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Household Smartphone Use and Consumption: Evidence from the China Household Finance Survey

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Abstract: Smartphones allow households to search for products and complete payments on the same device. This study examines how household smartphone use relates to consumption when it is measured separately from the digital behaviors it enables. We analyze 28,325 households from the 2017 China Household Finance Survey. The preferred specification includes household demographic and economic controls, province fixed effects, and county-clustered standard errors. Household smartphone use is positively associated with household consumption, and the association remains robust across alternative specifications and a matched 2015–2017 sample. Smartphone use is also positively associated with mobile-payment adoption and gift expenditure, which remain positively associated with consumption when included jointly with smartphone use. These findings are consistent with both transaction and social-relation channels. The association is stronger among lower-income households but similar across urban and rural households. This study distinguishes household smartphone use from downstream payment and social behaviors, providing a clearer understanding of how household-level digital participation relates to consumption. The findings represent conditional associations rather than causal effects.

Keywords: Household Smartphone Use; Mobile Internet Access; Household Consumption; Mobile Payment; Gift Expenditure; China Household Finance Survey

1. Introduction

Smartphones have changed how households shop. Consumers can search for products, compare prices, read reviews, and complete payments on the same device [1,2]. Digital markets also help consumers search for products and assess their quality at lower cost, while making geographic distance less important [3]. Households that use smartphones may therefore find it easier to discover products and complete purchases.

However, households do not participate in digital markets to the same extent. Differences in Internet use remain even when devices and networks are widely available [4,5]. In China, households also differ in their use of smartphones and mobile-payment tools, and these differences are related to financial literacy, employment, and liquidity [6]. Understanding how digital participation relates to consumption therefore requires measures that reflect household behavior rather than only the digital environment in which households live.

Most existing studies do not isolate smartphone use at the household level. One stream uses regional digital-finance indexes or composite measures of local digital services [7–10]. These measures describe the digital environment in a region, but they do not show whether a particular household uses a smartphone. Another stream examines mobile-payment adoption and household spending [11–13]. These studies focus on a specific payment behavior and therefore do not separate smartphone use from the activities that it enables.

This study asks how household smartphone use is related to household consumption when it is measured separately from downstream digital behaviors. We treat household smartphone use as the focal variable and as a proxy for mobile Internet access. We then examine mobile-payment adoption and gift expenditure as two distinct downstream behaviors. This distinction allows us to separate basic digital participation from payment activity and social spending.

Two channels may connect smartphone use to consumption. First, smartphones can make transactions easier. Consumers can search, compare, and pay without changing devices or visiting a physical store. This may expand the range of products they consider and shorten the path from discovery to purchase [1,3,14,15]. Payment methods may also affect spending by changing how visible and immediate the outflow of money feels [16–19]. Experimental evidence shows that mobile-payment convenience can increase willingness to pay among existing users [20].

Second, smartphones can affect how households interact with family members, friends, and other social contacts. They make it easier to exchange information and maintain networks that provide informal support [21–23]. They also make peer consumption and social obligations more visible [24–29]. These interactions may encourage spending through reciprocal gift giving, social comparison, or reduced precautionary saving. We therefore examine whether mobile-payment adoption and gift expenditure show patterns consistent with transaction and social-relation channels.

We analyze 28,325 households from the 2017 China Household Finance Survey. The preferred specification includes province fixed effects and clusters standard errors by county. We test robustness using alternative measures, a per-capita outcome, and survey weights. We also use a matched 2015–2017 sample to examine whether earlier smartphone use is associated with later consumption. Additional models examine mobile-payment adoption, gift expenditure, urban–rural differences, income differences, and eight consumption categories.

The findings show that household smartphone use is positively associated with total household consumption. The association remains positive across the robustness checks and the matched analysis. Mobile-payment adoption and gift expenditure also remain positively associated with consumption when smartphone use is included. These findings are consistent with both proposed channels. The association is stronger among lower-income households but statistically similar across urban and rural households. It also varies across expenditure categories, with the largest positive coefficient for education, culture, and recreation.

This study makes several contributions. First, it examines reported smartphone use at the household level rather than relying only on regional digital-finance measures. Second, it distinguishes smartphone use from mobile-payment adoption and gift expenditure, providing evidence consistent with both transaction and social-relation channels. Third, it shows how the association varies across income groups and consumption categories. From a practical perspective, the findings suggest that broader digital participation should be accompanied by support for safe and effective use, especially among lower-income households.

2. Literature Review and Hypothesis Development

2.1 Household Smartphone Use and Household Consumption

Household consumption depends not only on available resources [30–32] but also on what households can find and how easily they can make a purchase [33,34]. Smartphones allow consumers to search for products, compare prices, read reviews, and complete payments on the same device [1,14,15,33]. Online platforms further expand the range of available products and reduce the cost of assessing product quality [3,34]. Smartphone use may therefore help households discover more products and purchase them with less effort.

Prior research in China generally finds a positive relationship between digital participation and household consumption [6–10,35]. Some studies use regional digital-finance indexes that combine payment, lending, insurance, and other services [7–10]. These indexes describe the digital services available in a region, but they do not show whether a particular household uses a digital device. Other studies focus on mobile or electronic payment and find that adopters tend to spend more [11–13]. These studies capture a specific payment behavior rather than smartphone use itself.

Household smartphone use provides a direct household-level measure. It records whether a household reports using a smartphone and serves as a proxy for mobile Internet access [36]. By lowering search and transaction costs and expanding access to products, smartphone use may be positively related to household consumption [1,14,33]. We therefore propose:

H1. Household smartphone use is positively associated with total household consumption.

2.2 Mobile Payment as a Transaction Channel

Payment methods can affect spending by changing how consumers experience the outflow of money. Consumers tend to spend less when payment feels immediate and tangible, but they may spend more when payment requires little effort and receives less attention [16–19]. Mobile payment reduces this effort because consumers can move directly from browsing to checkout on the same device. Experimental evidence shows that this convenience can increase willingness to pay among mobile-payment users [20].

Smartphones also provide access to mobile-payment tools. Households that use smartphones may therefore be more likely to adopt mobile payment. Once adopted, mobile payment may encourage consumption by reducing transaction costs and making payment less salient. Studies based on Chinese household data report a positive association between mobile or electronic payment and consumption, with payment convenience, liquidity, and mental accounting offered as possible explanations [11–13]. Evidence from mobile-money systems also shows that lower transfer costs can support consumption and risk sharing [37–39]. We therefore propose:

H2. Household smartphone use is positively associated with mobile-payment adoption, and mobile-payment adoption is positively associated with household consumption conditional on smartphone use.

2.3 Gift Expenditure and the Social-Relation Channel

Households make consumption decisions within networks of family members, friends, and other social contacts [21–23,40]. These networks may reduce the need for precautionary saving by providing informal support during difficult periods [21–23]. They may also influence spending through social comparison, shared consumption norms, and reciprocal obligations [24–29].

Smartphones can strengthen these influences by making communication easier and social activities more visible. Households can exchange information, coordinate support, and learn about the consumption and social events of others more quickly. Smartphone use may therefore increase both the support available through social networks and the pressure to meet social obligations.

Gift expenditure reflects one form of social engagement. In China, households give cash and non-cash gifts during holidays and ceremonial events to maintain relationships and return past favors [27,28]. Smartphone users may be more aware of these occasions and maintain more frequent contact with members of their networks. Gift expenditure may also be positively related to broader consumption because social ties provide support, transmit consumption information, and create reciprocal obligations. We therefore propose:

H3. Household smartphone use is positively associated with gift expenditure outside the household, and gift expenditure is positively associated with household consumption conditional on smartphone use.

Figure 1 summarizes the three hypothesized associations.

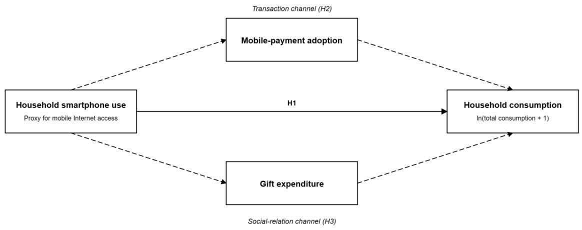

Figure 1. Conceptual Framework and Hypothesized Associations

3. Materials and Methods

3.1 Data and Analytic Samples

We use data from the China Household Finance Survey (CHFS), administered by the Survey and Research Center for China Household Finance at Southwestern University of Finance and Economics [41]. The survey collects information on household demographics, finances, consumption, payment behavior, and technology use. The 2017 wave covers 40,011 households in 29 provincial-level administrative units.

We construct the baseline sample in four steps. First, we restrict the sample to households whose heads are aged 20–65, leaving 29,057 households. Second, we require valid data on household smartphone use and total consumption, leaving 29,048 households. Third, we require complete data on the demographic controls, leaving 28,926 households. Finally, we require complete data on the economic controls, including net assets, which yields 28,325 households across 356 counties.

We use this fixed sample for the descriptive statistics and all nested baseline models. Changes across these models therefore reflect the addition of controls rather than changes in the sample. The results apply to households whose heads are aged 20–65.

For the matched analysis, we link households observed in both 2015 and 2017 using CHFS identifiers. Of the 26,824 linked households, 18,741 have a household head aged 20–65 in 2017, valid smartphone-use and consumption measures in both waves, and the full set of 2017 controls used in the matched models. These households are located in 355 counties.

3.2 Measures

Household consumption. The main outcome is ln(total household consumption + 1) in 2017. The official CHFS aggregate covers eight categories: food; clothing; housing; household equipment and services; transport and communication; education, culture, and recreation; health care; and other consumption. Gift transfers are excluded from this aggregate and analyzed separately. For the robustness analysis, we use ln(household consumption per capita + 1). In the category analysis, each expenditure category is transformed as ln(x + 1), which retains households that report zero expenditure.

Household smartphone use. The focal variable equals one when a household reports using a smartphone and zero when it reports using a phone without smartphone functions or having no phone. Following prior research [36], we use this measure as a proxy for mobile Internet access. It captures reported device use but not the quality or intensity of Internet use. We use household smartphone count as an alternative measure. In the matched analysis, Model (1) uses smartphone use measured in 2017, while Models (2) and (3) use smartphone use measured in 2015.

Control variables. The demographic controls cover characteristics of the household head and the household structure. They include age, age squared, gender, years of education, marital status, Communist Party membership, self-reported good health, household size, child share, older-adult share, and employment in an enterprise or public institution. We include missing-response indicators for Communist Party membership and employment.

The economic controls include rural residence, household business operation, credit-card use, total household income, household debt, and net assets. Income and debt are transformed as ln(x + 1). Net assets use the inverse hyperbolic sine transformation to retain zero and negative values.

Channel and grouping variables. Mobile-payment adoption equals one when a household reports paying through a mobile terminal, such as a phone or tablet. Gift expenditure includes cash and non-cash gifts given to people outside the household during holidays and ceremonial events. We transform gift expenditure as ln(x + 1). The gift-expenditure analysis includes 21,113 households with valid gift data.

For the income heterogeneity analysis, we divide households at the baseline-sample median annual income of CNY 63,100. Households above the median form the higher-income group.

3.3 Empirical Strategy

We first estimate the association between household smartphone use and household consumption:

$$ln(Consumption_i + 1) = \beta_0 + \beta_1 Smartphone_i + \gamma X_i + \delta_p + \varepsilon_i \quad (1)$$

In Equation (1), i indexes households and p indexes provinces. $Smartphone_i$ indicates household smartphone use, X_i contains the control variables described in Section 3.2, and δ_p denotes province fixed effects. The coefficient β_1 captures the conditional association between smartphone use and household consumption.

We estimate four nested models using the same 28,325 households. Model 1 includes only household smartphone use. Model 2 adds the demographic controls. Model 3 adds the economic controls and missing-response indicators. Model 4 adds province fixed effects and serves as the preferred specification. Standard errors are clustered by county.

We assess robustness in three ways. We replace the binary smartphone-use measure with household smartphone count, replace total consumption with per-capita consumption, and apply the CHFS household sampling weight to the preferred specification.

We then use the matched 2015–2017 sample to examine temporal ordering. The most complete specification is:

$$\ln\left(Consumption_{i,}{}^{2017}+1\right) = \beta_0+\beta_1 Smartphone_{i,2015} +\beta^2 \ln\left(Consumption_{i,}{}^{2015}+1\right) +\gamma X_{i,2017}+\delta_p+\varepsilon_i \quad (2)$$

All matched models use the same 18,741

households, the full set of 2017 controls, and province fixed effects. Model 1 uses smartphone use measured in 2017. Model 2 replaces it with smartphone use measured in 2015. Model 3 further controls for household consumption in 2015, as shown in Equation (2). Standard errors are clustered by county.

To examine the transaction channel, we first estimate a logit model of mobile-payment adoption on household smartphone use. We report the average discrete change in the predicted probability of adoption when smartphone use changes from zero to one. We then estimate an OLS consumption model that includes smartphone use and mobile-payment adoption jointly.

We use a parallel approach for the social-relation channel. The first model estimates the association between smartphone use and gift expenditure. The second includes smartphone use and gift expenditure jointly in the consumption model.

We test heterogeneity with pooled interaction models. One model interacts smartphone use with rural residence, and the other interacts smartphone use with the higher-income indicator. We report the smartphone-use association within each group and use the interaction p value to test whether the group estimates differ.

Finally, we estimate separate OLS models for the eight consumption categories. Each model follows the preferred baseline specification. We report Holm-adjusted p values for the eight tests and the share of households reporting zero expenditure in each category.

Unless otherwise stated, the additional models include the full controls and province fixed effects, with standard errors clustered by county. Because the study uses observational data, we interpret the estimates as conditional associations. The matched analysis improves temporal ordering, while the channel models test whether the results follow the patterns predicted by H2 and H3.

As a supplementary diagnostic, we use the leave-one-out county smartphone-use rate as an instrument for household smartphone use. The instrument is calculated from all other valid households in the same county. Both stages use the baseline sample and full controls, include province fixed effects, and cluster standard errors by county. Because the instrument may also reflect local conditions related to consumption, we report the IV results only as a supplementary analysis.

4. Results

4.1 Descriptive Statistics and Baseline Association

Table 1 presents descriptive statistics for the analytical sample of 28,325 households. Smartphone use is reported by 74.8% of households, and 30.9% live in rural areas. Mean log household consumption is 10.808. All variables listed in Table 1 are observed for all 28,325 households, so the nested baseline models use the same sample.

Table 2 reports the baseline estimates. The coefficient for household smartphone use declines from 0.688 in Column (1) to 0.238 in the preferred specification as household controls and province fixed effects are added. It remains significant at the 1% level in all four models. Because the outcome is ln(total household consumption + 1), the preferred coefficient corresponds to an approximate 26.9% conditional difference on the original consumption-plus-one scale. We retain the log-scale coefficient as the primary estimate. These estimates are consistent with H1.

Table 1. Descriptive Statistics for the Analytical Sample

Variable	N	Mean	SD	Minimum	Maximum
Log total household consumption	28,325	10.808	0.831	7.151	15.049
Household smartphone use	28,325	0.748	0.434	0.000	1.000
Age of household head	28,325	49.720	10.308	20.000	65.000
Age squared / 100	28,325	25.783	9.778	4.000	42.250
Male household head	28,325	0.813	0.390	0.000	1.000
Years of education	28,325	10.014	3.914	0.000	22.000
Married	28,325	0.883	0.321	0.000	1.000
Communist Party member	28,325	0.101	0.301	0.000	1.000
Good self-reported health	28,325	0.522	0.500	0.000	1.000
Household size	28,325	3.404	1.499	1.000	15.000
Share of children	28,325	0.118	0.164	0.000	0.800

Share of older adults	28,325	0.068	0.164	0.000	1.000
Enterprise/public-institution employment	28,325	0.165	0.371	0.000	1.000
Rural residence	28,325	0.309	0.462	0.000	1.000
Household operates a business	28,325	0.176	0.381	0.000	1.000
Credit card use	28,325	0.247	0.431	0.000	1.000
Log total household income	28,325	10.809	1.585	0.000	15.955
Log household debt	28,325	4.288	5.425	0.000	16.823
Household net assets (IHS)	28,325	12.617	4.905	-16.109	18.472

Notes: N = 28,325. Variable definitions and transformations are provided in Section 3.2.

Table 2. Baseline Estimates of Household Smartphone Use and Household Consumption

Variable	(1)	(2)	(3)	(4) Preferred
Household smartphone use	0.688***	0.442***	0.257***	0.238***
	(0.020)	(0.015)	(0.013)	(0.012)
Basic demographic controls	No	Yes	Yes	Yes
Six household economic controls	No	No	Yes	Yes
Missing-response indicators	No	No	Yes	Yes
Province fixed effects	No	No	No	Yes
Observations	28,325	28,325	28,325	28,325
R-squared	0.129	0.265	0.409	0.436
County clusters	356	356	356	356

Notes: OLS estimates. The dependent variable is ln(total household consumption + 1). County-clustered standard errors are in parentheses. Full estimates are reported in Table 3. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 3. Full Coefficient Estimates for the Baseline Specifications

Variable	(1)	(2)	(3)	(4) Preferred
Household smartphone use	0.688*** (0.020)	0.442*** (0.015)	0.257*** (0.013)	0.238*** (0.012)
Age of household head	—	-0.033*** (0.004)	-0.018*** (0.004)	-0.012*** (0.004)
Age squared / 100	—	0.029*** (0.005)	0.013*** (0.004)	0.007* (0.004)
Male household head	—	-0.142*** (0.015)	-0.049*** (0.013)	-0.041*** (0.011)
Years of education	—	0.058*** (0.003)	0.023*** (0.002)	0.024*** (0.002)
Married	—	0.209*** (0.017)	0.131*** (0.015)	0.137*** (0.014)
Communist Party member	—	0.066***(0.016)	0.045***(0.015)	0.050***(0.014)
Good self-reported health	—	0.088*** (0.012)	0.022** (0.010)	0.012 (0.009)
Household size	—	0.116*** (0.005)	0.084*** (0.005)	0.089*** (0.004)
Share of children	—	-0.068* (0.038)	-0.034 (0.033)	-0.020 (0.031)
Share of older adults	—	-0.026 (0.027)	-0.013 (0.024)	-0.010 (0.023)
Enterprise/public-institution employment	—	0.081*** (0.014)	0.054*** (0.013)	0.054*** (0.011)
Rural residence	—	—	-0.251*** (0.016)	-0.237*** (0.014)
Household operates a business	—	—	0.218*** (0.013)	0.223*** (0.012)
Credit card use	—	—	0.272*** (0.012)	0.247*** (0.011)
Log total household income	—	—	0.138*** (0.005)	0.125*** (0.005)
Log household debt	—	—	0.011*** (0.001)	0.012*** (0.001)
Household net assets (IHS)	—	—	0.010***(0.001)	0.008***(0.001)
Missing Party-membership response	—	—	0.034** (0.013)	0.030** (0.012)
Missing employment response	—	—	0.166*** (0.013)	0.149*** (0.012)
Constant	10.293*** (0.017)	10.256*** (0.103)	8.850*** (0.123)	9.133*** (0.127)
Province fixed effects	No	No	No	Yes
Observations	28,325	28,325	28,325	28,325
R-squared	0.129	0.265	0.409	0.436
County clusters	356	356	356	356

Notes: OLS estimates. The dependent variable is ln(total household consumption + 1). County-clustered standard errors are in parentheses. An em dash indicates that the variable is not included. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

4.2 Robustness and Temporal Ordering

Table 4 reports the robustness checks. In the sample of 28,241 households with valid smartphone-count data, the coefficient for the binary smartphone-use measure remains positive at 0.236, while each additional household smartphone is associated with a 0.130-unit difference in ln(total household consumption + 1). The coefficient also remains positive when per-capita consumption is used as the outcome (coefficient = 0.232) and when the CHFS household weights are applied (coefficient = 0.252). All estimates are significant at the 1% level. The positive association is stable across these alternative specifications.

Table 5 presents the matched-wave analysis. The contemporaneous estimate in the matched sample is 0.237, which is close to the preferred baseline estimate. Household smartphone use measured in 2015 is positively associated with consumption in 2017 (coefficient = 0.167, $p < 0.001$). After household consumption in 2015 is added, the coefficient for 2015 household smartphone use decreases to 0.087 but remains significant ($p < 0.001$).

The lower coefficient after adjustment for 2015 consumption is consistent with part of the contemporaneous association reflecting persistent household differences. The lagged specification improves temporal ordering relative to the cross-sectional model.

Table 4. Robustness Checks

Variable	(1) Baseline	(2) Common sample	(3) Smartphone count	(4) Per capita	(5) Weighted
Household smartphone use (2017)	0.238***	0.236***	—	0.232***	0.252***
	(0.012)	(0.012)	—	(0.012)	(0.017)
Household smartphone count	—	—	0.130***	—	—
	—	—	(0.004)	—	—
Outcome	Total	Total	Total	Per capita	Total
Full controls	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes
Survey weights	No	No	No	No	Yes
Observations	28,325	28,241	28,241	28,325	28,325
R-squared	0.436	0.436	0.451	0.482	0.420
County clusters	356	356	356	356	356

Notes: OLS estimates. Outcomes are transformed as ln(x + 1). County-clustered standard errors are in parentheses. An em dash indicates that an entry is not included or not applicable. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 5. Temporal-Ordering Checks Using the Matched 2015–2017 Sample

Variable	(1) Current use	(2) Lagged use	(3) Lagged + baseline
Household smartphone use (2017)	0.237*** (0.014)	—	—
Household smartphone use (2015)	—	0.167*** (0.012)	0.087*** (0.011)
Log household consumption in 2015	—	—	0.250*** (0.008)
Full 2017 controls	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Observations	18,741	18,741	18,741
R-squared	0.431	0.426	0.470
County clusters	355	355	355

Notes: The dependent variable is ln(total household consumption in 2017 + 1). All models use the matched sample and do not include household fixed effects. County-clustered standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

4.3 Transaction and Social-Relation Channels

Table 6 reports the results for the two proposed channels. For the transaction channel, household smartphone use is associated with a 20.5-percentage-point higher predicted probability of mobile-payment adoption (average discrete change = 0.205, $p < 0.001$). When household smartphone use and mobile-payment adoption are included jointly in the consumption model, mobile-payment adoption remains positively associated with consumption (coefficient = 0.207, $p < 0.001$), while the coefficient for household smartphone use remains positive at 0.209 ($p < 0.001$). These findings are consistent with H2.

For the social-relation channel, household smartphone use is positively associated with ln(gift expenditure + 1) (coefficient = 0.214, $p < 0.001$). In the joint consumption model, ln(gift expenditure + 1) remains positively associated with consumption (coefficient = 0.086, $p < 0.001$), while the coefficient for household smartphone use remains positive at 0.200 ($p < 0.001$). These findings are consistent with H3.

Overall, the estimates are consistent with both proposed channels. Because the channel variables and consumption are measured contemporaneously, the evidence remains correlational.

Table 6. Mobile Payment and Gift Expenditure: Channel-Consistent Associations

Panel A. Mobile-payment channel			
Variable	(1)	(2)	(3)
Dependent variable	Mobile-payment adoption	Log consumption	Log consumption
Household smartphone use	0.205*** (0.008)	0.238*** (0.012)	0.209*** (0.011)
Mobile-payment adoption	—	—	0.207***(0.010)
Observations	28,325	28,325	28,325
Panel B. Gift-expenditure channel			
Variable	(1)	(2)	(3)
Dependent variable	Log gift expenditure	Log consumption	Log consumption
Household smartphone use	0.214*** (0.028)	0.218*** (0.013)	0.200*** (0.012)
Log gift expenditure	—	—	0.086*** (0.005)
Observations	21,113	21,113	21,113

Notes: Panel A, Column (1) reports the average discrete change from a logit model; all other estimates are OLS coefficients. All models include full controls and province fixed effects. County-clustered standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

4.4 Urban-Rural and Income Heterogeneity

Table 7 reports the interaction-based heterogen-ity tests. The estimated smartphone-use association is 0.240 for urban households and 0.236 for rural households. The rural-minus-urban difference is -0.004 and is not statistically significant ($p = 0.840$). The association is therefore statistically similar across urban and rural households.

The estimated association is 0.243 for lower-income households and 0.194 for higher-income households. The higher-minus-lower-income difference is -0.049 ($p = 0.026$), indicating that the association is significantly stronger among lower-income households.

Table 7. Interaction-Based Heterogeneity Tests

Statistic	Residence heterogeneity	Income heterogeneity
Reference group	Urban	Lower income
Comparison group	Rural	Higher income
Reference-group association	0.240*** (0.015)	0.243*** (0.013)
Comparison-group association	0.236*** (0.016)	0.194*** (0.019)
Difference (comparison - reference)	-0.004 (0.021)	-0.049** (0.022)
p value for difference	0.840	0.026

Notes: Estimates are linear combinations from pooled OLS interaction models with full controls and province fixed effects. Higher-income households have annual household income above CNY 63,100. County-clustered standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

4.5 Consumption Categories

Table 8 reports the category-specific estimates. Household smartphone use has the largest positive coefficient for education, culture, and recreation (coefficient = 1.003), followed by clothing (coefficient = 0.931). The coefficients for food, housing, household equipment and services, and transport and communication are also positive and remain significant after Holm adjustment (adjusted $p < 0.001$).

The coefficient for health care is negative (coefficient = -0.120) and remains significant after Holm adjustment (adjusted $p = 0.048$). The coefficient for other consumption is small and does not reach the 5% significance level (coefficient = 0.050, adjusted p = 0.082).

Because the categories differ substantially in their distributions and shares of zero expenditure, these coefficients should be interpreted as descriptive associations rather than directly comparable percentage or welfare effects. Figure 2 summarizes the subgroup and category-specific estimates with 95% confidence intervals.

Table 8. Household Smartphone Use and Consumption by Expenditure Category

Expenditure category	Coefficient (SE)	Raw p value	Holm-adjusted p value	Zero share
Food	0.243 (0.011)	<0.001	<0.001	0.0%
Clothing	0.931 (0.040)	<0.001	<0.001	8.1%
Housing	0.319 (0.021)	<0.001	<0.001	0.7%
Household equipment and services	0.504 (0.025)	<0.001	<0.001	1.2%
Transport and communication	0.514 (0.019)	<0.001	<0.001	0.3%
Education, culture, and recreation	1.003 (0.065)	<0.001	<0.001	35.9%
Health care	-0.120 (0.053)	0.024	0.048	17.3%
Other consumption	0.050 (0.029)	0.082	0.082	92.7%

Notes: Each row reports a separate OLS model with ln(category expenditure + 1) as the outcome. All models include full controls and province fixed effects. County-clustered standard errors are in parentheses. Holm-adjusted p values account for the eight category tests.

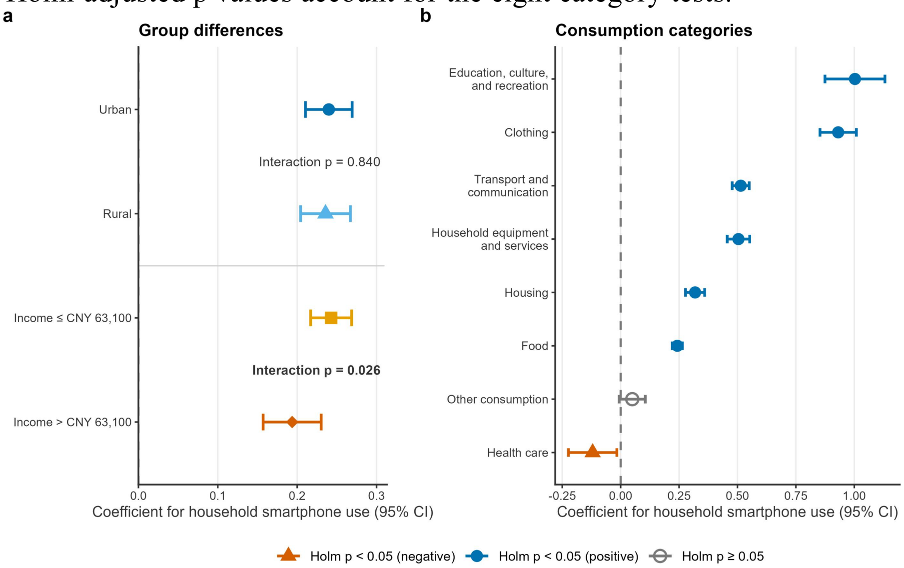

Figure 2. Household Smartphone Use, Group Differences, and Consumption Categories. Points Show Coefficients with 95% Confidence Intervals: Panel (a) Presents Group-Specific Estimates from Pooled Interaction Models, and Panel (b) Presents Category-Specific Estimates.

4.6 Supplementary Instrumental-Variable Diagnostic

The leave-one-out county smartphone-use rate strongly predicts household smartphone use. The first-stage coefficient is 0.291, and the excluded-instrument F statistic is 156.31. The corresponding two-stage least-squares coefficient is 2.614, substantially larger than the preferred OLS estimate of 0.238. Table 9 reports the full IV results.

Although the instrument has a strong first stage, it may also capture county-level economic conditions or digital infrastructure related to household consumption. We therefore treat the IV estimate as a supplementary diagnostic and base the main conclusions on the associational models.

Table 9. Instrumental-Variable Diagnostics and Two-Stage Least-Squares Estimates

Variable	(1) First stage	(2) Preferred OLS	(3) 2SLS
Dependent variable	Household smartphone use	Log consumption	Log consumption
Leave-one-out county smartphone-use rate	0.291*** (0.023)	—	—
Household smartphone use	—	0.238*** (0.012)	2.614*** (0.261)

Full controls	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Observations	28,325	28,325	28,325
First-stage F statistic	156.31	—	—
Endogeneity-test F statistic	—	—	217.26
County clusters	356	356	356

Notes: The excluded instrument is the leave-one-out county smartphone-use rate. All models include full controls and province fixed effects. County-clustered standard errors are in parentheses. The model is exactly identified, so no overidentification test is reported. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

5. Discussion

5.1 Main Findings and Relation to Prior Research

This study finds that household smartphone use is positively associated with household consumption. The association remains stable across alternative measures, outcomes, survey weights, and the matched 2015–2017 sample. After baseline consumption is controlled, the coefficient for lagged smartphone use becomes smaller but remains positive. This pattern suggests that persistent household differences explain part of the contemporaneous association.

These findings complement prior research on digital finance and mobile payment. Existing studies often use regional digital-finance indexes to capture the digital environment [7–10] or focus on households that have already adopted mobile payment [11–13]. In contrast, we examine reported smartphone use at the household level as a proxy for mobile Internet access and measure mobile-payment adoption separately. This distinction separates a basic form of digital participation from one specific transaction behavior.

The results are also consistent with the proposed transaction and social-relation channels. Smartphone use is positively associated with mobile-payment adoption, which remains positively associated with consumption when smartphone use is included. Smartphone use is also positively associated with gift expenditure, and gift expenditure remains positively associated with consumption. These findings suggest that smartphone use may relate to consumption through both easier transactions and stronger social interactions. Because the channel variables are measured contemporaneously with consumption, however, the results do not establish causal mediation.

5.2 Heterogeneity and Consumption Categories

The association between smartphone use and consumption is statistically similar across urban and rural households. This finding suggests that the relevance of smartphone use is not limited to rural households or explained only by the conventional urban–rural digital divide. Nevertheless, a binary measure of smartphone use cannot capture differences in connection quality, affordability, digital skills, or specific online activities within urban and rural areas.

The association is stronger among lower-income households. This finding is consistent with prior research showing that digital finance and mobile payment may matter more when households face tighter resource constraints [7,12,42,43]. Lower search and payment costs may be particularly valuable when budgets restrict household choices [7,12]. At the same time, a stronger consumption association does not necessarily imply a larger welfare gain [44–46]. Lower-income households may also be more vulnerable to fraud, costly digital credit, and impulsive spending [42,47–50].

The category results show that the association is concentrated in particular types of expenditure. Education, culture, and recreation has the largest positive coefficient, followed by clothing. These categories may benefit more from wider product variety, easier information search, and access to online services [33,34,51]. The negative association with health care should be interpreted cautiously because it does not show that smartphone use improves health or reduces medical needs. More generally, the expenditure categories differ in their distributions and shares of zero values. The category estimates should therefore be treated as descriptive associations rather than directly comparable effect sizes or welfare effects.

5.3 Theoretical and Practical Implications

The main theoretical implication is that different stages of digital participation should be examined separately. Regional digital-finance indexes describe the local digital environment. Household smartphone use captures reported device use and serves as a proxy for mobile Internet access. Mobile-payment adoption represents a specific transaction behavior, while gift expenditure reflects one form of social spending. Separating these measures clarifies what each estimate represents and shows how digital access may be related to consumption beyond the adoption of a particular payment tool.

The findings also suggest that smartphone use may relate to household consumption through both market and social processes. Existing research often emphasizes lower search and payment costs. Our results indicate that social communication and obligations may also be relevant. The income and category differences further show that the association is not uniform across households or expenditure types.

From a practical perspective, expanding smartphone and mobile Internet access should be accompanied by support for safe and effective use. Public agencies can combine affordable access with training in digital skills, payment security, and fraud prevention. Platforms and payment providers can offer clear fees, transparent transaction records, and accessible dispute resolution. These safeguards may be especially important for lower-income households. The similar urban and rural estimates also suggest that policies should address affordability and digital capability in both settings rather than focusing only on rural access.

5.4 Limitations and Future Research

We acknowledge several limitations of this study. First, the main analysis relies on cross-sectional data. Although the matched 2015–2017 analysis improves temporal ordering, it cannot eliminate unobserved household differences or establish causality. Future research could use longer household panels or exogenous changes in mobile Internet access to strengthen causal identification.

Second, household smartphone use is only a proxy for mobile Internet access. It does not capture connection quality, usage intensity, digital skills, or specific online activities. More detailed measures would help identify which aspects of smartphone use are most closely related to household consumption.

Third, mobile-payment adoption and gift expenditure are measured contemporaneously with consumption. The results are therefore consistent with the proposed transaction and social-relation channels but do not establish causal mediation. Future studies could use transaction records, network measures, or experimental designs to test these processes more directly.

6. Conclusions

Using data from 28,325 households in the 2017 China Household Finance Survey, this study examines the association between household smartphone use and household consumption. Household smartphone use, measured as a proxy for mobile Internet access, is positively associated with total consumption. This association remains stable across alternative measures, outcomes, survey weights, and the matched 2015–2017 analysis. It is stronger among lower-income households but does not differ significantly between urban and rural households.

The study also distinguishes household smartphone use from mobile-payment adoption and gift expenditure. The results are consistent with both the transaction and social-relation channels: smartphone use is positively associated with these two downstream behaviors, which are in turn positively associated with household consumption. The category analysis further shows that the association varies across expenditure types and is strongest for education, culture, and recreation and for clothing.

Overall, the findings highlight the importance of separating basic digital access from the specific behaviors enabled by that access. Because the evidence remains associational, future research should use stronger causal designs and more detailed measures of mobile Internet use.

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