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The Impact of Digitalization on Household Carbon Emissions: Evidence from the CFPS Database

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Abstract. With global climate change and the pursuit of "dual carbon" goals, households have drawn growing attention as key contributors to energy use and carbon emissions. The spread of digital technologies is reshaping daily life and energy consumption patterns, yet how digitalization affects household carbon emissions remains poorly understood. To address this gap, we combine macroeconomic indicators of the digital economy with micro-level household panel data and estimate a model with two-way fixed effects, examining the effect of digitalization on per capita household carbon emissions and their composition. Our findings show that digitalization significantly reduces total per capita household emissions, but it also produces a clear "differentiation effect" on the emission structure: direct emissions from fossil fuels fall noticeably, while indirect emissions embedded in electricity use and the consumption of goods and services rise. Heterogeneity analysis indicates that the emission reduction benefits are stronger in urban areas and among better-educated households, pointing to a possible inequality in carbon reduction capacity arising from the digital divide in the green transition. This paper provides micro-level evidence on the environmental consequences of the digital economy and offers theoretical support for aligning digitalization with low-carbon development and for designing differentiated emission reduction policies.

Keywords: Digitalization, Household Carbon Emissions, Direct Emissions, Indirect Emissions, Heterogeneity

1. Introduction

Global climate change remains a serious issue. As the room for further emission reductions in the industrial sector shrinks, policymakers have turned more attention to households. With the gradual narrowing of emission reduction space in the industrial sector, household consumption, as an important source of carbon emissions, has become a key focus of low-carbon development work. In China, household consumption-related carbon emissions account for 42% to 49% of the total carbon emissions, and this proportion is still expanding with the advancement of urbanization. Therefore, exploring what drives household carbon emissions and seeking effective micro-level emission reduction paths are important prerequisites for achieving comprehensive green development.

Digital technologies such as big data, artificial intelligence, and the Internet of Things are increasingly permeating all aspects of household life, and their impact on household carbon emissions is complex and multi-dimensional. On the one hand, digitalization can improve household energy use efficiency through intelligent energy management, and replace offline travel and consumption with online forms, thus exerting a "technological emission reduction effect"; on the other hand, the continuous growth of electricity consumption of digital terminal equipment, the logistics carbon emissions brought by the boom of online shopping, and the "rebound effect" of household consumption triggered by income growth may all expand the household carbon footprint. This complex interactive relationship means that the impact of digitalization on household carbon emissions cannot be simply judged, and it is necessary to conduct an in-depth empirical analysis of its causal mechanism and actual effect.

Existing research on the relationship between digitalization and carbon emissions is mostly based on macro-level accounting and analysis, and there are two obvious research gaps. First, there is a lack of quantitative research on how macro-level digital economy development is transmitted to the micro level and affects household carbon emission behavior, and the micro-mechanism of digitalization's carbon emission effect is not clear. Second, existing studies have not paid sufficient attention to the structural differences between direct energy emissions and indirect emissions embedded in goods and services consumption in the process of digitalization affecting household carbon emissions, and it is difficult to accurately grasp the structural changes of household carbon emissions under the digital background. In view of this, this paper combines macro digital economy indicators with micro household panel data, constructs a rigorous empirical analysis framework, and systematically examines the impact of digitalization on household carbon emissions and its internal transmission mechanism, in order to make up for the deficiencies of existing research.

2. Literature review

Researchers both domestically and internationally have carried out in-depth research on the influencing factors of household carbon emissions, and identified a variety of key determinants covering demographic characteristics, socioeconomic status and regional development factors. First, income level is the most fundamental driving factor of household carbon emissions, and its relationship with carbon emissions generally conforms to the Environmental Kuznets Curve (EKC) hypothesis. Li et al. pointed out that with the increase of per capita income, household consumption shifts from survival-oriented basic consumption to enjoyment-oriented high-carbon consumption, which significantly pushes up the household carbon footprint [1]. Second, household scale and age structure have complex non-linear effects on carbon emissions. Büchs & Schnepf[2] found that larger household scale can form the "economies of scale" of shared energy use, thus reducing per capita carbon emissions [2]; while Liu & Wang argued that population aging will increase the demand for medical and heating energy, thus changing the evolution trend of household carbon emissions. Third, the urban-rural dual structure is a key determinant of household carbon emissions in emerging economies [3]. Wiedenhofer et al. pointed out that urbanization reshapes residents' consumption patterns in essence, and urban households have significantly higher indirect carbon emissions embedded in service consumption than rural households [4]. Fourth, human capital represented by education level acts as an important regulatory variable of household carbon emissions. Zhuang et al. found that higher education level is associated with stronger environmental protection awareness, which helps households to better adopt energy-saving technologies and low-carbon consumption behaviors [5]. In addition, regional factors such as industrial structure and regional economic development level will also affect household carbon emission intensity through the energy supply structure and consumption environment [6,7]. Clarifying the above influencing

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factors is the basis for effectively isolating the net effect of digitalization on household carbon emissions in the empirical model.

3. Measurement methods and structural analysis of household carbon emissions

3.1. Construction of a comprehensive measurement system

To systematically assess the full-caliber carbon emissions of the household sector, this study integrates micro-level household survey data with macro-level environmental-economic parameters to construct a comprehensive measurement system covering both direct and indirect emissions. The research is based on the China Family Panel Studies (CFPS) database, which provides data on household monthly energy expenditures and detailed consumption expenditures, laying a solid foundation for accurately quantifying household carbon footprints at the micro level. The measurement methods primarily integrate the emission factor method recommended by the Intergovernmental Panel on Climate Change (IPCC) and Input-Output Analysis (IOA). The former is used to calculate carbon emissions from direct household energy consumption, while the latter is used to capture indirect carbon emissions arising from the consumption of goods and services.

3.2. Measurement of direct energy consumption carbon emissions

Direct carbon emissions originate from households' final consumption of electricity and fossil fuels (such as coal, natural gas, liquefied petroleum gas, etc.). Since the CFPS data provides household energy expenditures in monetary form rather than physical quantities, this study converts expenditure data into carbon emissions by introducing emission factors and energy price parameters. First, based on the survey's "monthly electricity expenditure" (fp403) and "monthly fuel expenditure" (fp404), the annual total expenditure is calculated:

$$E_{elec} = fp403 \times 12, E_{fuel} = fp404 \times 12 \tag{1}$$

Here, E_{elec} and E_{fuel} represent the household's annual electricity and fuel expenditures (unit: yuan/year). Subsequently, the carbon emission conversion factor per unit of monetary expenditure is determined. The electricity emission factor (EF_{elec}) is calculated using the ratio of the average carbon intensity of China's power grid (0.785 $kgCO_2/kWh$) to the average residential electricity price (0.6 yuan/kWh). The fuel emission factor (EF_{fuel}) is obtained from the ratio of the emission coefficient for standard coal (2.493 $kgCO_2/kg$ standard coal) to the estimated market price (6 yuan/kg standard coal). The calculation formulas are as follows:

$$EF_{elec} = \frac{0.785}{0.6} \approx 1.308\ \mathrm{kgCO_2/yuan}, EF_{fuel} = \frac{2.493}{6} \approx 0.416\ \mathrm{kgCO_2/yuan} \tag{2}$$

After obtaining the conversion factors, the household's total annual direct carbon emissions (C_{direct} , unit: tons/year) and per capita direct carbon emissions (C_{direct_pc}) can be calculated using the following formulas:

$$C_{direct} = \frac{E_{elec} \times EF_{elec} + E_{fuel} \times EF_{fuel}}{1000}, C_{direct\_pc} = \frac{C_{direct}}{N} \tag{3}$$

Where N is the household population size. The emission coefficients and price parameters used in the calculations primarily refer to the "2006 IPCC Guidelines for National Greenhouse Gas

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Inventories," the "China Energy Statistical Yearbook," and relevant authoritative literature, and are assumed to remain relatively stable during the study period.

3.3. Measurement of indirect energy consumption carbon emissions

The measurement of indirect energy consumption carbon emissions adopts the Input-Output Analysis method, aiming to capture the full lifecycle carbon emissions indirectly induced by households consuming non-energy goods and services. The CFPS data divides household consumption expenditures into eight categories: Food, Clothing, Housing, Household Equipment and Daily necessities, Medical Care, Transportation and Communication, Education, Culture and Entertainment, and Others, making categorical accounting possible. The key to this study is assigning a carbon emission intensity coefficient (α_i , unit: $kgCO_2$/yuan) to each consumption category, which represents the average amount of carbon emissions embedded per unit of monetary expenditure.

Table 1. Carbon emission intensity coefficients for household consumption expenditures

Consumption Category	Variable Name	Carbon Intensity Coefficient ($kgCO_2$/yuan)
Food Expenditure	food	0.52
Clothing Expenditure	dress	0.89
Housing Expenditure	house	0.35
Household Equipment & Daily Necessities	daily	0.78
Medical Care	med	0.43
Transportation& Communication	trco	0.95
Education,Culture& Entertainment	eec	0.61
Other Consumption	other	0.55

For the i consumption category, the amount of indirect carbon emissions generated C_i (unit: kg) is determined by the product of the annual consumption expenditure for that category E_i and its carbon intensity coefficient α_i

$$C_i = E_i \times \alpha_i \tag{4}$$

It is important to note that when calculating the indirect carbon emissions from "Housing Expenditure," to avoid double-counting with direct energy emissions, the separately calculated electricity and fuel expenditure portions must be deducted from the total housing expenditure($house$), i.e.:

$$C_{house} = (house - E_{elec} - E_{fuel}) \times 0.35 \tag{5}$$

By summing up the indirect carbon emissions from all eight consumption categories and converting the unit to tons, we obtain the household's total annual indirect carbon emissions $C_{indirect}$ and its per capita value $C_{indirect\_pc}$:

$$C_{indirect} = \frac{\sum_{i=1}^{8} C_i}{1000} , C_{indirect\_pc} = \frac{C_{indirect}}{N} \tag{6}$$

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3.4. Total household carbon emissions and derived indicators

Finally, the full-caliber total annual carbon emissions of the household sector C_{total} are the sum of direct and indirect emissions:

$$C_{total} = C_{direct} + C_{indirect} \tag{7}$$

The corresponding per capita total carbon emissions are $C_{total\_pc} = C_{total}/N$. To further analyze the structural characteristics of carbon emissions and consumption carbon efficiency, this study constructs a series of derived indicators based on the above accounting results, mainly including: the proportion of direct/indirect carbon emissions ($S_{direct}, S_{indirect}$), used to reveal the composition of emission sources; and the carbon emission intensity per unit of consumption expenditure (I_{carbon}, unit: kg/ thousand yuan), used to measure the carbon efficiency of household consumption activities.

4. Research design and model specification

4.1. Econometric model specification

To overcome unobservable, time-invariant household heterogeneity and time-varying common shocks, and to accurately identify the net effect of digitalization on household carbon emissions, this paper constructs a two-way fixed effects model. The benchmark econometric model is specified as follows:

$$\begin{aligned}\text{CarbonPer}_{it} &= \beta_0 + \beta_1\text{Digital}_{it} + \beta_2\text{Per\_GDP}_{ct} + \beta_3\text{Industry\_GDP}_{ct} + \beta_4\text{Age}_{it} + \beta_5 \\ &\text{Consumption}_{it} + \beta_6\text{Per\_income}_{it} + \beta_7\text{Educate}_{it} + \mu_i + \lambda_t + \epsilon_{it}\end{aligned} \tag{8}$$

Where CarbonPer_{it} represents the per capita carbon emission level of the i -th household in year t . In the empirical analysis, this is substituted with household per capita total carbon emissions, household per capita indirect carbon emissions, and household per capita direct carbon emissions. . Digital_{it} is the core explanatory variable, representing the digitalization level index of the i -th household in year t Per_GDP_{ct} , Industry_GDP_{ct} , Age_{it} , Consumption_{it} , Per_income_{it} , Educate_{it} are control variables. μ_i denotes the household individual fixed effect, used to absorb the influence of all time-invariant household characteristics. λ_t denotes the year fixed effect, used to absorb annual macro shocks common to all households. ϵ_{it} is the random disturbance term. β_1 is the core coefficient, reflecting the marginal impact of digitalization level on household per capita carbon emissions.

4.2. Construction and measurement of the core explanatory variable: digitalization level

Referring to the research method of Li Ming from the Journal of Management Science in China, the frequency of vocabulary related to the innovation field in local government work reports is quantitatively counted to measure the policy attention local governments pay to innovation development. In the specific research process, the defined innovation-related vocabulary includes core terms such as innovation, creation, R&D, science, scientific research, technology, patent, technique, etc. The regional innovation level serves as a key indicator for measuring the capacity for sustainable economic and social development. The raw data is obtained by conducting text analysis on local government work reports using Python (jieba segmentation, stop word list using Harbin

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Institute of Technology stop word list), subsequently organized using Stata, and finally formed into panel data format.

4.3. Control variable selection and data description

The definitions of the key variables in this study are as follows:

Economic Development Level (Per GDP): Measured by regional per capita GDP divided by 1000, used to control the impact of economic development level on household carbon emissions. According to the Environmental Kuznets Curve hypothesis, the relationship between economic development level and environmental pollution presents an inverted U-shape. During economic development, there is a turning point in the relationship between regional per capita GDP and environmental quality. In the early stages of economic development, the consumption of energy and minerals is higher; the higher the per capita GDP, the more pollutant emissions, until environmental degradation reaches its peak. As the economic development level gradually rises, the region's energy structure continuously optimizes, which is beneficial for environmental quality protection.

Industrial Structure (Industry GDP): Measured by the ratio of the city's secondary industry added value to the city's GDP, used to characterize the city's industrial structure. Industrial structure can reflect the city's economic structure and energy structure. The achievement of the "dual carbon" goals depends on factors such as energy structure adjustment, technological breakthroughs in carbon capture, utilization, and storage, smooth production-consumption-distribution-circulation links, and industrial structure upgrading. The added value of the secondary industry involves multiple stages of CO2 generation, treatment, and emission, and is closely related to the economic and social structure and operational processes. Therefore, it is necessary to control for changes in carbon emissions caused by different regional industrial structures.

Household Head Age (Age): Household head age reflects the household life cycle and is one of the factors affecting household carbon emissions. As the household head's age increases, the dynamic trajectory of household carbon emissions changes. For example, elderly families consume more health services and energy, and less transportation and education, reducing the supply of labor factors of production, thus affecting carbon emissions from both the consumption and supply sides. Given that household heads who are too young or too old have a minor impact on household carbon emission behavior, this paper does not include samples with household heads under 16 years old or over 90 years old.

Household Consumption Rate (Consumption): The household consumption rate reflects the proportion of consumption expenditure in households with different income levels. This paper uses the ratio of total household consumption expenditure to total household income as the indicator for the household consumption rate.

Household Per Capita Income (Per income): In terms of scale, an increase in household per capita income level promotes household consumption. In terms of structure, as per capita income level increases, households shift their consumption structure from primarily purchasing survival-type goods to increasing consumption of enjoyment-type goods. Different types of goods and services have different carbon emission intensities, thereby causing changes in the household carbon footprint.

Education Level (Educate): The household's education level is closely related to household carbon emissions. Families with higher education levels tend to have stronger low-carbon environmental awareness. The highest education level options for the household head in the CFPS questionnaire are: primary school, junior high school, senior high school, secondary/vocational high school, associate degree, undergraduate, master's, and doctorate. This paper measures the

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household's education level by the years of schooling of the household head. The highest education level is converted into years of schooling, sequentially as 6, 9, 12, 11, 15, 16, 18, and 22.

4.4. Data sources and descriptive statistics

The household-level micro data used in this study originates from the nationally representative China Family Panel Studies (CFPS). Regional macro data comes from the China City Statistical Yearbook. The sample time span is from 2014 to 2020. After merging the data and cleaning missing values and outliers, a balanced panel dataset covering multiple provinces across the country is ultimately formed, with 15,799 valid household-year observations. As presented in Table 2, the descriptive statistics for the key variables are as follows. The average per capita total carbon emissions across households is 10.079, with a standard deviation of 14.853, suggesting considerable variation in carbon emission levels among the sample households. Further decomposition reveals that household per capita indirect carbon emissions (mean 8.634) are much higher than direct carbon emissions (mean 0.639), which is consistent with the common characteristic of China's household carbon emission structure dominated by indirect emissions. The mean of the core explanatory variable, digitalization level, is 5.221, with a standard deviation of 0.043. Regarding control variables, the average age of household heads is about 55 years, the average years of education is about 15.5 years, male household heads account for 80.7%, married household heads account for 88.2%, the average household consumption rate is 1.2%, and household heads with financial literacy account for 32.4%. These statistical characteristics are generally consistent with the basic situation of current Chinese households.

Table 2. Descriptive statistics

Variable Name	Observations	Mean	Std. Dev.	Min	Max
Household Carbon Emissions (per capita)	21584	10.079	14.8534	0	893.6527
Household Indirect Carbon Emissions (per capita)	21584	8.6338	13.766	0	892.8678
Household Direct Carbon Emissions (per capita)	21584	0.6390	0.7038	0	20.8715
Digitalization Level	18909	5.221	0.0429	0	6.119
Economic Development Level	18909	58.987	38.006	6.695	199.017
Industrial Structure	18909	43.237	10.672	14.1	81.4
Financial Development Level	18909	1.363	0.807	0.133	6.193
Household Head Age	21584	55.212	12.867	17	97
Household Per Capita Income (log)	21584	9.196	1.399	-3.534	14.779
Education Level (Years)	21584	15.495	6.29	0	22
Household Head Gender	21584	0.807	0.394	0	1
Household Head Marital Status	21584	0.882	0.323	0	1
Household Consumption Rate	21584	0.012	0.022	0	0.467
Financial Literacy	21584	0.324	0.468	0	1

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5. Empirical results and analysis

5.1. Baseline regression results

To accurately identify the net effect of digitalization level on household carbon emissions, this paper controls for relevant variables at the household and regional levels and employs a panel model that includes both household individual fixed effects and year fixed effects for estimation. Table 3 reports the baseline regression results of digitalization level on household per capita total carbon emissions, per capita indirect carbon emissions, and per capita direct carbon emissions.

Regression Results:

Table 3. Baseline regression results

Variable	Carbon Emissions	Indirect Carbon Emissions	Direct Carbon Emissions
	(1)	(2)	(3)
Digitalization Level	−0.1752*	0.1821*	−0.2662*
	(0.1060)	(0.1105)	(0.1424)
Control Variables	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes
R^2	0.4550	0.4515	0.4608
Observations	15799	15799	15799
Constant	−0.4303***	1.9928***	1.8238***
	(0.0039)	(0.0091)	(0.0081)

Column (1) shows the impact of digitalization level on household per capita total carbon emissions. The estimated coefficient of the core explanatory variable "Digitalization Level" is -0.1752, and it is statistically significant at the 10% level. This result indicates that, after controlling for other factors, household inherent characteristics, and time trends, an increase in the household's digitalization level can significantly reduce its per capita total carbon emissions. Digitalization may achieve overall carbon reduction by promoting intelligent household energy management, optimizing transportation modes, changing consumption patterns, and through other pathways. Columns (2) and (3) respectively examine the impact of digitalization on per capita indirect and per capita direct carbon emissions. The results show significant differences: the coefficient of digitalization level on indirect carbon emissions is 0.1821 (significantly positive at the 10% level), while the coefficient on direct carbon emissions is -0.2662 (significantly negative at the 10% level). The discovery of this "dual effect" carries profound policy implications. It reveals the complexity of the digital emission reduction pathway: while digitalization effectively reduces households' direct consumption of end-use fossil fuels like coal and gas, it may lead to more indirect emissions due to changes in lifestyle. For example, increased household electricity demand and deeper reliance on internet services can cause a rise in indirect carbon emissions embedded in electricity consumption. Therefore, the overall carbon reduction effect of digitalization is the net result of offsetting the direct fuel savings effect against the increased indirect electricity consumption effect.

Regarding control variables, the constant term is highly significant in all three models. The R^2 values for each model are around 0.45, indicating that the models have some explanatory power for

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the variation in household carbon emissions, consistent with the explanatory power found in similar micro-level empirical studies.

5.2. Heterogeneity analysis

The baseline regression reveals the average effect of digitalization, but its impact may differ systematically across groups. To delve deeper into this issue, this paper conducts grouped regressions based on two key dimensions: household registration location (urban/rural) and the household head's human capital (education level).

5.2.1. Urban-rural heterogeneity

The regression results in Table 4 show that an increase in digitalization level has a significant inhibiting effect on per capita total carbon emissions in urban households (coefficient -0.1304, significant at the 1% level), but its impact on rural households is statistically insignificant (coefficient -0.0557). This difference may stem from multiple reasons. First, the urban-rural digital divide persists, with urban households generally having better access to digital infrastructure and digital skills than rural households. Second, urban and rural energy consumption structures differ. The proportion of direct combustion of biomass and bulk coal in rural household energy use may still be high, and the penetration rate and effectiveness of digital alternatives or optimization technologies for these high-carbon energy sources might be insufficient. Finally, lifestyle differences exist. Urban households rely more on convenient digital services, which may increase indirect emissions, offsetting the direct emission reduction effects. Rural household lifestyles are relatively stable, and the transformation of consumption patterns brought about by digitalization might be smaller.

5.2.2. Education level heterogeneity

Table 4 shows that the carbon reduction effect of digitalization is significantly stronger for households with a high education level (coefficient -0.1771, significant at the 1% level) compared to households with a low education level (coefficient -0.1179, significant at the 10% level). Education is a core manifestation of human capital. Household heads with higher education levels typically possess stronger information acquisition and processing capabilities, higher environmental awareness, and a greater ability to adopt and utilize new technologies. Therefore, they are better able to understand and use digital tools for precise energy savings, and are more likely to actively choose digitalized green lifestyles. In contrast, even if low-education households have access to digital technology, they may primarily use it for entertainment and social interaction, with relatively weaker awareness and capacity for energy saving and carbon reduction, resulting in the underutilization of digitalization's emission reduction potential.

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Table 4. Heterogeneity regression results

Variable	Urban	Rural	High Education	Low Education
	(1)	(2)	(3)	(4)
Digitalization Level	-0.1304*	-0.0557	-0.1771*	-0.1179*
	(0.0007)	(0.0501)	(0.0009)	(0.0701)
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.8650	0.8961	0.5310	0.3187
Observations	4740	11059	8751	7048
Constant	0.726***	0.975***	0.0417***	0.0313***
	(0.228)	(0.204)	(0.0063)	(0.0052)

6. Research conclusions and policy implications

6.1. Main research conclusions

On the base of micro-level longitudinal survey data from Chinese households and employing a two-way fixed effects model, this study empirically examines the effect of digitalization level on household carbon emissions and its heterogeneous effects. The main conclusions are as follows: First, overall, an increase in household digitalization level helps to reduce per capita total carbon emissions, providing micro-level evidence supporting the use of digital technologies to promote emission reduction on the consumption side. Second, the impact of digitalization on household carbon emissions exhibits apparent "structural differentiation." Its emission reduction effect is primarily manifested in directly reducing the consumption of end-use fossil fuels, but it simultaneously promotes indirect carbon emissions, mainly those embedded in electricity consumption. Finally, the carbon reduction effect of digitalization shows significant heterogeneity across different groups. Its emission reduction effect is more pronounced and robust for urban households and households with higher education levels.

6.2. Policy implications

Based on the above research conclusions, to give full play to the carbon reduction potential of digitalization, guide the digital economy to develop in a green and inclusive direction, and facilitate the low-carbon transition of the household sector, this paper proposes the following policy implications:

First, implement precise and differentiated digital emission reduction empowerment strategies to bridge the digital divide in carbon reduction. For urban and high-education households, the policy focus should be on deepening the application of digital low-carbon technologies and strengthening behavioral incentives, encouraging the development of intelligent energy management, green online consumption and other low-carbon models, and further releasing the carbon reduction potential of digitalization. For rural and low-education households, the primary policy goal is to bridge the digital infrastructure and skill divide, increase investment in rural digital infrastructure construction, carry out targeted digital skill and low-carbon consumption training through community and village-

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level organizations, and design localized digital low-carbon solutions for the high-carbon energy consumption characteristics of rural households, and provide appropriate policy subsidies to promote the popularization and application of digital low-carbon technologies in rural and low-education groups.

Second, strengthen the synergistic transformation of digitalization and energy system greening to solve the problem of indirect emission increase caused by digitalization. The increase of indirect carbon emissions from digitalization is mainly due to the growth of electricity consumption of digital equipment and the high carbon intensity of the power system. Therefore, on the one hand, it is necessary to expedite the development of a new power system centered on renewable energy sources, raise the share of clean energy in electricity generation,, and reduce the carbon intensity of electricity production, so as to reduce the indirect carbon emissions embedded in electricity consumption; on the other hand, it is necessary to promote the energy conservation and carbon reduction of the digital industry itself, formulate and implement mandatory energy efficiency standards for digital infrastructure such as data centers and cloud computing platforms, and set green electricity consumption ratio requirements, so as to realize the green development of the digital industry chain.

Third, build a consumption guidance and capacity-building system that deeply integrates digital and green elements, and cultivate residents' digital low-carbon consumption awareness and ability. It is necessary to integrate low-carbon environmental protection publicity into digital popularization and training, use digital media and platforms to carry out low-carbon consumption publicity and education, and improve the low-carbon environmental awareness of all residents, especially rural and low-education groups. At the same time, it is necessary to improve the digital low-carbon service system, launch more user-friendly digital low-carbon tools and platforms, reduce the threshold for residents to use digital technologies for low-carbon consumption, and guide residents to form a green and low-carbon consumption lifestyle driven by digitalization.

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