objective unsupervised method to measure the comprehensive index, yielding more scientific and objective results. Secondly, it reveals the potential impact mechanisms through which AI promotes consumer upgrading, including regional heterogeneity analysis. Thirdly, it enriches the research on the theme of AI and consumer upgrading, considering spatial spillover effects and constructing a threshold regression model. This will help deepen the understanding of the impact of AI on consumer upgrading and provide empirical evidence for future policy formulation.

## 2. Theory and Methods

### 2.1. Theoretical analysis

Artificial intelligence promotes consumption upgrading mainly through two paths: firstly, cultivating new consumer products, opening up new consumption fields [17], meeting diverse and personalized consumer needs, and stimulating market vitality; The second is to deeply integrate with various industries, build new e-commerce models, improve service efficiency, and optimize market structure [18]. In terms of technological innovation, artificial intelligence has driven innovation on both the supply and consumption sides, meeting diverse consumer needs, promoting industrial upgrading and new product development, and improving the quality of life. In terms of efficiency improvement, artificial intelligence provides accurate demand information to assist in sales strategy formulation, predict market trends, and collaborate with the logistics industry to improve supply chain efficiency, bringing consumers a convenient and efficient shopping experience. Based on the given context, this article advances the following hypothesis:

H1: Artificial intelligence has a promoting effect on consumer upgrading.

Artificial intelligence utilizes big data analysis to optimize the allocation of production factors, reduce production costs, ensure quality stability, improve labor productivity, increase enterprise output, and stimulate research and development enthusiasm [19]. This transition fosters the steady progression of affiliated industries, furthering the enhancement and refinement of the entire industrial landscape. At the same time, the optimization of industrial structure focuses on supply side adjustment and optimization of economic development mode [20], which directly enhances household consumption level by increasing resident income, thereby promoting consumption upgrading.

The widespread application of artificial intelligence provides strong technical support for industrial structure upgrading. However, the upgrading of industrial structure is not achieved overnight under the promotion of artificial intelligence, but rather shows a clear threshold effect. For many traditional enterprises, they may lack sufficient technological reserves and talent support, making it difficult to effectively apply artificial intelligence technology to promote industrial upgrading; In addition, they need to invest a lot of time and resources to build a comprehensive data infrastructure, while also possessing professional data analysis capabilities to explore the value in the data. Therefore, only those enterprises that can cross the barriers of data, innovation, and market can fully utilize the potential of artificial intelligence to promote industrial upgrading and consumption upgrading. Based on this, this article proposes the following hypothesis:

H2: The advancement of artificial intelligence aids in facilitating the harmonious enhancement and optimization of both the industrial structure and the interplay between various systems, ultimately stimulating the elevation of consumer spending among the populace.

H3: Artificial intelligence's effect on consumption upgrading through industrial structure enhancement exhibits a threshold phenomenon.

On the one hand, the development of artificial intelligence technology has empowered the sustained growth of the platform economy, further breaking down the restrictions and barriers of commodity circulation. Artificial intelligence, with its high degree of intelligence, innovation, integration, and collaboration, has become a new driving force for promoting market-oriented allocation of factors [21]. Furthermore, the utilization of artificial intelligence technology has significantly improved the accuracy and efficiency of product traceability. This advancement not only aids in the safeguarding of consumer rights but also facilitates swift investigation of dispute responsibilities, ultimately fostering further refinement of the consumption environment and system.

Driven by artificial intelligence, the improvement of the efficiency of commodity and factor market allocation has played a crucial role in upgrading consumption, but this process has also shown a clear threshold effect. For companies with weaker technological capabilities and a lack of necessary infrastructure, they may not be able to fully utilize the potential of artificial intelligence, thereby failing to improve market allocation efficiency. And the application of artificial intelligence requires professional technical personnel for development, deployment, and maintenance. However, the current demand for artificial intelligence talents in the market far exceeds the supply, making it difficult for many companies to recruit suitable talents to support the implementation of their artificial intelligence strategies. Therefore, only those enterprises that can cross the barriers of technology, data, and talent can fully utilize the potential of artificial intelligence, improve market allocation efficiency, and promote consumption upgrading. Based on this, this article proposes the following hypothesis:

H4: The progression of artificial intelligence contributes to enhancing the efficiency of commodity and factor market allocation, which in turn spurs the advancement of household consumption levels.

H5: The increased efficiency in commodity and factor market allocation demonstrates a threshold effect in bolstering the elevation of consumption standards propelled by artificial intelligence.

The development of artificial intelligence technology has shown significant spatial spillover effects [22]. The high level of artificial intelligence in developed regions promotes consumption upgrading and economic growth, and generates a "demonstration effect", prompting underdeveloped regions to imitate their development models and achieve common development. Under government

promotion and market expansion, this effect is more significant. At the same time, the saturation of industries in developed regions leads to the spillover of capital, labor, and technology to peripheral areas, promoting the development of artificial intelligence technology throughout the region and ultimately achieving consumption upgrading.

H6: There is a spatial spillover effect of artificial intelligence in promoting consumption upgrading.

## 2.2. Research method

### 2.2.1. Variable selection

This article establishes a comprehensive framework to assess the advancement of artificial intelligence (AI) from an input-output viewpoint. With regard to investment, factors such as talent pools, platform establishment, and environmental facilitation were taken into account. While for intelligent output, the focus was on technological innovation and its translation into practical applications. The final evaluation score was derived through a hybrid approach combining entropy method and TOPSIS method.

In terms of measuring the level of consumption upgrading (Con), this paper adopts the idea of factor analysis and dimension reduction, and uses the principal component analysis method to extract, taking the per capita consumption expenditure, per capita disposable income, per capita total retail sales of consumer goods, the proportion of the tertiary industry, and Internet popularization as five consumption capacity factors; Unemployment rate, education level, social security level, and urbanization rate are four factors used as consumer security; The proportion of advanced consumption and Engel's coefficient are used as consumption structure factors; Consumption rate as a factor of willingness to consume.

Regarding control variables, this article opts for the following: openness level (Open), gauged by the proportion of total import and export volume to GDP, indicating the region's external openness. Financial development (Fin) is assessed by comparing the combined balances of regional deposits and loans to GDP. The urban-rural income disparity (Theil) is evaluated using the Theil index. The infrastructure level (Road) is determined by the ratio of road mileage per province to the administrative area.

### 2.2.2. Equation construction

To estimate the impact of artificial intelligence on consumer upgrading among residents, the following time and individual bidirectional fixed effects benchmark model is constructed:

$$Con_{it} = \alpha_1 + \beta_1 AI_{it} + \lambda_1 X_{\mathrm{it}} + \delta_i + \gamma_t + \varepsilon_{it} \tag{1}$$

Among them, i represents the province and t represents the viewing time. $\alpha_1$ is a constant term, $\beta_1$ is a regression coefficient for $Con_{it}$, $X_{it}$ is a matrix of control variables related to household consumption upgrading, including the level of opening up to the outside world (Open), financial development level (Fin), urban-rural income gap (Theil), infrastructure level (Road), $\delta_i$ represents regional fixed effects, $\gamma_t$ represents time fixed effects, and $\varepsilon_{it}$ is a random disturbance term.

Drawing upon benchmark regression analysis, this article incorporates spatial considerations to comprehensively assess the impact of artificial intelligence (AI) on enhancing consumer behavior among residents. Following rigorous testing through the Hausman, LM, LR, and Wald tests, a spatial Durbin model with dual fixed effects was chosen to analyze the spatial spillover effect of AI levels on the magnitude of household consumption upgrading. The specific modeling approach is outlined below:

$$\begin{aligned} Con_{it} = {} & \beta_1 W_{ij} Con_{it} + \beta_2 AI_{it} + \beta_3 W_{ij} AI_{it} + \\ & \beta_4 X_{it} + \beta_5 W_{ij} X_{it} + \delta_i + \gamma_t + \varepsilon_{it} \end{aligned} \tag{2}$$

Among them, $W_{ij}$ is a spatial distance weight matrix based on longitude and latitude, representing the spatial distance between provinces $i$ and $j$.

Based on the preceding analysis, it is evident that artificial intelligence can influence household consumption upgrading via two primary routes: upgrading of the industrial structure and market enhancement. Consequently, a mediation effect model has been employed to assess and verify the direct and indirect impacts of artificial intelligence on household consumption upgrading, mediated by the variables of industrial structure enhancement and market improvement. The detailed model is presented as follows:

$$Stru_{it} = \alpha_2 + \beta_2 AI_{it} + \lambda_2 X_{\text{it}} + \delta_i + \gamma_t + \varepsilon_{it} \tag{3}$$

$$Con_{it} = \alpha_3 + \beta_3 AI_{it} + \varphi_3 Stru_{it} + \lambda_3 X_{\text{it}} + \delta_i + \gamma_t + \varepsilon_{it} \tag{4}$$

$$Market_{it} = \alpha_4 + \beta_4 AI_{it} + \lambda_4 X_{\text{it}} + \delta_i + \gamma_t + \varepsilon_{it} \tag{5}$$

$$Con_{it} = \alpha_5 + \beta_5 AI_{it} + \varphi_5 Mar_{it} + \lambda_5 X_{\text{it}} + \delta_i + \gamma_t + \varepsilon_{it} \tag{6}$$

Among them, $Stru_{it}$ represents the upgrading of industrial structure, $Mar_{it}$ represents market upgrading, other definitions remain unchanged.

Furthermore, to investigate the threshold effect of industrial structure enhancement and market improvement on the influence of artificial intelligence levels on household consumption upgrading, this article develops the following panel threshold model:

$$\begin{aligned} Con_{it} = {} & \alpha + \beta_1 AI_{it} \times I(Stru_{it} \le \theta_1) + \beta_2 AI_{it} \times I(\theta_1 < Stru_{it} \le \theta_2) + \\ & \cdots + \beta_n \ln AI_{it} \times I(\theta_{n-1} < Stru_{it} \le \theta_n) + \\ & \beta_{n+1} AI_{it} \times I(Stru_{it} > \theta_n) + \lambda X_{it} + \delta_i + \gamma_t + \varepsilon_{it} \end{aligned} \tag{7}$$

$$\begin{aligned} Con_{it} = {} & \alpha + \beta_1 AI_{it} \times I(Mar_{it} \le \theta_1) + \beta_2 AI_{it} \times I(\theta_1 < Mar_{it} \le \theta_2) + \\ & \cdots + \beta_n \ln AI_{it} \times I(\theta_{n-1} < Mar_{it} \le \theta_n) + \\ & \beta_{n+1} AI_{it} \times I(Mar_{it} > \theta_n) + \lambda X_{it} + \delta_i + \gamma_t + \varepsilon_{it} \end{aligned} \tag{8}$$

Among them, $n$ represents the threshold quantity; $\theta_1$, $\theta_2$, …, $\theta_n$ represent the threshold value; The definitions of other variables remain unchanged.

## 3. Empirical analysis

### 3.1. Data sources and preprocessing

This paper uses panel data from 30 provinces in China (excluding Xizang, Hong Kong, Macao, and Taiwan) from 2013 to 2022. The data for each variable is sourced from various statistical yearbooks, including the China Statistical Yearbook, China High Tech Industry Statistical Yearbook, China Labor Statistics Yearbook, China Science and Technology Statistics Yearbook, and provincial statistical yearbooks. Missing data in some years are supplemented by interpolation. The descriptive statistics of the variables are shown in Table 1.

**Table 1.** Descriptive statistics of variables

| Variable | Variable Description | Sample size | Average value | Standard deviation | Min | Max |
|---|---|---|---|---|---|---|
| Con | Consumption upgrade | 300 | 0.394 | 0.165 | 0.1 | 1 |
| AI | Artificial intelligence | 300 | 0.169 | 0.129 | 0.01 | 0.807 |
| Stru | Industrial upgrading | 300 | 2.413 | 0.118 | 2.132 | 2.836 |
| Market | Market upgrade level | 300 | 8.351 | 1.882 | 3.58 | 12.864 |
| Open | Level of opening-up to the outside world | 300 | 3.534 | 1.087 | 1.912 | 7.609 |
| Fin | Financial development | 300 | 0.259 | 0.257 | 0.008 | 1.257 |
| Theil | Income gap between urban and rural areas | 300 | 0.083 | 0.038 | 0.017 | 0.211 |
| Road | Infrastructure level | 300 | 11.726 | .852 | 9.444 | 12.913 |

### 3.2. Benchmark regression and robustness testing

Before conducting the panel regression, the data was initially tested using the variance inflation factor (VIF) test. The results indicated that the VIF values of each variable were all below 5, indicating the absence of a strict multicollinearity problem. Subsequently, a Hausman test was performed on the estimation results of the model's fixed and random effects, which yielded a P-value of 0, thereby rejecting the null hypothesis at the 1% significance level. Consequently, using a fixed effects model is the more appropriate choice.

Table 2 reports the estimated results of artificial intelligence level on household consumption upgrading under bidirectional fixed effects. The benchmark regression in this paper excludes the influence of endogenous problems. The first column represents the estimated results when using artificial intelligence level for regression without considering control variables and fixed effects, the second column represents the estimated results when controlling for fixed effects for provinces and years, and the third and fourth columns represent the estimated results when adding control variables on top of the first and second columns, respectively. The empirical results show that regardless of whether fixed effects or control variables are included, the impact of regional artificial intelligence level on household consumption upgrading is significantly positive, that is, the improvement of artificial intelligence level can significantly promote household consumption upgrading. Hypothesis H1 is valid.

**Table 2.** Benchmark regression results

| Variable | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Con | Con | Con | Con |
| AI | 0.380*** | 0.100*** | 0.380*** | 0.071** |
| | (0.069) | (0.033) | (0.069) | (0.034) |
| Open | | | 0.084*** | -0.031 |
| | | | (0.008) | (0.027) |
| Fin | | | -0.197*** | 0.024*** |
| | | | (0.041) | (0.006) |
| Theil | | | -2.482*** | 0.230* |
| | | | (0.189) | (0.120) |
| Road | | | 0.013 | 0.042* |
| | | | (0.012) | (0.024) |
| Fixed year | NO | YES | NO | YES |
| Fixed Province | NO | YES | NO | YES |
| Constant term | 0.141 | 0.377*** | 0.141 | -0.204 |
| | (0.153) | (0.006) | (0.153) | (0.291) |
| Sample size | 300 | 300 | 300 | 300 |
| R2 | 0.679 | 0.984 | 0.679 | 0.985 |

Note: *, * *, * * * are significant at the 10%, 5%, and 1% levels, and the values in parentheses are standard errors, the same below.

To further ensure the reliability of the test results, this article adopts the following three methods for robustness testing: first, considering that extreme values in the sample may have an impact on the results, Beijing, which has the highest level of consumer upgrading among residents in 2022, and Qinghai Province, which has the lowest level, are excluded, and then a two-way fixed effects model is used again for regression. Secondly, this article introduces the core explanatory variable, artificial intelligence level lagging by one period, as the instrumental variable, and uses the instrumental variable to regress. Thirdly, replace the measurement indicators of the dependent variable, use the proportion of the sum of development-oriented consumption and enjoyment-oriented consumption to the total consumption expenditure to measure the degree of consumer upgrading among residents, and estimate it as the dependent variable. According to the results in Table 3, whether it is removing extreme data, replacing the dependent variable, or considering endogeneity issues, the estimated core results remain unchanged and are basically consistent with the benchmark regression results. Therefore, it can be concluded that the conclusion is robust.

**Table 3.** Robustness test results

| Variable | Consider the influence of extreme values | Endogeneity issues | Replace the dependent variable |
|---|---|---|---|
| | Remove extreme data | Instrumental variable method | Changing measurement methods |
| AI | 0.083** | | 0.068** |
| | (0.035) | | (0.027) |
| L.AI | | 0.072** | |
| | | (0.035) | |
| control variable | YES | YES | YES |
| Fixed year | YES | YES | YES |
| Fixed Province | YES | YES | YES |
| Constant term | -0.206 | -0.236 | -0.270 |
| | (0.299) | (0.298) | (0.233) |
| sample size | 280 | 300 | 300 |
| R2 | 0.982 | 0.985 | 0.771 |

### 3.3. Heterogeneity analysis

Currently, due to the regional development gap in China, there is a significant disparity in the levels of artificial intelligence and consumer upgrading across different regions, affecting impact paths and outcomes. Therefore, considering that AI's influence on household consumption upgrading may vary by region, this article divides China into three parts: eastern, central, and western regions, and conducts regional heterogeneity tests on the promotion effect of AI on household consumption upgrading. The results are shown in Table 4. According to the location heterogeneity test results, in the eastern region, AI development's effect on consumption upgrading is not significant, while in the central and western regions, AI positively promotes the upgrading of resident consumption, with improvements exceeding the national average. Hypothesis H4 holds.

**Table 4.** Heterogeneity analysis based on spatial features

| Variable | Eastern | Middle part | West |
|---|---|---|---|
| | Con | Con | Con |
| AI | -0.015 | 0.847*** | 0.601*** |
| | (0.033) | (0.146) | (0.162) |
| Control variable | YES | YES | YES |
| Fixed year | YES | YES | YES |
| Fixed Province | YES | YES | YES |
| Constant term | 1.208*** | -1.266*** | -0.743 |
| | (0.423) | (0.449) | (0.551) |
| Sample size | 110 | 90 | 100 |
| R2 | 0.993 | 0.983 | 0.979 |

### 3.4. Analysis of spatial autocorrelation and spillover effects

There may be a spatial autocorrelation relationship between the level of artificial intelligence and the upgrading of household consumption. To analyze the spatial agglomeration degree of these two factors more intuitively, this article uses the spatial distance weight matrix as an example and employs the Moran index and scatter plot to explore the presence of spatial autocorrelation between the level of artificial intelligence and the upgrading of household consumption. The results are presented in Table 5.

**Table 5.** Moran Index of Artificial Intelligence Level and Residential Consumption Upgrade from 2013 to 2022

| Year | Artificial Intelligence Index | | | Residential consumption upgrading | | |
|---|---|---|---|---|---|---|
| | Moran's I | Z | P | Moran's I | Z | P |
| 2013 | 0.230 | 3.498 | 0.000 | 0.227 | 3.647 | 0.000 |
| 2014 | 0.235 | 3.564 | 0.000 | 0.232 | 3.748 | 0.000 |
| 2015 | 0.250 | 3.734 | 0.000 | 0.187 | 3.179 | 0.001 |
| 2016 | 0.224 | 3.406 | 0.001 | 0.162 | 2.823 | 0.005 |
| 2017 | 0.215 | 3.290 | 0.001 | 0.169 | 2.954 | 0.003 |
| 2018 | 0.207 | 3.195 | 0.001 | 0.151 | 2.673 | 0.008 |
| 2019 | 0.250 | 3.751 | 0.000 | 0.143 | 2.585 | 0.010 |
| 2020 | 0.246 | 3.689 | 0.000 | 0.163 | 2.835 | 0.005 |
| 2021 | 0.240 | 3.618 | 0.000 | 0.158 | 2.754 | 0.006 |
| 2022 | 0.234 | 3.540 | 0.000 | 0.177 | 3.001 | 0.003 |

According to Table 5, under the spatial distance weight matrix, the Moran'I index of artificial intelligence level and resident consumption upgrading from 2013 to 2022 are basically significant at the 1% level, indicating that the artificial intelligence level and resident consumption upgrading of various provincial administrative regions in China have significant spatial autocorrelation from 2013 to 2022.

On this basis, this article further adopts local spatial correlation to verify the robustness of the spatial correlation between the two. Taking the artificial intelligence level and resident consumption upgrading index in 2015 and 2020 as examples, the Moran index scatter plot is used to divide the spatial correlation characteristics of the artificial intelligence level and resident consumption upgrading index into four quadrants. The first and third quadrants are spatial positive autocorrelation, and the second and fourth quadrants are spatial negative autocorrelation. According to Figure 1, in the test of artificial intelligence level, in 2015, 9 provinces, cities, and autonomous regions were located in the first quadrant, and 14 were located in the third quadrant, accounting for 76.67% of the total sample size; In 2020, there were 6 provinces, municipalities, and autonomous regions located in the first quadrant and 12 in the third quadrant, accounting for a total of 60%. In the inspection of consumer upgrading among residents, in 2015, there were 6 provinces and autonomous regions

located in the first quadrant, 13 in the third quadrant, accounting for 63.33% of the total. In 2021, there were 8 in the first quadrant and 12 in the third quadrant, accounting for 66.67% of the total. This indicates that regions with high (low) levels of artificial intelligence and consumer upgrading index have higher (low) levels of artificial intelligence and consumer upgrading index in their neighboring areas. In 2015 and 2020, there was a spatial correlation between the level of artificial intelligence and the upgrading index of household consumption in China, characterized by "high high" clustering and "low low" clustering. Therefore, the spatial correlation of urban-rural income gap needs to be considered in this empirical analysis.

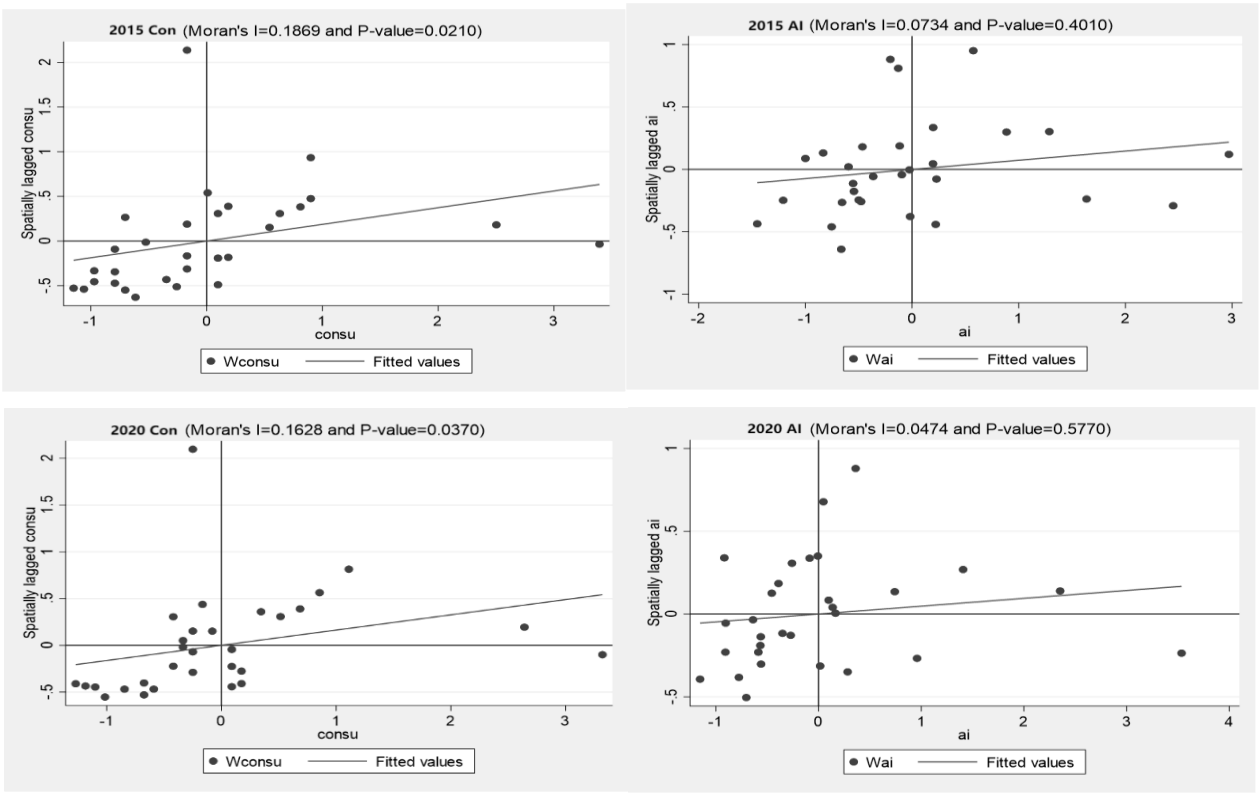



**Figure 1.** Scatter plot of Moran index for artificial intelligence level and household consumption upgrading in 2015 and 2020

Based on the benchmark regression, this article considers spatial influence to comprehensively explore the role of artificial intelligence in promoting consumer upgrading among residents. After conducting the Hausman test, LM test, LR test, and Wald test, a spatial Durbin model with dual fixed effects was established to examine the spatial spillover effect of artificial intelligence on the upgrading of household consumption.

Table 6 presents the spatial econometric regression results under the spatial distance weight matrix. The direct effect represents the immediate impact of artificial intelligence on the consumption upgrading of local residents. In contrast, the indirect effect refers to the spillover effect generated by the development of artificial intelligence in a province, which influences the consumption upgrading of residents in other regions. According to the results, the overall effect is significantly positive at the 1% level, indicating a strong positive correlation between artificial intelligence and the overall upgrading of household consumption. The direct effect is significantly positive at the 1% level, suggesting that a higher level of artificial intelligence in the local area significantly promotes consumer upgrading among residents. The indirect effect is also significantly positive, indicating that the development of local artificial intelligence plays a driving role in the consumption upgrading of residents in other regions, demonstrating a spatial spillover effect. Hypothesis H5 has been validated. The development of artificial intelligence in a province promotes consumption upgrading and economic growth, creating a "demonstration effect" that encourages neighboring areas to emulate its

development model, adopt advanced technologies, foster the growth of artificial intelligence, and subsequently drive consumption upgrading in other provinces.

**Table 6.** The SDM model estimation results of the impact of artificial intelligence level on household consumption upgrading

| Variable | Spatial distance weight matrix | | |
|---|---|---|---|
| | Direct effects | Indirect effects | Total effect |
| AI | 0.0465*** | 0.3437** | 0.3902*** |
| | (0.0074) | (0.0213) | (0.0232) |
| Control variable | YES | YES | YES |
| Sample size | 300 | 300 | 300 |

### 3.5. Analysis of Mediation Effect and Threshold Effect

#### 3.5.1. Mediating effect

Through theoretical analysis, it is known that industrial structure upgrading and market upgrading may play an important role in the path of artificial intelligence level affecting consumer upgrading among residents. While the development of artificial intelligence directly promotes the upgrading of consumer spending, it can also have indirect impacts through the effects of industrial structure upgrading and market upgrading. In order to deeply analyze the impact mechanism of artificial intelligence level on resident consumption upgrading, this article will examine its mediating effect from two paths: "artificial intelligence level - industrial structure upgrading - resident consumption upgrading" and "artificial intelligence level - market upgrading - resident consumption upgrading". In the mainstream methods of mediating effect testing, compared to stepwise regression testing and Sobel testing, The Bootstrap sampling method has the advantages of high testing power and low sample requirements [23], so this article mainly uses the Bootstrap sampling method for mediating effect testing. In the Bootstrap sampling method, for direct and mediating effects, significance is evaluated based on whether the 95% confidence interval includes a "0" value. If a "0" value is included, it is not significant, and if it is not included, it is significant [24]. Tables 7 and 8 respectively present the estimated results of the two paths of industrial structure upgrading and market upgrading.

**Table 7.** Testing the mediating effect of industrial structure upgrading

| Influence | The direct effect of artificial intelligence on consumption upgrading | | | | The indirect effect of artificial intelligence on consumption upgrading | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | Effect | SE | LLCI | ULCI | Effect | SE | LLCI | ULCI |
| Numerical value | 0.0471 | 0.0163 | 0.0135 | 0.1342 | 0.0302 | 0.0039 | 0.0063 | 0.1211 |

**Table 8.** Testing the mediating effect of market upgrading

| Influence | The direct effect of artificial intelligence on consumption upgrading | | | | The indirect effect of artificial intelligence on consumption upgrading | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | Effect | SE | LLCI | ULCI | Effect | SE | LLCI | ULCI |
| Numerical value | 0.0191 | 0.0002 | 0.0056 | 0.1511 | 0.0586 | 0.0279 | 0.0326 | 0.1596 |

From the perspective of industrial structure upgrading, at the 95% confidence interval, the direct impact test results do not include 0 (LLCI=0.0135, ULCI=0.0302), and the direct effect is 0.0471, indicating that the increase in artificial intelligence level directly promotes the upgrading of household consumption. The test results for indirect effects do not include 0 (LLCI=0.0063, ULCI=0.1211), and the indirect effect is 0.0302, indicating that industrial structure upgrading has a significant mediating effect under the mechanism of artificial intelligence level affecting household consumption upgrading, expanding the promotion effect of artificial intelligence level on household consumption upgrading. Hypothesis H2 has been validated.

From the perspective of market upgrading, at the 95% confidence interval, the direct impact test results do not include 0 (LLCI=0.0056, ULCI=0.1511), and the direct effect is 0.0191, indicating that the increase in artificial intelligence level directly promotes the upgrading of household consumption. The test results for indirect effects do not include 0 (LLCI=0.0326, ULCI=0.1596), and the indirect effect is 0.0586, indicating that market upgrading has a significant mediating effect under the mechanism of artificial intelligence level affecting household consumption upgrading, that is, market upgrading is an important way for the development of artificial intelligence to affect household consumption upgrading, and market upgrading further promotes the level of artificial intelligence to further promote household consumption upgrading. Hypothesis H3 has been validated.

### 3.5.2. Analysis of Location Heterogeneity of Mediation Effect

Currently, there is an imbalance in economic development and technological levels across different regions in China, leading to a significant disparity in the development of artificial intelligence. The degrees of industrial structure upgrading and market upgrading also differ. Therefore, considering that the impact of artificial intelligence on residential consumption upgrading through industrial structure and market upgrading may vary by geographical location, this article divides China into three regions: eastern, central, and western. It conducts regional heterogeneity tests on two pathways: "artificial intelligence level - industrial structure upgrading - residential consumption upgrading" and "artificial intelligence level - market upgrading - residential consumption upgrading." The results are presented in Tables 9 and 10.

Regarding the heterogeneity of the intermediary effect of industrial structure upgrading, the test results for the central and western regions generally align with the overall intermediary effect test results for the entire country, with both direct and indirect effects being positive. Directly, the development of artificial intelligence has promoted consumption upgrading and further enhanced consumer upgrading through the indirect pathway of industrial structure upgrading. Due to factors such as the level of economic development and technological progress, the advancement of artificial intelligence in the central and western regions is relatively weak, and the consumer upgrading index of residents is not high, leaving considerable room for improvement. Consequently, the development of artificial intelligence can significantly promote consumer upgrading. In contrast, the indirect effect of industrial structure upgrading in the eastern region is not significant in this pathway. This may be because the degree of industrial structure transformation in the eastern region is already relatively high, leaving little room for further industrial structure upgrading, thus diminishing its intermediary role.

Regarding the heterogeneity of the intermediary effect of market upgrading, the test results for the central and western regions are generally consistent with the overall intermediary effect test results for the entire country, with both direct and indirect effects being positive. Directly, the development of artificial intelligence has played a role in promoting consumer upgrading and has further enhanced consumer upgrading among residents through indirect channels such as market upgrading.However, in the eastern region, the indirect effect of market upgrading in this pathway is not significant. The possible reason for this is similar to that of industrial structure upgrading. The economic development level in the eastern coastal areas is high, and the market is relatively mature, leaving little room for significant improvement. As a result, the intermediary effect generated is not pronounced.

**Table 9.** Heterogeneity testing of the mediating effect of industrial structure upgrading

| Region | The direct effect of artificial intelligence on consumption upgrading | | | | The indirect effect of artificial intelligence on consumption upgrading | | | |
|---|---|---|---|---|---|---|---|---|
| | Effect | SE | LLCI | ULCI | Effect | SE | LLCI | ULCI |
| Eastern | 0.0224 | 0.0142 | 0.0023 | 0.0651 | -0.0439 | 0.0351 | -0.1159 | 0.0281 |
| Middle part | 0.0350 | 0.0658 | 0.0069 | 0.2234 | 0.0899 | 0.0194 | 0.0546 | 0.1297 |
| West | 0.4455 | 0.1512 | 0.1395 | 0.7496 | 0.1303 | 0.0227 | 0.0252 | 0.3765 |

**Table 10.** Heterogeneity testing of intermediary effects in market upgrading

| Region | The direct effect of artificial intelligence on consumption upgrading | | | | The indirect effect of artificial intelligence on consumption upgrading | | | |
|---|---|---|---|---|---|---|---|---|
| | Effect | SE | LLCI | ULCI | Effect | SE | LLCI | ULCI |
| Eastern | 0.0224 | 0.0142 | 0.0023 | 0.0651 | -0.0439 | 0.0351 | -0.1159 | 0.0281 |
| Middle part | 0.0350 | 0.0658 | 0.0069 | 0.2234 | 0.0899 | 0.0194 | 0.0546 | 0.1297 |
| West | 0.4455 | 0.1512 | 0.1395 | 0.7496 | 0.1303 | 0.0227 | 0.0252 | 0.3765 |

### 3.5.3. Threshold effect test

The above analysis has verified that the two transmission paths of industrial structure upgrading and market upgrading do play a role in the mechanism of artificial intelligence affecting household consumption upgrading. To explore whether there are thresholds for industrial structure upgrading and market upgrading, further threshold effect tests will be conducted.

Firstly, utilizing 500 rounds of self-repeated sampling, threshold existence tests were conducted for industrial structure advancement and market development, respectively. The F and P values of the test results are presented in Table 11. According to the sampling outcomes, the levels of industrial structure and market development both passed the single threshold test at a significance level of 5%, with threshold values of 2.4776 and 5.3100, respectively. This indicates that both industrial structure advancement and market development have a single threshold effect on the impact of artificial intelligence on household consumption enhancement. Table 12 presents the estimated results of the threshold effect model. When the level of industrial structure advancement is below the threshold value, the development of artificial intelligence has a significant positive effect on consumer enhancement for residents. However, when the industrial structure advancement surpasses the threshold value, this effect is no longer significant. From the perspective of market development, when the level of market development is below the threshold value, the level of artificial intelligence significantly promotes consumer enhancement for residents. When the level of market development exceeds the threshold value, the level of artificial intelligence continues to positively impact consumer enhancement for residents, but this impact is lower than before surpassing the threshold value.

**Table 11.** Existence, estimation, and confidence interval testing of thresholds for industrial structure upgrading and market upgrading

| Threshold variable | Null hypothesis | F | P | 1% | 5% | 10% | Threshold value |
|---|---|---|---|---|---|---|---|
| Stru | Single threshold | 32.84 | 0.0233 | 34.6603 | 27.4016 | 21.6421 | 2.4776 |
| Mar | Single threshold | 15.46 | 0.0300 | 37.2115 | 30.1682 | 26.0082 | 5.3100 |

**Table 12.** Estimation results of panel threshold model

| Variable | Stru | Mar |
|---|---|---|
| C-1 | 0.245** | 0.497*** |
| | (0.0959) | (0.1605) |
| C-2 | 0.117 | 0.114** |
| | (0.0773) | (0.0512) |
| Constant term | -0.378 | -0.548*** |
| | (0.6001) | (0.1204) |
| Control variable | YES | YES |
| Sample size | 300 | 300 |

## 4. Conclusion and recommendations

This article empirically demonstrates that the development of artificial intelligence (AI) can promote the residents' consumption upgrading. Spatial analysis reveals a significant spatial autocorrelation between the level of AI and consumption upgrading in different provinces of China. The application of the spatial Durbin model confirms that the enhancement of AI not only drives consumption upgrading within the province but also promotes consumption upgrading in neighboring provinces. This study solved the endogeneity problem using the instrumental variable method and verified the robustness of the conclusion by substituting indicators. The impact of AI on promoting consumption upgrading exhibits regional heterogeneity, with a more significant effect in the central and western regions. Further research has found that the development of AI affects consumption upgrading through two pathways: industrial structure upgrading and market upgrading, with the intermediary effect path in the eastern region not significant. Threshold tests indicate the presence of a single threshold effect in both industrial structure upgrading and market upgrading.

This article offers three policy recommendations: firstly, to strengthen the research and application of artificial intelligence technology, encourage innovation, increase research and development investment, improve technological level, and widely apply it in multiple scenarios to meet market demand; The second is to strengthen regional cooperation, establish cooperation mechanisms, promote the flow and sharing of knowledge, technology, talent, and capital, and narrow the gap in artificial intelligence development between regions; The third is to promote fair competition, improve industrial supporting facilities, break down barriers, promote free flow of resources, strengthen government enterprise cooperation, promote industrial structure upgrading, and ultimately improve the consumption level of residents.

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