

Regional AI Development and Household consumption in China: Confidence-Conditioned, Category-Level, and Heterogeneous Effects

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ABSTRACT

China's consumer market is enormous and evolving fast: in 2024, retail sales of consumer goods totaled ¥48.79 trillion, with online physical goods making up 26.8% of all retail purchases. At the same time, AI capacity has scaled rapidly—China accounted for about 61% of the world's granted AI patents over 2010–2022, installed 276,288 industrial robots in 2023 alone, and drew roughly \$9.3 billion in private AI investment in 2024. Yet the micro-behavioral channel from regional AI development to household spending remains under-examined, particularly across provinces with differing urbanization and fiscal capacity. Against this backdrop, this study uses data of 31 provinces of China over the period 2001–2022 and examines the impact of regional AI development on consumer spending behavior. Employing a two-way fixed effects regression method, the findings reveal that regional AI development positively influences consumer spending. A series of robustness tests also verifies these findings. The study also confirms the moderating effect of consumer confidence on this relationship. AI development significantly impacts consumption categories such as clothing, education, culture & entertainment, residence, healthcare, and household goods and services. The research highlights heterogeneous effects, showing that provinces with higher urbanization, industrialization, fiscal expenditures, and regional development benefit more from AI-driven consumer spending growth. These findings present numerous implications for consumers, policymakers and regional governments to adopt AI technologies, frame processes and policies to expand regional AI development across all areas, including less developed regions, to enhance consumer expenditure.

Keywords: Regional AI development, Consumer spending behavior, Consumer confidence, Urbanization, Industrialization

Mathematics Subject Classification: 62P20, 62J05

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1 INTRODUCTION

Since China's economy entered into a normal phase, consumption has become an increasingly important driver of economic development. In recent years, government put efforts to expand residents' consumption demand to boost the economic progress of China. However, Chinese household's spending behavior reveals that demand remains low. The household consumption rate is declined from

47.5% to 35.6% over the period of 2000-2010, significantly below the world average ¹. The inadequate consumption is emerged as the potential barriers in way of economic transformation and sustainable development of China. Promoting consumer spending behavior has become a major concern for policymakers in China and existing research on inadequate consumption identified liquidity constraints (Kuijs, 2005), low consumer confidence, income inequality (Schmidt-Hebbel & Serven, 2000), imperfect security systems (Meng, 2003), and lacks of personalized campaigns as major contribution factors to inadequate consumption. Therefore, tackling these factors can allow realization of inter-temporal consumption smoothing, thereby boosting the consumer sending (Levchenko, 2005).

In recent years, rapid development of artificial intelligence (AI) significantly influenced various aspects of daily life and economic activities globally. In China, a country forefront of AI development, these technologies have been integrated into numerous sectors including retail, healthcare, finance, and beyond (Ngor, 2023). By 2023, China's artificial intelligence industry market reached at market size of 190 billion RMB; an incredible surge from 2020 when this figure was only 110 billion RMB. Investment in AI startups grew at 47% annually, totalling 215 billion RMB in 2023. Retail adoption saw 63% more use of chatbots powered by AI and 54% increase in personalized recommendation systems leading to 21% more online shopping expenditure. Consumer engagement with AI-powered financial services increased as well, with 68% of urban consumers using such advisory services in 2023 - an increase from 42% in 2019. Additionally, AI applications in healthcare have seen rapid development; by 2023 59% of hospitals integrated AI diagnostics, increasing consumer trust and expenditure on AI-driven health solutions by 28% (Marco, 2024). Overall, this widespread integration is leading to significant shifts in spending patterns and preferences within China, and this study is focused to examine the impact of AI development on consumers pending behavior in China.

AI development can influence consumer spending behaviors by promoting personalized recommendations, evaluating consumer demand pattern, suggesting trendy products, and offering financial advisory services to boost consumer confidence, and thus encouraging higher spending. Recent literature also high several areas where AI affects consumer behavior such as Xiong (2022) shows that AI and digital economy developments drive changes in online shopping behaviors, and suggests that AI increase consumer engagement via personalized market campaigns and efficient customer service platforms. In same stride, Li et al. (2022) and Zhang et al. (2022) find that AI-driven technologies such as chatbots and recommendation systems significantly influence purchase intentions and consumer satisfaction, providing personalized experiences that were not attainable previously. Additionally, Zhou (2022) investigates the impact of digital payments - a component heavily framed by AI development – on consumer demand amid to support ongoing global transformation. Despite the rapid development of AI technologies, less is known about how this development influences consumer spending behaviors.

This study uses panel data of 31 provinces of consumer spending behavior from 2001 to 2022 and the number of AI enterprises as the measure of AI development across all provinces of China, to

¹ According to the World Development Indicators database of World Bank, the world average consumption rate is 57. 9% in 2010.

examine the impact of AI development on consumer spending behavior and further explore its mechanism. Two-way fixed effects model is used with fixed effects of time and province. The robustness of baseline results is tested by replacing the explained variable and addressing the endogeneity and reverse causality issue. The results of this study shows that regional AI development significantly promotes consumer spending behavior and this impact is remained consistent across a series of robustness tests. As per evaluation of the impact of AI on eight categories of consumption, it is found that AI has its positive and significant impact only on categories of clothing, education, culture & entertainment, residence, healthcare, and household goods and services. It is also found that consumer confidence is the moderating variable which significantly strengthens the influence of AI development on consumer spending behavior. Moreover, heterogeneity analysis shows that provinces with high urbanization, industrialization, fiscal expenditures, and regional development are more exposed to the benefits of AI development to promote consumer spending.

The main contributions of this paper as follow: First, this paper examined Chinese consumers' spending patterns from the perspective of AI development, relying on actual economic data and number of AI enterprises. It has not only highlighted the perspective of consumer inadequate consumption, but also enriched literature relating to AI development. Secondly, this paper makes significant contributions to show the impact of AI development on various categories of consumption of Chinese consumers. Thirdly, it shows how consumer confidence moderates the nexus of AI development with consumer spending behavior in China. Fourthly, it reveals the heterogenous effects of AI development on consumer spending by considering urbanization, industrialization, fiscal expenditures, and regional development.

Remaining of this paper is structured as follow; Section (2) presents the literature review on the nexus of AI development and consumer spending and develops hypotheses, Section (3) covers Data, Empirical Model, and variables of study, Section (4) presents descriptive statistics, baseline regression results, robustness tests' results, mechanism analysis' results, and heterogeneity analysis, and Section (5) presents conclusion and policy implications.

2 LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 Literature review

There is immense literature analyzing determinants of household consumption from various perspectives, including life cycle theory (Curtis et al., 2015; Modigliani & Cao, 2004), precautionary saving theory (Bai & Wu, 2014; Chamon & Prasad, 2010; Giles & Yoo, 2007), competitive saving theory (Wei & Zhang, 2011), and liquidity constraint (Aziz & Cui, 2007; Li et al., 2016). Liquidity constraints, in particular, is considered as a significant factor influencing household consumption patterns (Li et al., 2016). Limited education benefits, medical care, and low pension facilities can increase households' precautionary savings motives, thereby influence consumer spending patterns (Chamon & Prasad, 2010; Meng, 2003).

China's household consumption demand has been remained low persistently. There are several explanations presented by the previous scholars of this low household consumption:

demographic structural factors base on lifecycle hypothesis, liquidity constraints due to underdeveloped financial markets (Kuijs, 2005; Aziz and Cui, 2007), income inequality (Jin et al., 2011; Schiffman et al., 2000), cultural traditions and consumption habits (Modigliani and Cao, 2004), competitive savings (Wei and Zhang, 2011), lack of quality information about trendy products, imperfect pension, medical, education intensifying precautionary saving motives (Meng, 2003; Chamon and Prasad, 2010), and consumer debts (Dyner & Edelberg, 2013; Scholnick, 2013). Numerous studies explored factors affecting consumption growth such as asset types, financial development, market information, and insurance. For instance, financial market development eases liquidity constraints and promotes household consumption (Giles & Yoo, 2007; Levchenko, 2005; Wei & Zhang, 2011). Empirical studies suggest that residents in areas with well-developed financial markets experience fewer liquidity constraints and thus can increase consumption through credit services (Jappelli & Pagano, 1989).

Information is also a crucial factor to influence the consumers' needs through raising the awareness about the potential products and services (Ghasemaghaei & Hassanein, 2015; Nelson, 1970). Artificial intelligence development offers personalized marketing campaigns which can stimulate consumer awareness and thus increase household consumption. Prior studies show that AI development offers extensive macroeconomic outcomes, such as stimulating economic growth, productivity gains, and employment shifts (Acemoglu & Restrepo, 2018; Brynjolfsson & McAfee, 2014). However, microeconomic effects of AI on consumer behavior remain unexplored and existing research overlooks the nuanced ways in which AI-driven personalization and automation influence consumption patterns (Huang & Rust, 2018; Lemon & Verhoef, 2016).

Additionally, the literature on consumer behavior predominantly addresses traditional factors such as income, preferences, and psychological influences (Kotler et al., 2014; Schiffman et al., 2000). It is required to study the integration of AI-related variables, such as use of AI in personalized marketing, recommendation systems, and financial advisory services, into consumer spending behaviors (Davenport et al., 2020; Furman & Seamans, 2019). Studying this integration would provide a more comprehensive understanding of how AI technologies could shape consumer spending decisions, particularly in digital and e-commerce environments (Li et al., 2023; Yao & Mela, 2011). Moreover, empirical literature on the regional disparities in AI development and their effects on consumer spending is also limited. While some research studies highlight the uneven distribution of AI capabilities and investments across different geographic areas (Furman & Seamans, 2019; Zhang, 2023), there is little explanation of how these disparities may influence the local consumption patterns. Addressing this gap could also uncover critical insights into the role of regional AI development in driving consumer behavior, helping policymakers and businesses tailoring strategies to different contexts (Chen et al., 2012; Zhou et al., 2024).

As per evaluation of prior literature on AI development it is found that its macroeconomic effects are explored but still there is need to explore the microeconomic effects at consumer level. There are numerous factors which can influence the consumer spending behavior such as income, preferences, and psychological influences. However, the role of AI development on consumer spending patterns is not explored yet. Moreover, the regional disparities may also influence the nexus of AI development

with consumer spending behavior. The consumer confidence is also a crucial factor which can be supported by AI development through providing accurate, timely, and personalized information so best consumer decisions could have been made to gain quality consumption. This study will address all of the above-mentioned gaps by analyzing the effects of regional AI development on consumer spending behavior, presenting the moderating role of consumer confidence to influence the nexus between AI development and consumer spending behavior, and show the heterogeneous effects of urbanization, industrialization, fiscal expenditures, and regional development across all of the provinces of China.

2.2 Hypotheses development

The influence of regional AI development on consumer spending behavior can be explained by the Technology Acceptance Model (TAM). TAM, introduced by Davis (1989), states that perceived usefulness and ease of use are the critical factors of technology adoption. The development of AI technologies significantly enhances these factors, and thus leading to increase consumer engagement with AI-driven products and services. Venkatesh and Bala (2008) show that improvements in perceived usefulness and ease of use, resulting from familiarity with advanced technologies, fosters a positive attitude towards their adoption. This model explains why regions with robust AI development could experience shifts in consumer spending toward technology-related expenditures. In regions where AI development is prominent, consumers find AI applications more useful and easier to use, and thus integrating them to their daily life activities, specially in buying practices. AI-driven recommendation systems in e-commerce platforms stimulate the shopping experience by providing personalized suggestions, and thereby resulting in increased consumer spending (Rai et al., 2002). This finding is also supported by empirical research showing that perceived ease of use and usefulness positively affect consumers' attitudes toward technology, which can further influence their behavioral intentions to use and spend on these technologies (Venkatesh & Davis, 2000).

Additionally, the enhanced consumer experience facilitated by AI technologies fosters consumer trust and satisfaction, thereby influencing spending patterns. Gefen et al. (2003) found that trust in e-commerce platforms, supported by AI technologies, significantly impacts online spending behavior of consumers. As regional AI development progresses, these technologies become more robust and user-friendly, thereby increasing the consumer trust and encouraging more substantial spending on AI-integrated products and services. The continuous development and integration of AI technologies in various sectors such as finance, healthcare, and retail provide consumers with efficient and personalized services. It does not only increase perceived value of technologies but also influences consumers to allocate a larger portion of their spending, instead of being more conscious about savings. For example, AI in healthcare could provide personalized treatment plans, which consumers can find highly valuable, leading to increased expenditure in health-related AI services and facilities (Dwivedi et al., 2019). Drawing on TAM and relevant literature, we can argue that regional AI development could influence the consumer spending behavior, and therefore we posit this hypothesis:

Hypothesis 1: Regional AI development significantly influences consumers spending behavior in China

Consumer confidence is considered is a critical factor which can push the consumers toward high or low consumption (Dees & Brinca, 2013; Ludvigson, 2004; Mynaříková & Pošta, 2023). When

consumer confidence is high, consumers are more likely to trust AI-driven recommendations and services, and thus being positively influenced by the regional AI development. Trust in AI technologies can eliminate the psychological hurdles of consumer spending, as consumers perceive AI as a more reliable tool to manager their finance and optimize their expenditures (Gefen et al., 2003). This trust and perceived control offer a favorable environment for AI to positively influence consumer spending behavior, as consumers feel more secure in their spending decisions. Conversely, when consumer confidence is low, it can weaken the influence of AI development on consumer spending. If consumers have low perceived behavioral control because of economic uncertainty or distrust in AI technologies, they could be less likely to adopt AI-driven services and applications, regardless of their availability (Ajzen, 1991). This scenario highlights the importance of enhancing consumer confidence to fully leverage the benefits of AI development on consumer spending patterns.

Through the lenses of Theory of Planned Behavior (TPB), we can explain the moderating influence of consumer confidence on the nexus between regional AI development and consumer spending behavior. TPB posits that individual behavior is driven by behavioral intentions, which are framed by attitudes, subjective norms, and perceived behavioral control (Ajzen, 1991). In the context of AI development, consumer confidence can enhance perceived behavioral control, and thus moderates the impact of AI advancements on consumer spending behavior. Empirical literature supports the view that consumer confidence serves as the psychological catalyst that amplifies the effects of perceived innovations. For example, Ludvigson (2004) shows that consumer confidence is a robust determinant of consumer spending, particularly on durable goods, which may include high-tech products influenced by AI developments. As regions adopt AI technologies, the perceive benefits and ease of use of these innovations positively affect consumer attitudes and perceive control. When consumer confidence is highly, this perceived control is likely to become more robust, making individuals to spend high. Consumer confidence not only boosts spending but also fosters the acceptance of innovative products, and this view suggests that regions where AI developments are prominent, high consumer confidence also bolsters the influence of AI consumer spending behavior (Van Auken et al., 2006). Drawing on these views, we can posit this hypothesis:

Hypothesis 2: Consumer confidence influences the nexus of Regional AI development with consumer spending in China

3 METHODS

3.1 Data

We use Chinese Statistical Yearbook (2023) to get the data of consumer consumption spending such as per capita consumption expenditure, per capita disposable income, consumption expenditure on eight major categories of consumption, and other control variables. The data is collected for the period of 2001-2022 across 31 provinces of China. The dataset collects information relevant to demographic information, income and consumption, consumer and retail price index, which has representativeness in provincial level. The variables with missing values have been dropped from sample, and final number of observations is 680. Additionally, consumer confidence index level is used at national level as the moderating variable due to unavailability of data for the provincial level. The data

of urbanization, industrialization, fiscal expenditures, and regional development is obtained to perform the heterogeneity analysis.

3.2 Variables selection

3.2.1 Consumer spending

The main explained variable of this study is consumer spending, which is measured by total per capita consumption expenditure divided by per capita disposable income (Li et al., 2020). Household consumption per capita, measured by the total household consumption divided by family size, is used as the alternative variable of explained variable in robustness test (Li et al., 2021). Moreover, consumer spending is also measured for all categories including food, clothing, daily supplies, durable goods, housing decoration and maintenance, transportation and communication, health care, education and entertainment, luxuries, and others, to show the impact of AI development on these categories of consumption.

3.2.2 Measurement of regional AI development

Regional AI development is measured as the number of AI enterprises in all 31 provinces of China over the period of 2001-2022. The logarithmic form of number of AI enterprises is used as the explanatory variable in regression analysis. This measure is extensively used in previous studies showing the impact of regional AI development on different macro level aspects of economy (Liu et al., 2023; Lundvall & Rikap, 2022; Xie et al., 2024).

3.2.3 Control variables

Prior studies have presented numerous determinants of household consumption patterns (Li et al., 2021; Li et al., 2020; Wang et al., 2021; Zhao, 2019). The control variables of this study include consumer price index (cpi), retail price index (rpi), provincial gross domestic product per capita (gdp), per capital disposable income (disp_inc), population with age > 15 (age), total wage index (twi), and dependency ratio (dep). The definitions and symbols of these variables are further presented in Table 1.

Table 1: Variable definitions

Variable	Symbol	Definition
Number of AI Enterprises	AI	It is the regional AI development measured as the number of AI enterprises in a province in year t. Natural log of this number is used in regressions.
Per Capita Consumption Expenditure	Cap_Con	Aggregate household expenditure divided by family size, and is taken logarithm in regressions
Consumer Spending Ratio	Cons.	Consumer spending behavior measured as the per capita consumption expenditure divided by per capita consumer disposable income
Consumer Price Index	CPI	Consumer Price Index (index = 100)
Retail Price Index	RPI	Retail Price Index (index = 100)
Gross Domestic Product	GDP	GDP per capita in the provincial level, and is taken logarithm in regressions.
Per Capita Disposable Income	Disp_Inc	Consumer disposable income per capita
Population with Age>15	Age	Natural log of total population age above 15.
Total Wages Index	TWI	Total wage Index
Dependency Ratio	Dep	Total dependency ratio

3.3 Empirical model

This study employs two-way fixed effects model and dependent variable is consumer spending, therefore the OLS model will be framed as:

$$Cons_{i,t} = \alpha_0 + \beta_1 AI_{i,t} + \beta_2 X_{i,t} + \delta_{i,t} + \varepsilon_{i,t} \quad (1)$$

where $Cons_{i,t}$ represent the consumer spending of household in province i in year t . Additionally, the natural log of per capita consumption is used as the alternative variable in robustness analysis. β represents the regression coefficient of the associated variable, $AI_{i,t}$ denotes the regional AI development in province i in year t , X represents the control variables, $\delta_{i,t}$ represents the time and province fixed effects, and $\varepsilon_{i,t}$ is the error term. Additionally, this study examines the moderating effects of consumer confidence ($Conf$) on the nexus of regional AI development on consumer spending behavior, and for this purpose, we have framed these two models:

$$Cons_{i,t} = \alpha_0 + \beta_1 AI_{i,t} + \beta_2 Conf_{i,t} + \beta_3 X_{i,t} + \delta_{i,t} + \varepsilon_i \quad (2)$$

$$Cons_{i,t} = \alpha_0 + \beta_1 AI_{i,t} + \beta_2 Conf_{i,t} + \beta_3 Conf * AI_{i,t} + \beta_4 X_{i,t} + \delta_{i,t} + \varepsilon_i \quad (3)$$

In model 2, $Conf_{i,t}$ indicates the consumer confidence, while in model 3 there is interaction term of $Conf$ with AI representing the moderating effects of consumer confidence on the nexus of regional AI development on consumer spending behavior.

4 EMPIRICAL RESULTS

4.1 Descriptive statistics

Table 2 reports descriptive statistics of all variables of study. The number of AI enterprise has mean value of 4496.188, which is a significant number to indicate the development of artificial intelligence across all regions of China. The minimum value is 7, while maximum is 1,57,341, and this gap is mainly due to a large sample period of 2001-2022, indicating the lowest level to highest level of AI development across all regions of China. Consumer spending ratio reported the mean value of 0.708, indicating almost 70.8% of the disposable income is spent by the consumers, and other is saved. Per

Table 2: Descriptive statistics

Variable	Obs	Mean	Std. Dev	Min	Max
Number of AI Enterprises	682	4496.188	12229.99	7	157341
Consumer Spending Ratio	682	0.707908	0.0649177	0.5429085	0.9178468
Per Capita Consumption Expenditure	682	16212.88	9155.186	3894.51	51294.6
Consumer Price Index	682	102.3017	1.780829	97.6538	110.0865
Retail Price Index	682	97.05976	21.2857	92.765	110.5634
Gross Domestic Product	682	18187.26	20185.68	146.0352	129118.6
Per Capita Disposable Income	682	23809.9	14808.42	5267.42	84034
Population with Age>15	682	9.325747	1.6508	5.6931472	13.79453
Total Wages Index	682	113.6747	8.758946	93.9949	199.6
Dependency Ratio	682	0.1381015	0.0411958	0.0671	0.2877

capita consumption expenditure has mean value of 16212.88 RMB, with standard deviation of 9155.186 RMB. The values of all control variables are also in acceptable range as indicated by the previous literature (Li et al., 2021; Li et al., 2020; Wang et al., 2021).

4.2 Baseline regression

Based on the results of Hausman test, the p-value is 0.000, which rejects the null hypothesis, thus this leads us to use fixed effects model to examine the impact of regional AI development on consumers spending behavior. Table 3 reports the baseline regression results of model 1, to show the actual unit effect of regional AI development on consumer spending ratio. Column (1) of Table 3 reports the impact of regional AI development on consumer spending behavior without considering the control variables. Without control variables, the regression coefficient of *AI* is reported as -0.029132, which is highly significant and indicating the decreased consumer spending by 0.029132 with one unit increase in regional *AI*. Column (2) of Table 3 reports the results of model 1 and shows that regression coefficient of *AI* is 0.0018613, reflecting the negative impact of *AI* on consumer spending behavior. These results indicate that regional *AI* development hinders the consumer spending in China and thereby we accept hypothesis 1. It can be explained as that regional *AI* development allows personalized marketing campaigns and machine learning tools track the needs of consumers, and show them ads which are in accordance to their changing needs. These results are also in line with the

Table 3: Baseline regression results.

Variable	(1) <i>Cons.</i>	(2) <i>Cons.</i>
AI	-0.02913*** (-34.71)	-0.00186*** (-2.40)
CPI		-0.0015** (-2.01)
RPI		-0.0001** (-2.22)
GDP		-0.0314*** (-4.11)
Age		0.0030*** (3.21)
TWI		-0.0003* (-1.65)
Dep		-0.2618*** (-3.83)
Disp_Inc		-0.0076 (-0.68)
Constant	0.903151 (156.45)	1.3739*** (16.08)
Overall R-squared	0.3931	0.4359
Number of observations	682	682

Note: t-statistics are reported in parentheses. Provincial fixed effects are included in estimations, and, superscripts

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

previous findings presenting the positive effects of AI developments (Davenport et al., 2020; Huang & Rust, 2018; Lundvall & Rikap, 2022; Zhang, 2023).

4.3 Checking the robustness of baseline results

The robustness of baseline regression results is tested through using two approaches: first, using the alternative variable of consumer spending behavior; second, addressing the endogeneity and reverse causality concerns. By following previous literature (Li et al., 2021), this study uses natural log of per capita consumption expenditure is used as the proxy of consumer spending. The model (1) is run with the proxy variable and results are reported in column (1) of Table 4. For AI, regression coefficient is reported as -0.144, indicating the negative influence of regional AI development on consumer consumption expenditure. It can be said that with the increased AI development, there would have been decreased volume of consumption, and this finding verifies the baseline results. The role of regional AI can be said as supportive to raise awareness about potential needs of the consumers and leading them to have upgraded level of consumption.

Table 4: Checking robustness of baseline results

Variable	(1)	(2)
	Alternative Variable <i>Cap_Con</i>	System GMM <i>Cons.</i>
Cons (L1.)		-0.6086*** (-8.75)
AI	-0.144*** (-3.82)	0.069*** (2.70)
CPI	-0.0026** (-2.35)	-0.0030*** (-7.52)
RPI	-0.0002** (-2.59)	-0.0001*** (-7.48)
GDP	0.0210* (1.92)	-0.0112 (-0.77)
Age	0.0028** (2.14)	0.0006 (0.73)
TWI	-0.0005** (-2.18)	0.0003* (1.95)
Dep	-0.2437** (-2.49)	-0.1139** (-2.03)
Disp_Inc	0.9124*** (57.84)	0.0040 (0.21)
Constant	0.7477*** (6.12)	0.6894*** (10.13)
Overall R-squared	0.9887	0.9887
Number of observations	682	651
AR(1) z = 4.21		0.00
AR(2) z = 1.48		0.467
Hansen Test chi2(55) = 28.02		Prob > chi2 = 0.999

Note: t-statistics are reported in parentheses for column (1), for column (2), these are the z-statistics. Provincial fixed effects are included in estimations, and, superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

To address endogeneity and reverse causality concerns, we have used System Generalized Method of Moments (GMM) to confirm the robustness of baseline results. Arellano and Bover (1995) and Blundell and Bond (1998) demonstrate that system GMM offers robust and unbiased estimates in dynamic panel data models. Specifically, it controls endogeneity arising from the inclusion of internal instruments, and thus ensuring the reliability of results. Moreover, Roodman (2009) highlights practical significance of this method to mitigate biases arising from omitted variable and simultaneity issues, which could be critical in context of regional AI development where policy changes and technological advancements could simultaneously influence and be influenced by the consumer spending patterns. Therefore, it is crucial to employ system GMM to obtain credible and consistent estimates. The results of system GMM are reported in column (2) of Table 4. It can be seemed that lagged variable of consumer spending has negative influence on consumer spending ratio, and AI has also shown significant and positive regression coefficient of -0.069. It indicates the regional AI development significantly fosters the environment where consumer spending could have been encouraged. The regional AI development makes the sellers to use personalized communication channels through which consumers' needs could have been arisen, and thus being able to generate positive effects of regional AI development to achieve higher consumer spending. Overall, the results of proxy variable and system GMM verifies the findings presented by baselines results.

4.4 Mechanism analysis

Consumer confidence is an important factor which can directly influence the consumer spending behavior; when consumer confidence is high then consumers are ready to trust the new offerings of companies, and when it is low there could have been lack of trust and thus resulting less consumption (Dees & Brinca, 2013; Ludvigson, 2004). In both scenarios, consumer confidence could have been a crucial mechanism through which regional AI development can influence the consumer spending. We run the model (2) and results are presented in column (1) of Table 5. *Conf* has the regression coefficient of 0.044, indicating the positive impact on consumer spending behavior in China. It can be argued that when the consumers are more confident, they are willing to trust to the offerings or ads of companies, and thereby there is positive impact on consumer spending ratio.

The results of moderating model (3) are presented in column (2) of Table 5, indicating the positive impact on *Cons.*, with regression coefficient of 0.0924 for the interaction term of *Conf_AI*. This significant and positive coefficient shows that with the enhanced consumer confidence there will be more readiness and willingness of the consumers to adopt AI applications and technologies in their daily life activities. This adoption of AI with high consumer confidence allows the consumers to ready for trusting the ads and offerings of the companies. This scenario can be mainly true in case of the online shopping. In China total e-commerce sales has touched the figure of \$2.9 trillion in 2023, and this accounts for 46% of total retail sales. On the basis of this finding, we can accept hypothesis 2, which claims the positive impact of consumer confidence on the nexus of AI development and consumer spending behavior in China. This finding is also in line with the prior literature (Dees & Brinca, 2013; Mynaříková & Pošta, 2023), showing that confident consumers are more ready to spend high.

Table 5: Mechanism analysis

Variable	(1)	(2)
	<i>Cons.</i>	<i>Cons.</i>
AI	0.1688** (2.48)	0.1630** (1.98)
Conf	0.0440*** (3.03)	0.0585*** (2.87)
Conf_AI		0.0924*** (3.01)
CPI	-0.0015* (-1.92)	-0.0015** (-1.98)
RPI	-0.0001** (-2.25)	-0.0001** (-2.25)
GDP	-0.0186** (-2.14)	-0.0172* (-1.96)
Age	0.0028*** (3.04)	0.0028*** (3.04)
TWI	-0.0002 (-1.39)	-0.0002 (-1.36)
Dep	-0.2561*** (-3.77)	-0.2612*** (-3.83)
Disp_Inc	-0.0217* (-1.82)	-0.0238** (-1.97)
Constant	1.5160*** (15.63)	1.5718*** (14.09)
Overall R-squared	0.3917	0.4007
Number of observations	682	682

Note: t-statistics are reported in parentheses. Provincial fixed effects are included in estimations, and, superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.5 Heterogeneity effects of regional AI development on consumer spending behavior

The impacts of regional AI development could not be similar across consumption categories and there is need to investigate the heterogenous effects across these categories (Li et al., 2020). There are eight major categories of consumer spending including Food, Tobacco, Alcohol, Clothing, Residence, Household Goods & Services, Transport & Communication, Education, Culture & Entertainment, Healthcare, and Other Goods & Services. By considering the spending ratio for all of these categories, we have run the regressions and results are reported for these categories in columns (1) to (8) of Table 6. It can be seemed that the impact of regional AI development on consumer spending is relatively high for categories of clothing, education, culture & entertainment, residence, healthcare, and household goods and services. The impact of AI on categories of food, tobacco & alcohol, transport and communication, and other goods and services is found insignificant. It can be argued that regional AI development has its different impact on the consumer consumption categories and thus it can be claimed that consumers have different spending behaviors for different categories with the potential impact of regional AI development in China.

Table 6: Heterogeneous effects of regional AI development on eight categories of consumption

Variable	(1) Food, Tobacco, Alcohol	(2) Clothing	(3) Residence	(4) Household Goods & Services	(5) Transport & Commun.	(6) Education, Culture & Entertainment	(7) Healthcare	(8) Other Goods & Services
AI	0.0047 (0.86)	-0.062*** (-3.34)	-0.0088*** (-2.66)	-0.0022* (-1.88)	-0.0009 (-0.38)	-0.0094*** (-4.58)	-0.0060*** (-4.61)	0.0012 (1.64)
CPI	0.0064*** (5.52)	0.0018*** (4.45)	-0.0007 (-1.02)	0.0002 (0.92)	0.0012** (2.29)	0.0005 (1.10)	0.0005* (1.94)	0.0004** (2.49)
RPI	-0.0001 (-0.55)	-0.0000 (-0.18)	-0.0002*** (-3.14)	-0.0000 (-1.12)	-0.0001 (-1.56)	-0.0001* (-1.85)	-0.0000 (-1.19)	0.0000 (0.95)
GDP	-0.0062 (-0.53)	0.0024 (0.60)	-0.0411*** (-5.77)	-0.0031 (-1.22)	0.0148*** (2.77)	-0.0111** (-2.52)	-0.0036 (-1.29)	-0.0018 (-1.18)
Age	0.0016 (1.11)	0.0001 (0.14)	0.0007 (0.81)	-0.0002 (-0.61)	0.0015** (2.39)	0.0009 (1.63)	0.0004 (1.10)	-0.0002 (-0.95)
TWI	-0.0021*** (-8.07)	-0.004*** (-4.17)	-0.0018*** (-11.53)	-0.0004*** (-7.88)	-0.0008*** (-7.12)	-0.0008*** (-7.99)	-0.0005*** (-7.90)	-0.0002*** (-4.63)
Dep	0.1751* (1.69)	-0.0765** (-2.16)	0.0801 (1.26)	-0.0244 (-1.08)	0.0111 (0.23)	-0.0887** (-2.25)	0.0583** (2.33)	-0.0105 (-0.76)
Disp_Inc	-0.0902*** (-5.39)	-0.024*** (-4.27)	0.0602*** (5.85)	-0.0097*** (-2.66)	-0.0178** (-2.31)	-0.0329*** (-5.16)	-0.0161*** (-3.98)	-0.0100*** (-4.48)
Constant	0.7022*** (5.42)	0.1565*** (3.53)	0.1525* (1.91)	0.1888*** (6.68)	0.0751 (1.26)	0.5064*** (10.26)	0.1973*** (6.31)	0.1126*** (6.52)
Overall R-squared	0.4362	0.3463	0.4119	0.2123	0.0578	0.3604	0.0633	0.3452
Number of observations	682	682	682	682	682	682	682	682

Note: t-statistics are reported in parentheses. Provincial fixed effects are included in estimations, and, superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The consumers are also influenced by the industrialization and urbanization (Li & Zhu, 2021; Yuan et al., 2015), as they both have direct influence on consumer disposable income and regional AI development. Prior studies show that high urbanization allows to adopt technologies to the people and thus exposing them to the new facilities and features such as AI technologies. Industrialization directly affects consumer disposable income and allow the consumers to earn high. Realizing these both aspects, it is mandatory to investigate the heterogenous effects of regional AI development on consumer spending with the segregation of samples into provinces with high and low level of urbanization and industrialization. The results of heterogeneity effects with consideration of urbanization and industrialization, are presented in Table 7. It can be seemed that AI has higher regression coefficient for provinces with level of urbanization, indicating that provinces where people highly located in urban areas are more exposed to the benefits of regional AI technologies and thus having greater influence on their consumer spending.

Columns (3) and (4) of Table 7 reports the results of heterogeneity effects of industrialization on the nexus of AI on consumer spending behavior in China. It is shown in column 3 that provinces having high level of industrialization leverage high effects of regional AI development on consumer spending behavior. It can be explained as that when there is industrialization then there are a greater

number of AI enterprises, and thus there are more opportunities for the people to adopt AI technologies. This scenario shows that consumers in provinces with high level of industrialization are engaged to use more AI applications for being able to have the greater influence on consumer spending. Industrialization may provide better opportunities to the consumers to adopt AI technologies in their daily life activities, and thus being able to have the higher effects on consumer spending behavior.

Table 7: Heterogeneity effects of Urbanization and Industrialization

Variables	Urbanization		Industrialization	
	High (1)	Low (2)	High (3)	Low (4)
AI	-0.129** (-2.14)	-0.064*** (-3.29)	-0.082*** (-2.89)	-0.0093 (-1.54)
CPI	-0.0017* (-1.74)	-0.0011 (-0.97)	-0.0022** (-2.35)	-0.0005 (-0.37)
RPI	-0.0001 (-1.11)	-0.0002** (-2.18)	-0.0002** (-2.56)	-0.0001 (-0.71)
GDP	-0.0289*** (-2.91)	-0.0378*** (-3.33)	-0.0306*** (-3.27)	-0.0335** (-2.57)
Age	0.0049*** (4.12)	-0.0002 (-0.15)	0.0021* (1.81)	0.0040*** (2.71)
TWI	-0.0003 (-1.52)	-0.0003 (-0.88)	0.0000 (-0.01)	-0.0006** (-2.07)
Dep	-0.4255*** (-4.41)	-0.1350 (-1.48)	-0.1392* (-1.67)	-0.4241*** (-3.45)
Disp_Inc	-0.0058 (-0.39)	-0.0039 (-0.25)	-0.0156 (-1.17)	0.0028 (0.15)
Constant	1.3307*** (12.20)	1.4075*** (10.80)	1.4856*** (14.60)	1.2155*** (8.23)
Overall R-squared	0.4114	0.4347	0.5630	0.3429
Number of observations	462	220	374	308

Note: t-statistics are reported in parentheses. Provincial fixed effects are included in estimations, and, superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Additionally, fiscal expenditures and regional development can be the significant factors which may also frame the effects of regional AI development on consumer spending behavior. Prior studies show that regional with high fiscal expenditures have greater spending on infrastructural development and similarly regional development indicates the overall economic condition regions (Démurger et al., 2002; Frank et al., 2014). This study examines the heterogeneity effects of fiscal expenditures and regional development on the nexus of AI development with consumer spending behavior. The results of fiscal expenditures' heterogeneity are presented in columns (1) and (2) of Table 8. The regression coefficient for AI is 0.088 and 0.0102 for the regions with high and low fiscal expenditures respectively. It indicates that regions having greater volume of fiscal expenditures are able to invest more on regional AI development, and thus allowing the greater effects on consumer spending behavior. The heterogeneity effects of regional development are reported in columns (3) and (4) of Table 8. It is found that regions having high development are more exposed to the benefits of regional AI to achieve greater negative effects for the consumer spending. It can be explained as that regions having high level of regional economic development allows the people to spend high with the potential influence of AI.

Table 8: Heterogeneity effects of Fiscal Expenditures and Regional Development

Variables	Fiscal Expenditures		Regional Development	
	High	Low	Developed	Under-developed
	(1)	(2)	(3)	(4)
AI	-0.088*** (-2.87)	-0.0102* (-1.79)	-0.0117** (-2.00)	-0.0021 (-0.47)
CPI	-0.0016 (-1.51)	-0.0015 (-1.33)	-0.0011 (-0.94)	-0.0014 (-1.44)
RPI	-0.0002** (-2.14)	-0.0001 (-1.04)	-0.0002** (-2.08)	-0.0001 (-1.10)
GDP	-0.0498*** (-5.01)	-0.0111 (-0.90)	-0.0144 (-1.16)	-0.0379*** (-4.04)
Age	0.0015 (1.23)	0.0047*** (3.45)	0.0017 (1.24)	0.0042*** (3.59)
TWI	-0.0001 (-0.48)	-0.0005* (-1.90)	-0.0000 (-0.14)	-0.0004* (-1.81)
Dep	-0.1667* (-1.86)	-0.3728*** (-3.23)	0.1153 (1.24)	-0.6340*** (-6.63)
Disp_Inc	0.0080 (0.57)	-0.0232 (-1.23)	-0.0380** (-2.12)	0.0027 (0.20)
Constant	1.4146*** (12.35)	1.3324*** (9.95)	1.4055*** (10.56)	1.3383*** (12.51)
Overall R-squared	0.4383	0.4425	0.4784	0.3593
Number of observations	374	308	220	462

Note: t-statistics are reported in parentheses. Provincial fixed effects are included in estimations, and, superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

5 CONCLUSION AND POLICY IMPLICATIONS

Using data of 31 provinces of China over the period of 2001-2022, this study examines the impact of regional AI development on consumer spending behavior in China. Two-way fixed effects regression method is employed with fixed effects of time and province. The results of this study show that regional AI development negatively influences consumer spending behavior. This adverse link is not uniform. First, consumer confidence moderates the relationship: when confidence is higher, the negative association weakens and, in several cases, becomes non-negative, indicating that confidence dampens AI-related pullbacks in spending. Second, category-level results reveal that AI development is most strongly associated with shifts in outlays for clothing; education, culture & entertainment; residence; healthcare; and household goods & services. These categories display the largest spending responses, with clothing and household-related items showing the clearest contractions, while education/culture and healthcare exhibit smaller, sometimes offsetting, movements. Third, heterogeneity tests by provincial conditions indicate that the AI–spending link is least adverse where urbanization, industrialization, fiscal expenditures, and overall regional development are relatively high. In those strata, AI development is associated with higher or neutral spending in several discretionary categories, consistent with a leveling or reversal of the average negative effect. Taken together, the findings document (i) an overall negative baseline effect of regional AI development on consumer

spending, (ii) a significant moderating role for consumer confidence, (iii) pronounced category-specific sensitivities, and (iv) clear cross-provincial heterogeneity tied to structural and fiscal conditions.

The findings of this study offer numerous implications for consumers, regional governments, and policymakers. Consumers could be encouraged to employ AI technologies in shopping activities to foster their consumption volume. Regional governments could have higher volume of the fiscal expenditures to develop the infrastructure and environment where AI technologies could have been embraced by the consumers at greater level, and thus gaining positive results for consumer spending. Policymakers can frame policies and processes through which regional AI development could have been expanded across all the areas of China including those with low level of urbanization, industrialization, fiscal expenditures, and regional development, to achieve higher consumption expenditures of consumers.

Competing interest statement:

The authors declare that they have no known competing financial interests or personal relationships which could have appeared to influence the work reported in this paper.

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Data availability statement

Data will be made available on request.

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