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Artificial Intelligence and Social Interaction: Evidence from Gift Money Expenditure

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Abstract: As artificial intelligence proliferates rapidly, understanding its impact on social interaction patterns becomes critical. Using national survey data and gift money expenditure as a proxy for social interaction, the study employs instrumental variable methods to identify the causal effect of AI use on individual social behavior. The study documents three key findings. First, AI use significantly reduces traditional social interaction through substitution effects, with instrumental variable estimates showing that OLS substantially underestimates the true magnitude, confirming the technology substitution hypothesis. Second, diminished social willingness serves as a key mediating mechanism—AI use reduces social behavior by weakening non-family social preferences, demonstrating how technology shapes behavior through preference channels. Third, the substitution effect exhibits significant demographic heterogeneity, with younger, more educated, and higher-income individuals displaying greater sensitivity to technology adoption, consistent with digital divide patterns. These findings provide micro-empirical evidence of social relationship transformation in the digital era. The results suggest policymakers should emphasize social inclusiveness in AI adoption while promoting balanced development between digital innovation and traditional social engagement.

Keywords: Artificial intelligence; Social interaction; Substitution effect; Gift money expenditure

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1. Introduction

In recent years, artificial intelligence has achieved national strategic importance in China through policies like the "Development Plan for New Generation Artificial Intelligence" and "Digital China" initiative, fundamentally altering traditional social interaction patterns.

Academic literature presents three AI conceptualizations: specialized discipline, intelligent automation process, and intelligent behavioral capability [1–3]. Despite definitional variations, scholars converge on AI's core ability to simulate human behavior and cognition [4]. International research demonstrates AI's potential to optimize industrial structure and enhance productivity, though employment effects show complexity with heterogeneous impacts across skill levels [5–9]. Chinese scholars argue AI promotes coordinated socioeconomic development by improving factor contributions and input-output efficiency, enhancing firm productivity, manufacturing innovation, and supply chain resilience at micro levels, while addressing demographic aging challenges at macro levels [10–15].

Social interaction encompasses interdependent communication activities through information exchange, influencing personal decisions [16]. Following Manski's framework, it comprises endogenous interaction, contextual interaction, and correlated effects [17]. Research shows social interaction significantly affects household financial decisions, asset allocation, and consumption choices, with online interaction effects consistently exceeding offline effects and narrowing urban-rural gaps [18–25].

However, research examining AI's impact on social interaction remains limited. While emotional AI enables humanized interaction, it may generate "pseudo-intimate relationships", disrupting traditional patterns. International scholars primarily examine social media's impact on face-to-face communication, while quantitative AI research remains scarce, particularly in China [26–27].

The study examines gift money exchanges as a social interaction proxy, investigating AI use's impact on traditional social interaction. The study pursues two objectives: identifying and quantifying AI's causal impact on individual social behavior, and understanding underlying mechanisms and demographic heterogeneity through mediation analysis. The contributions include pioneering AI examination from social interaction perspectives, employing instrumental variables to address endogeneity, and providing empirical evidence for digital transition policy implications. The paper proceeds as follows: Section 2 develops a theoretical framework and hypotheses; Section 3 introduces data and variables; Section 4 constructs econometric models; Section 5 reports empirical results and robustness tests; Section 6 concludes with policy implications.

2. Theoretical analysis and research hypotheses

2.1. Technology substitution effect

According to the technology substitution theory, artificial intelligence technology may reduce individuals' dependence on traditional social interaction by providing functionally similar but more efficient services [28–29]. Artificial intelligence systems' information retrieval, question-answering, and basic companionship functions may partially substitute for information exchange and emotional support functions in traditional face-to-face communication, thereby affecting individuals' social interaction [30–31]. Based on the technology substitution effect theory, this study proposes:

Hypothesis 1: Artificial intelligence use has a negative impact on individual social interaction behavior. Specifically, increases in daily artificial intelligence usage time significantly reduce individuals' gift money expenditure and gift frequency.

2.2. Social willingness changes

Based on social cognitive theory, long-term artificial intelligence usage experience may reshape individuals' social cognition and behavioral preferences [32]. The convenience and controllability of artificial intelligence interaction may reduce individuals' willingness to participate in traditional social activities, particularly more notably in non-kinship social networks [33–34]. Based on social willingness change mechanisms, this study proposes:

Hypothesis 2: Social willingness changes play a mediating role in the relationship between artificial intelligence use and social interaction. Artificial intelligence use reduces individuals' social interaction behavior by decreasing their social willingness.

2.3. Group heterogeneity effects

According to digital divide theory and technology acceptance models, different groups have significant differences in new technology acceptance and usage patterns [35]. Young groups, highly educated groups, and high-income groups typically have stronger technology adaptation capabilities and higher technology dependence, so artificial intelligence use's impact on their social interaction behavior may be more significant. Based on group heterogeneity theory, this study proposes:

Hypothesis 3: Artificial intelligence use's impact on social interaction exhibits heterogeneity across demographic groups. Young, highly educated, and high-income groups demonstrate more pronounced artificial intelligence effects.

3. Research design

3.1. Data sources and sample selection

This study employs primary data from a national questionnaire survey conducted May 18–31, 2025, targeting residents aged 18 and above. The structured instrument contains 68 questions measuring artificial intelligence usage, social interaction expenditure, social willingness, and demographic characteristics. Pre-survey validation confirmed instrument reliability and validity.

3.2. Variables

3.2.1. Dependent variables

Individual social interaction behavior serves as our core dependent variable. Following Sun and Lin's approach, we use gift money expenditure as a proxy for social interaction, with gift frequency for robustness testing [20]. In China's traditional cultural context, gift money expenditure represents an important manifestation of individuals participating in social networks and maintaining interpersonal relationships [20, 36]. Gift money expenditure and gift frequency derive from questionnaire questions 185 and 186, measuring respondents' frequency of giving gifts in the past year and reflecting social activity participation intensity.

3.2.2. Core explanatory variables

Artificial intelligence usage behavior serves as our core explanatory variable. Following established practices in digital technology adoption research, individual technology usage intensity through daily AI usage time is measured, capturing respondents' cumulative engagement with mainstream AI services, including intelligent voice assistants, navigation systems, recommendation algorithms, and chatbots [37–38]. Usage time is selected as our proxy for three reasons. First, time indicators intuitively reflect individuals' AI dependence and engagement depth, effectively measuring technology adoption intensity [39]. Second, continuous time variables facilitate precise econometric analysis compared to discrete frequency indicators. Third, this approach is widely applied in digital social science research with established comparability and reliability [40–41]. This specification enables accurate identification of AI technology's impact mechanisms on individual social behavior.

3.2.3. Control variables

Following existing research, the study controls for personal and household characteristics affecting individual social interaction [21, 36, 42]. Personal variables include actual age and its squared term (capturing nonlinear effects), gender, education years, marital status, and mobile payment dependence. Household variables include logarithmic total annual income, household size, number of AI-knowledgeable members, duration since first AI contact, and household head's employment status, derived from questionnaire items 1–10 and 104–120. This specification eliminates potential confounding influences, ensuring accurate identification of AI use's net effect on social behavior.

3.2.4. Mediating variables

To test internal mechanisms through which artificial intelligence use affects social interaction, the study specifies "changes in respondents' social willingness with family members and non-family members after using artificial intelligence" as mediating variables. Social willingness changes are measured using a continuous sliding scale from -100 to 100, where -100 indicates significantly weakened willingness, 0 indicates no change, and 100 indicates significantly enhanced willingness.

3.2.5. Instrumental variables

Considering potential endogeneity in artificial intelligence use, the study employs overall AI satisfaction as our instrumental variable. This choice satisfies standard instrument requirements: AI satisfaction directly influences usage intensity, primarily reflects objective technology evaluations rather than individual social preferences, and affects social behavior solely through usage patterns after controlling for other characteristics. This instrumental variable approach enables causal identification of AI use effects on social interaction. The variable measures respondents' overall AI technology evaluation on a 1–100 point scale. Main variable definitions, measurements, and descriptive statistics are shown in **Table 1**.

Table 1. Main variable definitions, measurements, and descriptive statistics

Variable type	Variable name	Variable definition and measurement	Mean	Std. dev.	Min	Max
Dependent Variables	Gift Expenditure (gift_expense)	Total gift expenditure in the past year (in 100 yuan)	105.40	173.43	0.00	1500.00
	Gift Count (gift_count)	Number of gifts given in the past year	6.02	9.14	0.00	83.00
Core Explanatory Variable	Daily AI Usage (ai_use)	Daily artificial intelligence usage time (minutes)	12.28	19.37	0.00	94.36
Mediating Variable	Social Willingness Change (social_change)	Change in social willingness with non-family members after using artificial intelligence	6.21	33.36	-100.00	100.00
Instrumental Variable	Overall Artificial Intelligence Satisfaction (ai_availability)	Overall evaluation of artificial intelligence technology	60.51	27.10	0.00	100.00
Household Control Variables	Log Household Income (log_income)	Natural logarithm of total household annual income	3.25	0.71	1.39	5.30
	Household Size (family_size)	Number of household members	3.62	1.09	1.00	7.00
	Household AI Penetration (family_ai_access)	Number of household members knowledgeable about artificial intelligence	2.61	1.25	0.00	9.00
	Artificial Intelligence Familiarity Duration (ai_access)	Time from first contact with artificial intelligence to survey (months)	19.04	11.08	0.00	30.00
	Household Head Employment (employ)	Current work status of household head (1=employed, 0=unemployed)	0.89	0.31	0.00	1.00
Personal Control Variables	Age (age)	Actual age at survey time (years)	31.29	12.06	16.00	63.00
	Age Squared (age_sq)	Squared term of age	1123.45	917.86	256.00	3969.00
	Gender (gender)	Respondent gender (1=male, 0=female)	0.51	0.50	0.00	1.00
	Education Level (education)	Respondent education stage	6.395	1.825	3.00	9.00
	Marital Status (marital_status)	Respondent marital status (1=unmarried, 2=married, 3=other)	1.384	0.563	1.00	4.00
	Mobile Payment Dependence (mobile_payment)	Dependence on mobile payment	3.734	1.524	1.00	5.00
Observations			177	177	177	177

3.3. Descriptive statistics

Table 1 presents descriptive statistics for key variables. Annual gift expenditure averages 10,540 yuan with a standard deviation of 17,343 yuan, while participants engage in approximately six gift exchanges per year. Daily artificial intelligence usage averages 12.28 minutes, with substantial individual variation reflected in the standard deviation of 19.37 minutes. The sample comprises predominantly young adults with a mean age of 31.29 years and a balanced gender distribution at 50.8 percent male. Educational attainment is high, averaging undergraduate level, with typical household sizes of three to four members. The social willingness change indicator averages 6.21, suggesting respondents perceive artificial intelligence use affects family social interaction. Overall, artificial intelligence satisfaction averages 60.51, indicating generally positive attitudes toward the technology.

4. Model specification

4.1. Benchmark regression model

To identify direct impact effects of artificial intelligence use on individual social interaction behavior, the study constructs the following benchmark regression model:

$$social\_interaction_i = \alpha_0 + \beta_1 ai\_use_i + \gamma controls_i + \varepsilon_i \quad (1)$$

4.2. Mediation effect model

To test Hypothesis 2 regarding the mediating mechanism of social willingness changes, the study adopts Jiang's two-step method for mechanism analysis [43]. Drawing on social cognitive theory and social network theory, the study first establishes the theoretical foundation: when individuals' social willingness decreases, their motivation to participate in traditional social activities weakens, thereby reducing gift expenditure. This theoretical logic is well-established in existing literature [44–47]. Social willingness's mediating role is tested through the following model:

$$social\_change_i = \alpha_1 + \delta\ ai\_use_i + \gamma_1 controls_i + \mu_i \quad (2)$$

Where $social\_change_i$ represents changes in individuals' social interaction willingness with non-family members after using artificial intelligence services, measured by questionnaire question 211. If δ is significantly negative, combined with the theoretical analysis, this validates social willingness changes' mediating role in artificial intelligence use's impact on social interaction.

4.3. Instrumental variable model

Artificial intelligence use may be endogenous due to three factors: omitted variable bias from unobservable characteristics such as technology preferences and social tendencies; reverse causality, where individuals with lower social needs may prefer artificial intelligence technology; and measurement error in self-reported usage time. To address these concerns, the study employs individuals' overall satisfaction with artificial intelligence technology as an instrumental variable.

First stage regression:

$$ai\_use_i = \delta_0 + \delta_1\ ai\_availability + \gamma_3 controls_i + \eta_i \quad (3)$$

Second stage regression:

$$social\ interaction_i = \alpha_3 + \beta_2\ \widehat{ai\_use}_{\boldsymbol{i}} + \rho social\_change_i + \gamma_4 controls_i + \zeta_i \quad (4)$$

Where $ai\_availability$ represents individuals' overall satisfaction with artificial intelligence technology, and $\widehat{ai\_use_i}$ represents the first-stage predicted value.

Overall, artificial intelligence satisfaction serves as the instrumental variable because it directly influences usage intensity while remaining independent of social behavior decisions and affects social expenditure solely through usage patterns, measured on a 1–100 point scale.

5. Empirical results and analysis

5.1. Regression results and analysis

Table 2 reports benchmark regression results examining daily artificial intelligence usage time's impact on social interaction. Models 1 and 3 include household and household head controls, while Models 2 and 4 add individual-level variables for robustness testing.

Daily artificial intelligence usage time exhibits significantly negative coefficients across all specifications, confirming the substitution effect on traditional social interaction. For gift expenditure, each one-minute increase in artificial intelligence usage reduces spending by 1.48 yuan in Model 1 and 1.46 yuan in Model 2, both significant at the 1% level. For gift frequency, the corresponding reductions are 0.062 and 0.054 gifts annually, significant at 1% and 5% levels, respectively. These consistent negative effects across both outcome measures strongly support Hypothesis 1 that artificial intelligence technology substitutes for traditional face-to-face social interaction.

Control variables yield expected results. Log household income positively affects both gift expenditure and frequency across all models, consistent with social activities as normal goods. Education level demonstrates positive significant effects in extended specifications, supporting higher social investment among educated groups [10]. Artificial intelligence familiarity duration shows positive effects in basic models but becomes insignificant when individual controls are added, suggesting this relationship operates through individual characteristics.

Model fit improves substantially with individual controls, with adjusted R^2 increasing from 0.173 to 0.205 for gift expenditure and from 0.156 to 0.172 for gift frequency, while core coefficient significance remains stable, confirming robustness of the substitution effect.

Table 2. Analysis of artificial intelligence use's impact on social interaction

	(1)	(2)	(3)	(4)	(5)	(6)
	Gift expenditure	**Gift expenditure**	**Gift count**	**Gift count**	**Social willingness**	**Social willingness**
Daily AI Usage	-1.480***	-1.455***	-0.062***	-0.054**	-0.294***	-0.318***
	(0.411)	(0.424)	(0.022)	(0.024)	(0.103)	(0.107)
Log Household Income	68.306***	62.671***	1.855**	1.661*	1.311	0.821
	(21.038)	(22.263)	(0.863)	(0.868)	(3.912)	(4.089)
Household Size	11.134	4.887	0.499	0.280	-1.789	-2.216
	(17.960)	(16.882)	(0.508)	(0.472)	(2.400)	(2.605)
Household AI Penetration	-0.317	6.679	-0.994	-0.769	0.801	1.044
	(11.259)	(10.825)	(0.632)	(0.473)	(2.389)	
Artificial Intelligence Familiarity Duration	4.835***	-0.415	0.151***	-0.018	0.716***	0.064
	(1.003)	(1.582)	(0.057)	(0.135)	(0.223)	(0.377)

Table 1 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	Gift expenditure	Gift expenditure	Gift count	Gift count	Social willingness	Social willingness
Household Head Employment	-55.512	-48.527	-0.371	-0.202	-4.140	-6.881
	(74.270)	(74.865)	(1.733)	(1.785)	(8.819)	(8.680)
Age		-2.896		-0.014		2.309
		(18.502)		(0.379)		(2.013)
Age (Squared)		0.005		-0.000		-0.034
		(0.212)		(0.005)		(0.027)
Gender		16.824		0.027		-6.818
		(19.318)		(1.218)		(4.965)
Education Level		37.002***		1.183**		1.369
		(12.230)		(0.586)		(2.566)
Marital Status		73.358		3.266		3.421
		(60.574)		(2.689)		(6.844)
Mobile Payment Dependence		1.799		0.215		3.368
		(8.286)		(0.774)		(2.595)
Constant	-176.987**	-329.213	-0.987	-9.290	0.014	-38.547
	(84.231)	(203.543)	(2.990)	(7.652)	(17.206)	(32.928)
Sample Size	177	177	177	177	177	177
Adjusted R^2	0.173	0.205	0.156	0.172	0.260	0.174

Note: Robust standard errors in parentheses. ***, **, * indicate significance at 1%, 5%, 10% levels respectively

5.2. Heterogeneity analysis

This study examines the differential effects of AI use on social interaction across demographic dimensions.

Age and Gender effects: Following the WHO classifications and approaches by Liu et al. and Lin et al., samples are divided into young (≤44 years) and middle-aged/elderly (≥45 years) groups [48–49]. Young individuals exhibit significant coefficients of -1.404, while middle-aged/elderly groups show insignificant effects (-0.752), reflecting higher digital acceptance and stronger substitution patterns among younger users who treat AI as behavioral replacements rather than supplements [35]. Gender analysis reveals universal substitution effects, with males (-1.498) and females (-1.282) both significant at the 10% level, though males demonstrate slightly stronger impacts.

Education and income heterogeneity. Following Sun et al., high education groups (bachelor's degree or above) show substantially larger coefficients (-2.279) compared to low education groups (-0.325), aligning with technology-skill complementarity theory where educated individuals more effectively utilize AI for social substitution [50–51]. Income analysis reveals threshold effects: high income groups demonstrate significant impacts (-1.123) while low income groups remain insignificant (-0.247), reflecting differential access to premium AI services and superior technological substitution capabilities [52].

Model performance: Adjusted R^2 varies substantially across groups, with middle-aged/elderly achieving the highest fit (0.535) due to stable behavioral patterns, while low income groups show the lowest explanatory power (0.150), indicating complex socioeconomic constraints beyond AI usage.

Table 3. Heterogeneity analysis of artificial intelligence use's impact on social interaction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Young	**Middle-aged/ elderly**	**Male**	**Female**	**Low education**	**High education**	**Low income**	**High income**
Daily AI Usage	-1.404***	-0.752	-1.282*	-1.498*	-0.325**	-2.279***	-0.247	-1.123**
	(0.489)	(1.022)	(0.647)	(0.816)	(0.149)	(0.758)	(0.480)	(0.487)
Constant	64.313	-472.384	-689.801***	69.142	-86.431	-1014.377*	-558.929*	-408.709
	(482.100)	(810.297)	(237.519)	(321.797)	(53.172)	(514.045)	(303.484)	(266.706)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample Size	143	34	90	87	63	114	67	110
Adjusted R^2	0.234	0.535	0.244	0.221	0.266	0.190	0.150	0.250

Note: Robust standard errors in parentheses. ***, **, * indicate significance at 1%, 5%, 10% levels respectively. "Yes" indicates inclusion of household and individual-level control variables

6. Conclusions and implications

6.1. Main research findings

Based on national survey data from 177 samples, this study employs instrumental variable methods to examine AI use impacts on traditional social interaction, validating three core hypotheses. First, AI use significantly reduces social interaction behavior, with each additional daily usage minute decreasing gift expenditure by 145.5 yuan in benchmark regression and 1,057.9 yuan under instrumental variable estimation, confirming technology substitution effects and Hypothesis 1. Second, social willingness serves as a crucial mediating mechanism, with AI use significantly reducing non-family social willingness through preference-shaping pathways, supporting Hypothesis 2. Third, substitution effects exhibit significant heterogeneity, with young, highly educated, and high-income groups demonstrating stronger technology sensitivity, validating digital divide theory manifestations and confirming Hypothesis 3.

6.2. Theoretical contributions and policy implications

This study enriches digital technology's social effects literature by identifying social willingness changes as a mediating mechanism, revealing preference-shaping processes in human-machine interaction. Findings provide new theoretical perspectives for understanding social relationship transformation and contribute to technology-society interaction research.

Policy implications emphasize social inclusiveness during AI adoption, particularly addressing substitution risks among young and high-skill groups. Educational guidance and institutional arrangements should promote balanced development between digital technology and traditional interaction. Social policy frameworks require updating to reflect technology-driven behavioral changes, while digital skill training for middle-aged, elderly, and low-income populations should be strengthened to narrow the digital divide.

6.3. Research limitations and future directions

Limitations include a small sample size (177 observations) constraining heterogeneity analysis, cross-sectional data preventing dynamic relationship examination, and gift expenditure as a limited social interaction proxy. Future research should employ large-scale longitudinal data to examine evolutionary trajectories, investigate differential effects across AI application types, and expand the scope to encompass broader social interaction forms for a complete understanding of digital-era social transformation.

This study provides micro-empirical evidence for AI-era social transformation, offering insights for addressing digital technology's challenges while promoting coordinated development between technological progress and social harmony.

Disclosure statement

The author declares no conflict of interest.

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