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ORIGINAL PAPER
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INDUSTRIAL INTELLIGENCE AND THE URBAN-RURAL CONSUMPTION DIVIDE IN CHINA

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ABSTRACT

Motives: China's rapid adoption of industrial intelligence (II) amid widening urban-rural consumption disparities necessitates investigation into II's impact on regional inequality through labor market mechanisms.
Aim: This study examines the relationship between industrial intelligence and regional disparity in consumption (RDC) in China from 2006 to 2019, analyzing displacement, productivity, and reinstatement effects on urban-rural consumption gaps.
Results: Findings reveal a U-shaped relationship: II initially reduces RDC through technology diffusion and policy reforms, but advanced II exacerbates disparities by favoring high-skilled urban labor. Industrial structure amplifies RDC, while urbanization and human capital mitigate it.
Policy Recommendation: Regional analysis shows stronger initial benefits by narrowing disparities in Western China but widening disparities at advanced II stages. Government should prioritize (i) large-scale skills development programs for rural labor, (ii) targeted subsidies for II adoption in underdeveloped regions, and (iii) investment in rural digital infrastructure.

Keywords: industrial intelligence, regional disparity, urban-rural divide, artificial intelligence, labor markets, China

INTRODUCTION

Historically, transformative technological advancements have shaped industrial revolutions. The First Industrial Revolution utilized hydropower and steam engines, while the Second employed electricity and the division of labor to advance production (Preuveneers & Ilie-Zudor, 2017; Wang et al., 2024c; Zhou & Li, 2024). The Third Industrial Revolution introduced digital manufacturing, driving economic growth, though its impact has diminished over time (Zhou & Li, 2024). The path of this transition and its influencing factors vary across time and space (Wang et al., 2024b). Presently, Artificial Intelligence (AI) is defining Industry 4.0, a new industrial era fostering innovative development trends (Kang et al., 2016;

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Zou, 2024). Some studies show however, that while AI enhances industrial efficiency, it also disrupts labor markets, potentially widening regional disparities (Li & Hao, 2021; Zhang et al., 2024).

There is little doubt that China's "Reform and Opening Up" policies, tailored to its national context, produced an economic miracle (Yuan & Gao, 2020; Zou & Xiong, 2023). However, GDP per capita growth fell from 8.40% in 2002 to 5.58% in 2019, reflecting the exhaustion of traditional growth drivers (Wang, 2024a; WDI, 2023; Zou, 2024). This slowdown highlighted the need for a new technological era and AI provided the answer, becoming a key growth engine for economic development in China (Wu et al., 2020). AI can be described as sub discipline of computer science which is related to data processing systems which perform functions like reasoning and learning associated with human intelligence. When integrated to production, it forms industrial intelligence – a systematic discipline dedicated to the design, validation, implementation, and management of AI solutions for industrial purposes (Peres et al., 2020). It refers to integration of a technological advancement in the manufacturing to transform manufacturing industry to intelligence (Xia et al., 2024b).

The Chinese government has actively promoted scientific innovation and encouraged industries to adopt Artificial Intelligence (AI) to drive economic benefits. At its 19th National Congress, the Communist Party of China emphasized integrating AI with the real economy (Liu et al., 2020; Zou & Xiong, 2023). To advance industrial intelligence (II) for economic development, China launched initiatives such as the "14th Five-Year Plan for Intelligent Manufacturing" and "Made in China 2025" (Tian et al., 2024). In 2017, the New Generation AI Development Plan (2015–2030) was introduced, aiming to position China as the world's leading AI innovation hub by 2030 (Wu et al., 2020). Through these and other national-level policies, China is striving to establish global leadership in AI (Qiu, 2016; Wang et al., 2024c; Zou & Xiong, 2023).

Today, AI is thriving in China, being widely used in everyday life. Fig. 1 illustrates the dynamic growth of the Industrial Intelligence Index introduced by (Wang et al., 2024c) – a composite metric that evaluates the integration of advanced technologies like AI, IoT, and big data in industrial systems, measuring their impact on production efficiency, innovation, and economic growth. It specifically assesses technological adoption, automation, data-driven decision-making,

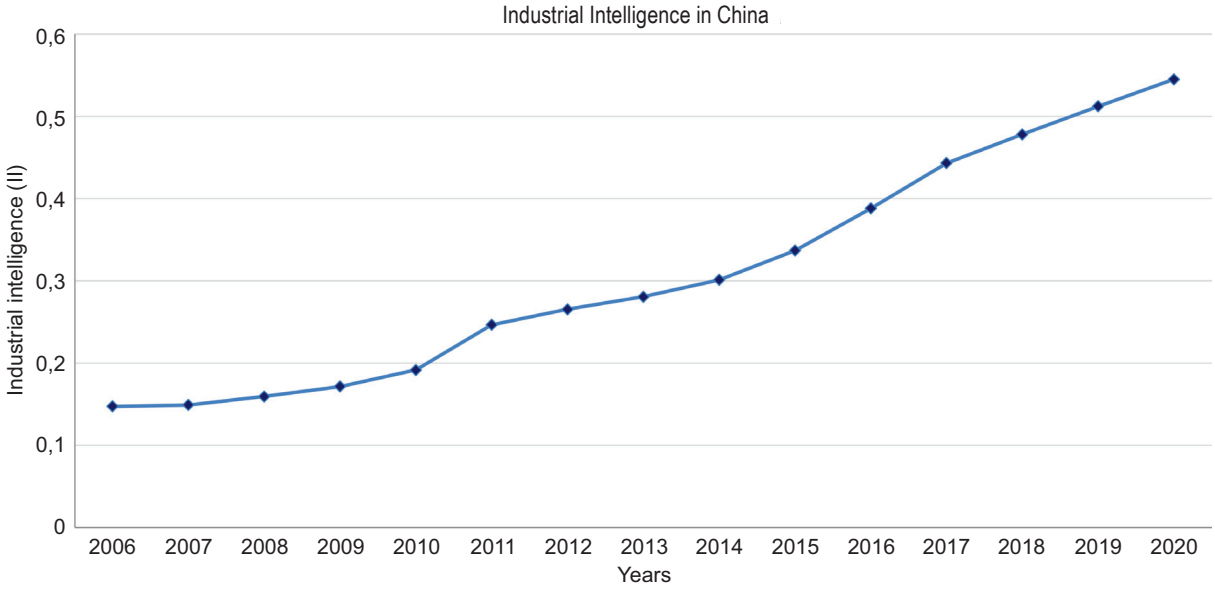


Fig. 1. Industrial Intelligence Index development in China
Source: Wang et al. (2024c).

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and regional industrial transformation. The China Internet Development Report 2020 even suggests that China leads globally in AI patent applications and AI relevant publications (Wang et al., 2024c; Zou & Xiong, 2023). According to the China Internet Development Report 2023, significant progress in industrialization and digitalization has driven the adoption of internet applications in production processes (CNNIC, 2024). Enterprises are increasingly integrating AI and robotics, which offer greater efficiency than human labor without requiring ongoing wage increases, necessitating only a one-time technological upgrade (Cheng & Zhang, 2024). Since 2020, AI adoption across industries has advanced digitalization (Li et al., 2022) delivering benefits in manufacturing, including autonomous decision-making (Dwivedi et al., 2021), smart warehouse management (Geunes & Su, 2020), enhanced efficiency, and reduced production times (Varriale et al., 2023).

AI drives a transition in businesses by mechanizing human tasks, leading to job displacement in some areas, job creation in others, and significant changes in many roles, increasing demand for workers with advanced skills and adaptability to new technologies (Manyika & Sneader, 2018). While AI benefits society and businesses, it also causes disruptions, exacerbating labor market inequality (Zhang et al., 2024). This inequality is likely to widen disparities among rural and urban areas in China, where over 50% of the labor force comprises rural-to-urban migrants, representing the largest labor migration in history with 274 million internal migrant workers (Démurger & Wang, 2016). High-skilled jobs are concentrated in urban areas with robust job markets, while less--developed rural regions lag behind. The replacement of low-skilled workers with automated equipment may further intensify regional disparities (Zhang et al., 2024). Thus, China provides a compelling context for examining the impact of industrial intelligence on regional disparities in consumption.

This study makes several contributions to literature. First, it examines the impact of industrial intelligence (II) on regional disparity in consumption (RDC) in China. Existing research has primarily focused on II's effects on carbon neutrality (Chen et al., 2022; Chen et al., 2023; Dong et al., 2020; Meng et al., 2022; Tian et al., 2024; Wang et al., 2024c), factor productivity (Huang et al., 2024; Luo et al., 2024), industrial structure upgrading (Dong et al., 2023; Lasi, 2013; Zou & Xiong, 2023) and foreign direct investment (Varriale et al., 2023). Second, this paper employs a comprehensive proxy for II, incorporating multiple indicators (Wang et al., 2024c) unlike prior studies that relied on single indicators such as robot penetration or patent applications (Lasi, 2013; Peres et al., 2020; Tian et al., 2024; Varriale et al., 2023; Yang et al., 2021). Third, it assesses regional disparity in the context of China's urban-rural divide (Ul-Haq et al., 2023b) differing from studies that analyzed disparities across geographical regions (e.g., Eastern, Central, and Western China) and compared them (Li & Hao, 2021).

Fourth, this paper is investigating regional disparity in consumption (RDC) (Ul-Haq et al., 2023b) in contrast to prior research that used income-based measures of regional disparity (Cai et al., 2002; Gao et al., 2024; Huo et al., 2024; Liu et al., 2024) which may not fully capture welfare dynamics (Blundell & Preston, 1998; Ul-Haq et al., 2023b).

The remaining part of the research is structured as follows: Section 2 depicts theoretical background of the study. Section 3 reviews the existing literature. Section 4 presents the data and methodology. The estimated results are elaborated in Section 5. Section 6 provides discussion relevant to results and Section 7 elaborate on the conclusion.

THEORETICAL BACKGROUND

This study investigates the impact of industrial intelligence (II) on regional disparity in consumption (RDC) within China's urban-rural context, focusing on its effects on skilled and unskilled labor markets. Industrial intelligence influences labor income through three mechanisms: a negative displacement effect, and positive productivity and reinstatement effects, which provide the theoretical framework for this analysis (Acemoglu & Restrepo, 2019a; Xinyue et al., 2024). The displacement and productivity effects

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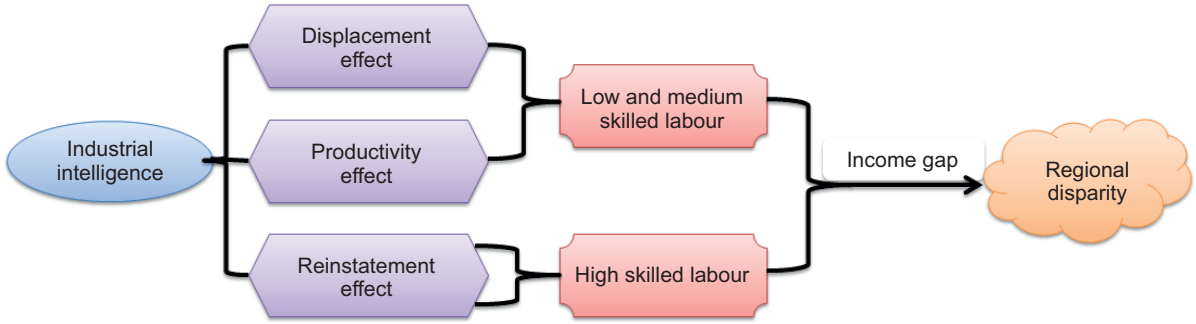


Fig. 2. Conceptual Framework
Source: own elaboration.

predominantly impact low- and medium-skilled labor (Xinyue et al., 2024) while the reinstatement effect generates new tasks and opportunities for the skilled labour (Acemoglu & Restrepo, 2018, 2019b; Zhang et al., 2024). Consequently, skilled workers, being more adaptable to innovative technologies, benefit from increased employment and higher incomes, whereas low- and medium-skilled workers face employment challenges and income inequality, exacerbating regional disparities (Zhang et al., 2024).

Industrial intelligence (II) is closely linked to labor income, exerting contrasting effects through displacement, productivity, and reinstatement mechanisms (Grimshaw, 2020; Huo et al., 2024; Wang et al., 2024d; Xinyue et al., 2024) see Fig. 2. This study examines the impact of industrial intelligence (II) on regional disparity in consumption (RDC) through three mechanisms affecting labor income: displacement, productivity, and reinstatement effects.

Displacement Effect

Automation and human labor excel in distinct tasks, but when automation is more efficient, it substitutes labor through a significant displacement effect. In China, II reduces demand for low- to medium-skilled labor, creating a mismatch between labor supply and demand in an intelligent industrial environment (Acemoglu & Restrepo, 2018, 2019b; Xinyue et al., 2024). When supply exceeds demand, equilibrium wage levels decline, reducing income for low- and medium-skilled workers and contributing to increased regional disparity, as illustrated in Fig. 3.

Productivity Effect

II enhances productivity and reduces costs, generating higher profits (Acemoglu & Restrepo, 2018, 2019b; Haltiwanger et al., 2013). Simultaneously, increased productivity lowers commodity prices, stimulating consumption and, consequently, increasing labor demand and wages (Xinyue et al., 2024). This effect can mitigate regional disparity by boosting employment and income.

Reinstatement Effect

Acemoglu and Restrepo (2019a) argued that despite displacement and productivity effect there is a powerful force which increase demand for labour and also rise its share in national income. That force is reinstatement effect where creation of new tasks, functions and activities provides comparative advantage to labour relative to robots.

While II displaces certain jobs, it also creates new tasks, such as industrial robot programming and data analysis, which are less susceptible to automation and offer competitive advantages (Acemoglu & Restrepo, 2018, 2019b). The deep integration of II increases demand for research and development (R&D) personnel, leading to a skills mismatch that raises equilibrium wages for high-skilled labor (Xinyue et al., 2024). This effect can reduce regional disparity by increasing income for skilled workers, as shown in Fig. 4. However, at early stages of II adoption, broad productivity gains and labor demand expansion may as well dominate, compressing the gap.

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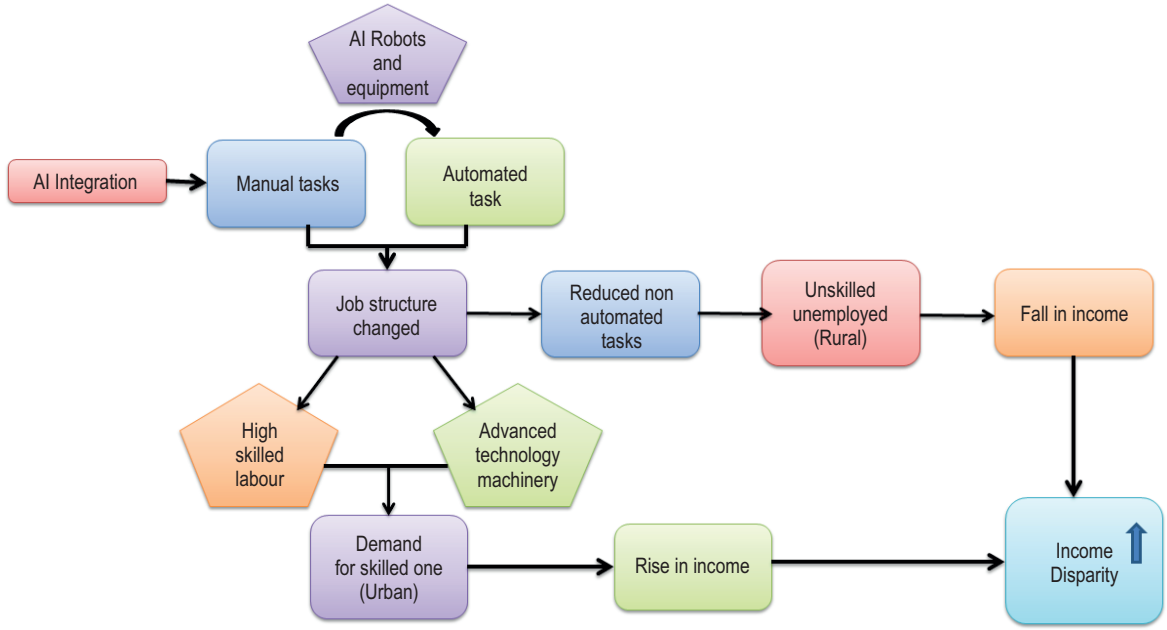


Fig. 3. Displacement Effect
Source: own elaboration.

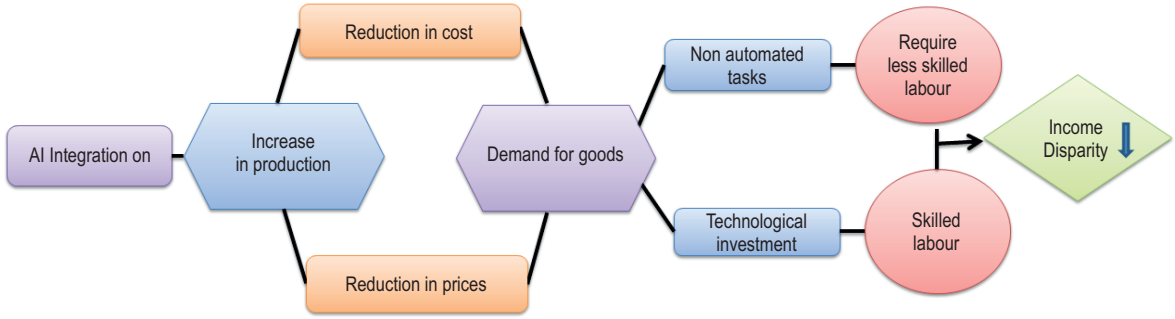


Fig. 4. Productivity and Reinstatement Effect
Source: own elaboration.

Our theoretical framework identifies these three modalities through which II influences job structures and, consequently, regional disparity. However, the dominant effect in practice remains an empirical question. The forthcoming analysis will clarify the actual impact of II on RDC.

LITERATURE REVIEW

Researchers have extensively studied the societal impacts of Artificial Intelligence (AI) and industrial intelligence (II) across various dimensions. Fan and Liu (2021) analyzed AI's direct and indirect effects on economic growth through industrial structure changes, using data from 28 Chinese provinces (2015–2018). Their findings indicate that AI's contribution was limited before 2008 but became a significant driver of economic growth during China's recovery. Studies found that II significantly reduces carbon intensity, particularly in Eastern China, with negligible effects in Western China, and identified industrial structure upgrading (ISU) as a key channel for II's impact. Wu et al. (2023) examined II's effect on regional innovation efficiency (2010–2019) using provincial

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panel data and identified an inverted U-shaped relationship. Tian et al. (2024) investigated II's role in carbon mitigation (2006–2019) using Chinese provincial data, highlighting industrial structure upgrading and technological innovation as primary mechanisms for reducing CO_2 emissions.

Luo et al. (2024) explored AI's impact on total factor productivity (TFP) across 30 Chinese provinces (2003–2021), noting that AI's positive effect on TFP strengthens as TFP increases. (Ul-Haq et al. 2025) Investigated the impact of industrial intelligence in promoting energy security and proved that II enhance energy security in China.

While these studies clarify II's role in labor markets, they often lack comprehensive empirical evidence on its impact on regional disparity. Acemoglu and Restrepo (2020) highlighted AI's adverse labor market effects, noting that each additional robot reduces employment by 0.2 percentage points. Jung and Lim (2020) confirmed AI's substitution effect on employment and observed employment declines due to reduced demand for low- and medium-skilled labor Goyal and Aneja (2020).

Studies directly referring to the link between AI/II and regional disparities are rather scarce. Li and Hao (2021) examined II's impact on disparity through consumption and production across Chinese regions (Eastern, Central, and Western), finding that II improves consumer welfare inequality but may exacerbate regional innovation disparities. Xia et al. (2024a) used robot penetration as a proxy for II and found an increasing gap between less-skilled and high-skilled labor. Meng et al. (2022) identified an inverted U-shaped relationship between circular II and the urban-rural income gap, emphasizing the importance of including quadratic terms to capture nonlinear dynamics. Their findings suggest that II initially benefits urban areas through innovation investment before extending to rural areas, reflecting a nonlinear impact on disparity.

In summary the existing literature underscores the significance of industrial intelligence (II) but primarily focuses on its impacts on carbon neutrality, factor productivity, industrial structure upgrading, and foreign direct investment (FDI). Most studies employ narrow proxies for II, such as robot penetration or patent applications, limiting their scope. Additionally, research on regional disparity often relies on income-based measures, which may not fully capture welfare dynamics. While Gao et al. (2024) explored II's role in regional disparity, their study used a narrow proxy (patents) and examined disparity at an aggregate level across Eastern, Central, and Western China, focusing on innovation without providing a comprehensive picture. Wang et al. (2024d) empirically assessed II's impact on the labor market but relied on time-series analysis with a narrow proxy. In contrast, this study employs panel data to investigate the impact of II on regional disparity in consumption (RDC), offering a broader perspective. To the best of our knowledge, no empirical study has examined II's effect on RDC in China. This research aims to fill this gap, providing a novel contribution to the literature.

MATERIALS AND METHODS

This study examines the impact of industrial intelligence (II) on regional disparity in consumption (RDC) in China, using provincial panel data from 2006 to 2019. Following Ul-Haq et al. (2023b), RDC is measured as the ratio of urban to rural per capita expenditure. Industrial intelligence (II), the core independent variable, is measured using an industrial intelligence index constructed from three dimensions – intelligent input, intelligent production capacity, and intelligent output – as proposed by (Wang et al., 2024c). The indicators used to construct the II index are presented in Fig. 5, with data sourced from (Wang et al., 2024c).

Intelligent input reflects the capital and infrastructure necessary for II development (Liu et al., 2023). Intelligent production capacity denotes the ability to integrate II into manufacturing processes, while intelligent output captures the technological and economic outcomes of II (Wang et al., 2024c). Control variables include: (1) Industrial Structure, measured as the share of secondary sector value added in GDP (%), which influences RDC due to uneven

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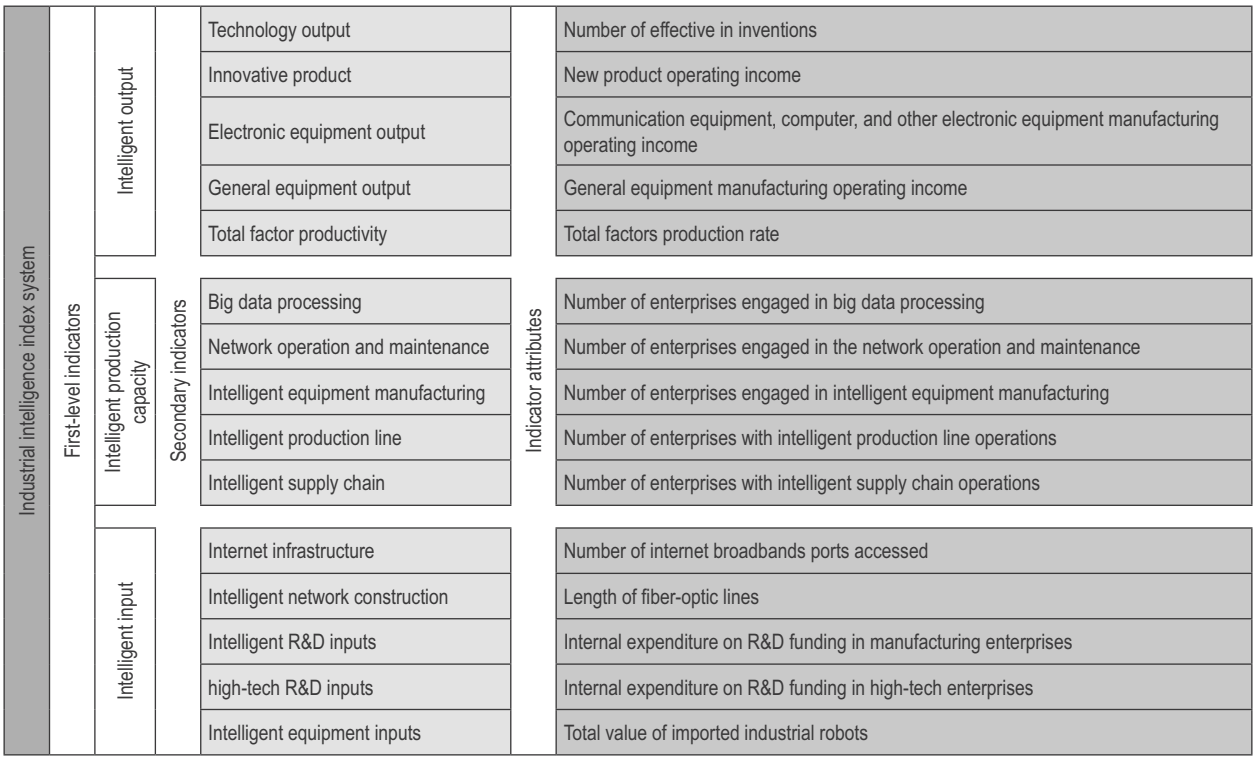


Fig. 5. Indicators of II
Source: Wang et al. (2024c).

Table 1. Description of variables

Variable	Indicator	Description	Sources
Regional disparity in consumption	RDC	The ratio of urban to rural per capita expenditure	CNBS*
Industrial intelligence	II	Industrial intelligence index (Entropy weight method)	Wang et al. (2024c)
Industrial structure	IS	Share of secondary sector value added in GDP (%)	CNBS
Urbanization	URBAN	Share of urban population	CNBS
Human capital	LUG	Log of number of under-graduates student enrolled in general institutions of higher learning (10,000 people)	CNBS

Note: CNBS – China National Bureau of Statistics.
Source: own elaboration.

distribution across provinces (Cheong & Wu, 2014) (2) Urbanization, measured as the share of urban population in the total population, which affects RDC by attracting rural migrants to urban areas following Hukou system reforms, thereby enhancing urban productivity (Huang & Zhan, 2005a; Yao & Jiang, 2021) and (3) Human Capital, measured as the log of undergraduate students enrolled in general higher education institutions (in 10,000s), which can reduce regional disparity (Fleisher et al., 2010; Ul-Haq et al., 2023b). Data for this study are sourced from the China National Bureau of Statistics (CNBS). Variable descriptions are provided in Table 1, and descriptive statistics are reported in Table 2. China's selection as the study context is motivated by its global leadership in AI patent applications (Zou & Xiong, 2023).

This study aims to analyze the impact of industrial intelligence (II) on regional disparity in consumption

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(RDC) within China's urban-rural context. We employ the following empirical model:

$$RDC_{pt} = \alpha_0 + \beta_1 II_{pt} + \beta_2 II^2{}_{pt} + \beta_3 X_{pt} + e_{pt} \quad (1)$$

In the above equation RDC is regional disparity in consumption, measured as the ratio of urban to rural per capita consumption in province p and time t. II is the industrial intelligence and is its square term, incorporated to capture potential nonlinear relationship (Xia et al., 2024a) X is a vector encompassing control variables that may influence RDC. α_0 is intercept term capturing regional disparity when II has no effect. β coefficients indicate the direction and magnitude of the independent variables' effects, and e_{pt} is the error term.

The ratio of urban to rural per capita consumption serves as the indicator for RDC, as it provides a more accurate measure of welfare compared to income-based metrics (Blundell & Preston, 1998). This study extends the empirical model by incorporating II as a key predictor of RDC. Since displacement and reinstatement effects operate in opposing directions, we do not impose a sign restriction on β_1 *a priori*. We hypothesize a negative at low levels of II adoption (in line with dominant displacement and productivity spillover effects reducing disparity), and positive at advanced adoption stages, yielding a U-shaped relationship. Such pattern would be consistent with concerns that mature II concentrates benefits in urban high-skilled labor markets (Acemoglu & Restrepo, 2019a; Wang et al., 2024d; Zhang et al., 2024).

Following Chen and Ma (2022), industrial structure (IS) is expected to have a positive relationship with RDC, so we anticipate a positive coefficient for IS. Urbanization's effect on RDC is theoretically ambiguous: while higher urban productivity could widen the gap (Yao & Jiang, 2021), migration-driven remittances and hukou reforms may reduce it (Howell, 2017; Huang & Zhan, 2005a). We therefore do not impose a sign restriction on the urbanization coefficient. Human capital's impact on regional disparity is ambiguous: it may reduce disparity when invested in less-developed areas but could increase disparity due to brain drain following Hukou system reforms (Fleisher et al., 2010; Zeng et al., 2023). Thus, we expect an ambiguous coefficient sign for human capital.

This study employs fixed-effects Driscoll-Kraay standard errors (FE-DKSE) and feasible generalized least squares (FGLS) to estimate the relationship between industrial intelligence (II) and regional disparity in consumption (RDC). Cross-sectional dependence (CSD) in panel data can lead to biased estimations (Ul-Haq et al., 2023b). In contrast to standard techniques, the Driscoll and Kraay (1998) approach accounts for CST, assuming a nonparametric covariance matrix estimator that accommodates heteroskedastic and autocorrelated error structures up to a specific lag, as well as cross-entity correlation. This method is well-suited for large time periods, as it relies on large-T asymptotics, and effectively handles both balanced and unbalanced panel data, including missing data (Ul-Haq et al., 2023b). To address negative values after logarithmic transformation, absolute values are used to ensure data integrity.

The linear model for the Driscoll-Kraay standard error with pooled ordinary least squares is specified as:

$$Z_{pt} = Z_{1pt}\beta + \epsilon_{pt}\ p = 1, \ldots, N, t = 1, \ldots, T \quad (2)$$

where Z_{pt} represents the dependent variable (RDC), Z_{1pt} denotes the set of independent variables (II, II^2, IS, URBAN, LUG), β represents the unknown coefficients, and ϵ_{pt} is the error term, with p indicating the cross-secti onal unit and t – the time period.

The estimation process proceeds as follows: First, the study tests for cross-sectional dependence (CSD) using the Pesaran, Friedman, and Frees tests, as complete cross-sectional independence is unlikely in an era of economic integration (Qian & Madni, 2022; Ul-Haq et al., 2023a) Second, to address heteroskedasticity, the modified Wald test is applied. The Wooldridge test is used to detect serial correlation. Finally, FE-DKSE is employed to analyze the impact of II on RDC, given that the number of cross-sectional units (N) exceeds the number of time periods (T) (Ul-Haq et al., 2023a). To ensure robustness, results

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are validated using feasible generalized least square (FGLS) by Parks (1967) and panel corrected stander error (PCSE) by Beck and Katz (1995). FGLS generate OLS heteroscadasticity structure while PCSE obtain OLS estimate with panel corrected stander error. Both techniques control heteroscadasticity, cross sectional dependence and serial correlation hence generate robust long run estimates (Qian & Madni, 2022).

RESULTS

Table 2 presents the descriptive statistics for the variables. Regional disparity in consumption (RDC) has a mean of 2.660 and a standard deviation (S.D.) of 0.626, with the S.D. being less than the mean, indicating moderate data dispersion around the mean. Across Chinese provinces, RDC ranges from a minimum of 1.595 to a maximum of 5.209. For industrial intelligence (II), the mean is 0.290 and the S.D. is 0.399, with the S.D. exceeding the mean, suggesting high data variability.

Table 2. Descriptive Statistics

Var.	Obs	Mean	S.D	Min	Max
RDC	420	2.660	0.626	1.595	5.209
II	420	0.290	0.399	0.025	3.336
IS	420	45.162	8.509	16.157	59.045
URBAN	420	0.548	0.139	0.269	0.984
LUG	420	2.257	0.797	-0.527	3.361

Source: own elaboration.

Before proceeding to econometric estimations, we conducted diagnostic tests to ensure the reliability of our panel data analysis, as cross-sectional dependence (CSD), heteroskedasticity, and autocorrelation can bias results if unaddressed (Ul-Haq et al., 2023a). We applied the Pesaran (2004), Friedman, and Frees tests to detect CSD, the modified Wald test for heteroskedasticity, and the Wooldridge test for autocorrelation. Table 3 reports the results, confirming the presence of CSD, heteroskedasticity, and autocorrelation, necessitating robust estimation methods like fixed-effects Driscoll-Kraay standard errors (FE-DKSE).

Table 3. Diagnostic tests

TEST	ISSUE	RDC
Modified Wald (χ^2)	Heteroscedasticity	341.62***
Wooldridge test	Autocorrelation	138.455***
Pesaran's test	CSD	8.237***
Friedman's test	CSD	48.103**
Frees test	CSD	1.957*

Note: ***denotes P<0.01, **denotes P<0.05 and *denotes P<0.1
Source: own elaboration.

Table 4 further details the Pesaran (2004) CD test results, confirming statistically significant CSD across the panel, reinforcing the appropriateness of FE-DKSE for addressing spatial correlations in our provincial data.

Table 4. Pesaran (2004) CD test for CSD

Variables	CD-test
RDC	63.03***
II	67.76***
IS	57.43***
URBAN	60.98***
LUG	73.02***

Note: ***denotes P <0.01, **denotes P<0.05 and *denotes P<0.1
Source: own elaboration.

We now check multicollinearity before proceeding for further econometric estimations. It is essential to check for multicollinearity because if it is present, p-value are unstable. Value of coefficient is influenced by other variable in model. Table 5 represents the Variance Inflation Factor (VIF) test to assess multicollinearity. Results indicate no multicollinearity among variables as every value of VIF is less than 5.

Table 5. VIF test

Variables	VIF	1/VIF
II	1.41	0.711
LUG	1.33	0.751
URBAN	1.31	0.762
IS	1.17	0.854
MEAN VIF	1.30	

Source: own elaboration.

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The FE-DKSE regression results examining the impact of industrial intelligence (II) on regional disparity in consumption (RDC) from 2006 to 2019 show that the coefficient of II is negative and statistically significant ($p < 0.01$), indicating that initial II adoption reduces RDC, likely due to broad economic gains from technology diffusion (Table 6). Conversely, the squared term (II^2) is positive and significant ($p < 0.05$), revealing a U-shaped relationship: as II adoption intensifies, RDC increases, reflecting urban-biased benefits from advanced II implementation. The turning point of the U-shaped relationship, calculated as $-\beta_1/(2\,\beta_2) = -(-1.365)/(2 \times 0.403) = 1.693$, falls within the observed range of II. This confirms that the inflection from disparity-reducing to disparity-widening effects occurs at an economically meaningful level of industrial intelligence adoption.

Table 6. Impact of II on RDC in China

Variables	FE-DKSE	FGLS	PCSE
II	-1.365*** (0.268)	-1.190*** (0.087)	-1.365*** (0.217)
II^2	0.403*** (0.085)	0.320*** (0.041)	0.403*** (0.116)
Constant	2.959*** (0.191)	2.886*** (0.034)	2.959*** (0.050)
F/Wald	12.95	588.29	64.97
N	420	420	420

Note: RDC is dependent variable in all columns. Standard errors given in parentheses. *** denotes P<0.01, ** denotes P<0.05 and * denotes P<0.1.
Source: own elaboration.

To validate the consistency of results, we also incorporated control variables in Table 7. Control variables align with theoretical expectations. Industrial structure (IS) exhibits a positive and significant coefficient ($p < 0.01$), with a 1% increase

Table 7. Impact of II on RDC in China (Robustness checks)

FE-DKSE	(1)	(2)	(3)	FGLS (4)	PCSE (5)
II	-1.410*** (0.267)	-0.741*** (0.173)	-0.499** (0.166)	-0.863*** (0.148)	-0.499*** (0.176)
II^2	0.425*** (0.091)	0.233*** (0.054)	0.163** (0.057)	0.305*** (0.074)	0.163** (0.066)
IS	0.022*** (0.004)	0.010** (0.004)	0.011** (0.004)	0.016*** (0.002)	0.011*** (0.002)
URBAN		-2.173*** (0.318)	-2.173*** (0.303)	-2.262*** (0.136)	-2.173*** (0.195)
LUG			-0.096** (0.039)	-0.098*** (0.032)	-0.096*** (0.036)
Cons	1.945*** (0.247)	3.541*** (0.428)	3.669*** (0.437)	3.531*** (0.139)	3.669*** (0.197)
F/Wald stat	29.72***	357.12***	728.53***	671.23***	322.95***

Note: RDC is dependent variable in all columns. Standard errors are given in parentheses. *** denotes P<0.01, **denotes P<0.05 and * denotes P<0.1.
Source: own elaboration.

Table 8. Impact of II on RDC in China and across regions

Variables	Overall	Eastern	Central	Western
II	-0.499** (0.166)	-0.293* (0.140)	-1.382** (0.924)	-9.926*** (2.327)
II^2	0.163** (0.057)	0.061 (0.047)	0.270 (1.628)	11.84*** (3.692)
IS	0.011** (0.004)	0.008*** (0.002)	0.002 (0.002)	0.037*** (0.003)
URBAN	-2.173*** (0.303)	-1.258*** (0.098)	-5.126*** (0.231)	-3.165*** (0.910)
LUG	-0.096** (0.039)	-0.030 (0.047)	0.222*** (0.066)	0.333*** (0.073)
Constant	3.669*** (0.437)	3.052*** (0.135)	4.708*** (0.162)	3.160*** (0.397)
F-Stat	728.53	74.72	170.83	355.17

Note: RDC is dependent variable in all columns. Standard errors are given in parentheses. *** denotes P<0.01, ** denotes P<0.05 and * denotes P<0.1.
Source: own elaboration.

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in IS raising RDC by approximately 0.02%, consistent with Chen and Ma (2022), who highlight urban dominance in secondary industries. Urbanization (URBAN) has a negative and significant coefficient ($p < 0.05$), suggesting it narrows RDC, aligning with Li et al. (2019) Human capital (LUG) also shows a negative and significant coefficient ($p < 0.05$), indicating its role in reducing RDC, consistent with Fleisher et al. (2010).

To ensure robustness, we employed feasible generalized least squares (FGLS) and panel-corrected standard errors (PCSE), reported in Table 7 (columns 4–5), alongside FE-DKSE estimates (columns 1–3). The U-shaped relationship between II and RDC persists across all specifications, with consistent coefficient signs and significance levels for II and II^2. IS remains a significant driver of RDC, with a 1% increase raising RDC by 0.011–0.022% across models. Urbanization and human capital consistently mitigate RDC, reinforcing the primary findings' reliability.

Finally, Table 8 disaggregates the analysis across Eastern, Central, and Western China to explore regional heterogeneity. The coefficient of II is negative and significant across all regions ($p < 0.01$), with a 1 percentage point increase in II reducing RDC by 0.499 (overall), 0.293 (Eastern), 1.382 (Central), and 9.926 (Western) percentage points. The larger effect in Western China suggests that less-developed regions initially benefit more from II diffusion. However, the II^2 coefficient is positive, indicating rising RDC as II matures, with increases of 0.163 (overall), 0.061 (Eastern), 0.270 (Central), and 11.84 (Western) percentage points per 1 percentage point rise in II^2. Notably, II^2 coefficients for Eastern and Central regions are statistically insignificant, suggesting that the disparity-widening effect of advanced II is most pronounced in Western China, where urban-rural gaps are starkest. These regional variations highlight the importance of context-specific policy responses.

DISCUSSION

China's rapid adoption of industrial intelligence (II) exhibits a U-shaped relationship with regional disparity in consumption (RDC). Initially, II reduces disparity, possibly through technology diffusion, inclusive policies, and remittances, but as it matures, urban areas disproportionately benefit from advanced manufacturing, widening the urban-rural gap. This dynamic aligns with the theoretical framework of displacement, productivity, and reinstatement effects (Acemoglu & Restrepo, 2019a; Xinyue et al., 2024), where initial convergence is driven by broad economic gains, but subsequent divergence occurs due to skill-biased technological change favoring urban, high-skilled labor.

Resource distribution in China is markedly uneven. Urban households benefit from social protections, such as medical care, employment insurance, and pensions, which are largely unavailable to rural households. Between 1995 and 2013, urban household savings rates increased, while rural savings declined, a trend reinforced by stricter enforcement of the one-child policy in urban areas compared to rural ones (Yang & Wang, 2023). The 2003 elimination of agricultural taxes significantly boosted rural incomes, narrowing the consumption gap (Liang et al., 2014) Internal migration further shaped this dynamic, with China's floating population growing from 79 million in 2001 to 221 million in 2010 (Howell, 2017) This migration alleviated rural poverty by increasing remittances, which supported rural consumption. However, migration patterns evolved: by 2010, approximately 26 million individuals migrated for education and training, reflecting a shift toward skill acquisition. The relaxation of the hukou system in 2001 allowed many migrants to settle in urban areas with their families, boosting urban productivity and incomes (Howell, 2017). These trends validate the U-shaped relationship, as initial II adoption supports rural income growth via remittances and policy reforms, but advanced II implementation concentrates benefits in urban areas, exacerbating disparity.

Industrial structure (IS) appears to significantly influence RDC, as secondary and tertiary industries, predominant in urban areas, offer higher wages than the primary industries dominant in rural regions (Chen & Ma, 2022; Zhou & Li, 2021). Urbanization, however, mitigates RDC, driven by market-oriented

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reforms and the 2001 hukou system relaxation, which granted residency rights to rural migrants (Howell, 2017; Huang & Zhan, 2005a). Migrants' remittances supported rural consumption, narrowing the urban-rural gap (Huang & Zhan, 2005b). Human capital reduces RDC overall by fostering economic convergence through education, increasing returns to schooling and closing the income gap (Adeleye, 2024; Fleisher et al., 2010; Fraumeni et al., 2019). However, the regional analysis reveals a sign reversal: LUG exerts a positive and significant effect in Central and Western China, consistent with brain drain dynamics, whereby higher education enrollment in less-developed regions accelerates skilled labor outmigration toward coastal urban centers, ultimately widening local consumption disparities (Fleisher et al., 2010; Zeng et al., 2023).

These findings underscore the complex interplay of II, structural factors, and policy reforms in shaping China's regional disparities.

CONCLUSIONS

This study underscores the role of industrial intelligence (II) in shaping regional disparity in consumption (RDC) in China. Using provincial panel data from 2006 to 2019, we investigate II's impact on RDC within the urban-rural context. The findings reveal a dual nature of II, characterized by a U-shaped relationship with RDC. Initially, II fosters convergence, reducing disparity through inclusive policies such as hukou system reforms, the elimination of agricultural taxes, and remittances from rural-to-urban migrants. However, as II matures, it exacerbates disparity by shifting employment patterns toward high-skilled labor, reducing demand for less-skilled workers, who are predominantly rural. This dynamic concentrate economic benefits in urban areas, widening the urban--rural consumption gap.

Industrial structure (IS) emerges as a key driver of RDC, with secondary and tertiary industries, prevalent in urban areas, contributing to higher wages and amplifying disparities compared to rural primary industries (Chen & Ma, 2022; Zhou & Li, 2021). In contrast, urbanization and human capital investment mitigate RDC. Urbanization, facilitated by market-oriented reforms and hukou relaxation, narrows the urban-rural gap by enhancing labor remuneration and consumption through remittances (Howell, 2017; Huang & Zhan, 2005b). Human capital, by fostering economic convergence through education, reduces disparities by increasing returns to schooling in less-developed areas (Adeleye, 2024; Fleisher et al., 2010; Fraumeni et al., 2019).

The long-term implications of II risk deepening urban-rural imbalances, necessitating a dynamic policy framework to ensure equitable growth. The Chinese government should prioritize skill development to prepare workers for the demands of II-driven industries. Large-scale training programs are essential to equip both urban and rural labor with skills relevant to advanced manufacturing and AI technologies. To promote balanced growth, the government should provide subsidies to industries in underdeveloped regions, encouraging the adoption of II in rural areas.

Furthermore, the government should invest in advanced digital infrastructure in rural areas to support the adoption of II and foster economic integration. Increased funding for education in rural regions is vital to build human capital aligned with the requirements of II-driven industries. Support for small-scale industries in rural areas, through financial incentives and infrastructure development, can stimulate local economies and mitigate the risk of widening disparities. These policies collectively aim to harness the benefits of II while addressing its potential to exacerbate urban-rural divides in the long term.

Despite its contributions, this study has limitations that offer avenues for future research. The analysis relies on provincial-level data, which provides a clear but aggregated perspective on the II-RDC relationship. Future studies should explore finer geographic scales to deepen understanding of II's localized impacts on RDC and inform more targeted policy interventions.

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