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Household Digitalization and Green and Low-Carbon Lifestyles: Micro-Level Evidence from Digital Household Pilot Programs in China

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Abstract

Promoting the transition toward green and low-carbon lifestyles is essential for advancing sustainable consumption and environmental sustainability. Based on 6903 valid survey responses from 19 digital household pilot regions in China, this study examines the relationship between household digitalization and green and low-carbon lifestyles. A household digitalization level (HDL) index is constructed using the entropy method across five dimensions: digital network services, digital infrastructure, digital literacy, digital skills, and digital applications. The empirical results show that higher HDL is positively associated with the adoption of green and low-carbon lifestyles, and this association remains robust across a series of sensitivity analyses. Exploratory mechanism analysis indicates that HDL is linked to green and low-carbon lifestyles through improved satisfaction with digital smart technologies and enhanced environmental awareness. Heterogeneity analysis shows that this association is stronger among larger households, urban and suburban households, and households with development-oriented consumption, but weaker among smaller, rural, and subsistence-oriented households. These findings provide micro-level evidence supporting the exploration of the linkage between household digitalization and sustainable household consumption and the coordinated development of digitalization and environmental sustainability.

Keywords: household digitalization; green and low-carbon lifestyles; carbon emissions from the consumer sector; pilot projects for digital household development

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1. Introduction

The global climate crisis and the resulting ecological crisis are emerging as the core challenges constraining sustainable development. In the "Global Environment Outlook 7", the UNEP notes that household consumption and lifestyles are the primary drivers of global greenhouse gas emissions, with approximately two-thirds of global greenhouse gas emissions closely linked to household consumption activities [1]. It is evident that climate governance relies not only on technological advancements and energy transition on the production side but also increasingly on behavioral adjustments and lifestyle changes on the consumption side [2]. The IPCC's Sixth Assessment Report further emphasizes that demand-side transformations hold significant emission reduction potential in sectors such as buildings, transportation, and consumption [3]. As the basic unit of society, households play an irreplaceable role in the low-carbon transition, making household-level lifestyle transformation an important pathway toward sustainable development.

In China, the significance of emissions from the consumption sector is also on the rise. Carbon emissions from consumption account for over 53% of China's total emissions, and household carbon emissions are the second-largest source of the country's total emissions [4]. As primary agents of consumption, households' behavioral choices, such as energy use, the selection of durable goods, and modes of transportation, significantly influence the carbon emissions landscape [5]. Household carbon emissions are closely related to residents' everyday consumption behaviors. Choices regarding energy use, transportation, and product purchases not only affect household emissions but also shape the development of sustainable consumption patterns. Green and low-carbon lifestyles can therefore be regarded as an important expression of the transition toward more sustainable household consumption. The development of digital technologies provides new support conditions for promoting sustainable consumption and enhancing household environmental sustainability. The development of digital homes has been emphasized as an important policy direction in China. The "Guiding Opinions on Accelerating the Development of Digital Homes and Improving Living Standards," issued by the Ministry of Housing and Urban–Rural Development and other departments, highlights the integration of digital technologies into residential environments and daily life. At the household level, such digitalization is reflected in multiple dimensions, including access to digital infrastructure, the use of digital network services, digital literacy and skills, and the adoption of digital applications. These dimensions may shape how households organize their daily activities and consumption choices, and are therefore potentially related to the adoption of greener and more sustainable lifestyle practices.

Against this backdrop, the relationship between household digitalization on green and low-carbon ways of living, as well as the underlying mechanisms, has become an important issue in advancing household sustainability and sustainable consumption. However, existing research on the relationship between digital households and green and low-carbon lifestyles remains in its infancy, focusing primarily on the macro-level interplay between the digital economy and green development, or on green innovation at the corporate level [6]. The theoretical linkage between household digitalization and green and low-carbon lifestyle behaviors remains underexplored, particularly in terms of behavioral and informational channels, while micro-level evidence and systematic measurement of household digitalization are still limited. Therefore, this study, grounded in the digital household pilot policy, concentrates on the relationship and potential channels through which HDL is linked with green and low-carbon lifestyles. This study provides micro-level evidence on the linkage between household digitalization and green and low-carbon lifestyles, thereby informing discussions on the coordinated development of digitalization and household sustainability.

2. Literature Review

This study reviews the existing literature and finds that early research on measuring household digitalization largely relied on macro-level indicators or single access variables, based on the core premise that the level of regional digital development determines the foundational environment for household digitalization. For example, some scholars have constructed a system for calculating China's digital economy value-added, using indicators such as internet penetration rates, broadband access rates, and regional digital economic development indices to indirectly reflect the digital environment in the regions where households are located [7]. In their research on measuring industrial digitization, other scholars have treated regional digital infrastructure indicators as external environmental variables affecting the digitization of micro-level entities [8]. Additional studies have used "whether a household has internet access" as a proxy for household digitalization to analyze

the empowering effects of the digital economy on rural residents' consumption [9]. While these indicators capture the macro-level environment, they are limited in reflecting within-household heterogeneity and actual usage patterns. In recent years, behavior-oriented measurement paradigms based on micro-level survey data have gradually gained attention. For example, Huang Yanghua and colleagues utilized the China Household Digital Economy Survey (CHDES) database to develop the China Individual Digitalization Index (CIDI), thereby advancing the standardization and systematization of micro-level digitalization measurement [10]. Building on this foundation, subsequent research has further focused on actual household digital behaviors, overcoming the limitations of traditional measurement methods. It has established a multidimensional measurement framework centered on "behavioral practices" and employed principal component analysis to construct a comprehensive index of household digital transformation, thereby achieving a comprehensive assessment of household digitalization level. Other scholars, meanwhile, have adopted a three-dimensional approach—covering digital access, usage, and creation—and utilized the entropy method to construct a household digital capability index, thereby measuring household digitalization level [11]. However, these approaches primarily reflect external conditions or basic access and are limited in capturing within-household heterogeneity in digital usage intensity, skills, and actual application behaviors, thereby constraining their explanatory power at the micro level.

As the "dual carbon" goals are further advanced, households are increasingly becoming a major contributor to energy consumption and carbon emissions. Their adoption of green and low-carbon lifestyles encompasses multiple dimensions, including energy conservation, green consumption, and low-carbon transportation. Not only does the practice of green and low-carbon lifestyles among households enhance residents' well-being, but the various green behaviors it entails are also closely linked to achieving carbon reduction across society and fostering a low-carbon economic lifestyle [12]. Existing research on green and low-carbon lifestyles in households has largely focused on micro-level factors, particularly household demographic structure and income. For instance, a higher dependency ratio has been found to be associated with greater adoption of low-carbon consumption. Regarding economic determinants, some scholars highlight that the income-driven shift toward higher-end consumption contributes positively to the promotion of green and low-carbon lifestyles [13]. While these studies provide useful insights, their analyses primarily focus on socioeconomic factors, with relatively limited attention to the role of technological and informational factors in shaping behavior.

From a theoretical perspective, green and low-carbon lifestyle behaviors are commonly explained by the Theory of Planned Behavior (TPB) and the Value–Belief–Norm (VBN) theory [14]. These frameworks suggest that external factors, including access to information and technological conditions, may influence household behavior by affecting perceived costs, convenience, and environmental cognition, providing a theoretical basis for understanding how household digitalization may shape the adoption of green and low-carbon practices.

Regarding the impact of household digitalization on green and low-carbon lifestyles, the advancement of household digitalization provides new pathways through which households may adjust their consumption behaviors, shifting the research focus toward "carbon reduction at the household level". Drawing on micro-level data, some studies find that mobile payments and digital services can expand access to green consumption and are associated with greater adoption of low-carbon behaviors [15]. Other studies, focusing on cost-related mechanisms, suggest that digitalization may support greener lifestyles by reducing search and transaction costs [16]. However, digital technologies do not necessarily lead to greener outcomes. The improper use of smart devices may

increase energy consumption, and disparities in digital literacy may further widen these differences [17]. Overall, these findings suggest that the relationship is not unidirectional but may operate through multiple mechanisms.

To sum up, micro-level research on household digitalization in China remains scarce, plagued by inconsistent core concept definitions and a lack of standardized measurement frameworks, which hinders the accurate national evaluation of household digitalization levels. Furthermore, few studies have integrated HDL and green and low-carbon lifestyles into a unified theoretical framework, leaving an urgent gap in exploring association and potential channels. Building on the identified gaps in the literature, this study contributes in three main respects. First, at the methodological level, it develops a multidimensional household digitalization (HDL) index by synthesizing existing literature and local policy guidance, providing a systematic operationalization that captures digital access, usage, and capabilities at the household level. Second, it constructs a structured indicator system for household green and low-carbon lifestyles, addressing the limitations of previous single-indicator measures and better capturing the multidimensional nature of household environmental behaviors. Third, at the empirical level, it examines the association between HDL and green and low-carbon lifestyles, investigates the underlying behavioral and informational mechanisms, and analyzes heterogeneous effects across households, thereby providing micro-level evidence to inform both theoretical understanding and policy discussions on household green transitions.

3. Theoretical Analysis and Research Hypotheses

Household digitalization is expected to support the adoption of green and low-carbon lifestyles by reshaping household consumption patterns and daily decision-making [18]. Household consumption is closely related to both direct emissions from energy use and indirect emissions from the purchase of non-energy products [19]. From a sustainability perspective, digital platforms can reduce direct carbon emissions by connecting residents with public services, online shopping, utility payment systems, and other daily services beyond the time and space constraints of traditional offline models. This may reduce unnecessary travel and vehicle use, lowers the consumption of energy sources such as gasoline and electricity, and supports more resource-efficient daily routines. In this way, household digitalization may contribute to more sustainable consumption and mobility patterns, thereby potentially facilitating the adoption of green and low-carbon lifestyles [20]. In reducing indirect carbon emissions, a digital platform powered by artificial intelligence and big data uses intelligent matching and analysis to recommend products that better meet the needs of individual household members. This enables residents to purchase products with the desired features more quickly and accurately, thereby reducing the frequency of purchases and the costs associated with trial and error. Consequently, it reduces carbon emissions resulting from the purchase or return of non-energy products, fostering a green and low-carbon lifestyle [21].

Meanwhile, HDL can lower the barriers to adopting green behaviors for households, significantly reducing the time and effort required to do so [22]. By reducing the time and effort costs required from residents, smart devices can facilitate adopting green behaviors in the context of home digitalization [23]. Nevertheless, these effects are not automatic. Digital devices may increase electricity demand, online services may generate delivery-related emissions, and greater convenience may induce rebound effects or additional consumption [24]. Overall, although digitalization may induce rebound effects and additional emissions, these effects are context-dependent and may not necessarily offset its environmental benefits [25]. Accordingly, this study proposes the following hypotheses:

H1: *Household digitalization level (HDL) is positively associated with the Household Green Behavior Index (HGBI).*

Advances in HDL-driven by technological innovations such as the Internet of Things, big data analytics, and algorithm optimization-can fundamentally enhance the user experience of smart home systems and increase residents' satisfaction with them. This heightened satisfaction, in turn, reinforces residents' recognition of the eco-friendly attributes of smart home technology, thereby potentially encouraging the adoption of green behaviors and supporting a greener lifestyle [26]. Conventional smart home systems can receive user commands and perform corresponding actions, but different devices are typically unable to communicate with one another, making it difficult to achieve coordinated energy-saving effects and failing to meet the lifestyle habits and environmental needs of different households. In contrast, home digitization not only enables the interconnection of various smart home devices through technologies such as the IoT to build a fully integrated smart home system, but also uses big data to analyze the daily routines and energy and water consumption habits of different households, thereby precisely tailoring solutions to meet their specific energy-saving, water-saving needs [27]. In the realm of home digitization, big data and energy consumption monitoring technologies can be leveraged to provide residents with real-time feedback on household energy usage and energy-saving benefits, offering a clear visual representation of water and electricity savings as well as carbon emission reductions. This not only delivers direct economic benefits to households but also highlights the environmental value of smart home systems, thereby increasing residents' acceptance and recognition of these technologies. Higher satisfaction with smart home systems encourages households to actively use these technologies. With long-term use, stable green habits may gradually develop. These behavioral habits will extend to all aspects of family life, thereby promoting the normalization of green living practices [28]. Based upon this, this study proposes the following hypothesis:

H2: *HDL is linked to higher satisfaction with smart home technology, which is positively associated with HGBI.*

Environmental attitudes serve as a bridge between HDL and the HGBI. A deficiency in environmental knowledge can lead household residents to develop cognitive biases such as "environmental protection has nothing to do with me" and "I'm not sure how my personal actions affect the environment," thereby fostering negative environmental attitudes [29]. Under traditional lifestyles, residents' access to environmental knowledge is limited, costly, and often lacks specificity. This makes it difficult for them to systematically acquire such knowledge, leading some households to develop misconceptions about environmental protection and making it even harder for them to proactively adopt green and low-carbon lifestyles. However, HDL may help overcome the temporal and spatial limitations of environmental knowledge dissemination under traditional models. Residents can utilize various pockets of free time to browse short videos and articles on environmental science through short-video apps and environmental protection public accounts, significantly improving the convenience of accessing environmental knowledge for households and reducing the cost of acquisition [30]. Digital platforms, through intelligent filtering and algorithms, can accurately identify gaps in environmental knowledge and identify the specific needs of different households, thereby delivering more targeted and personalized environmental information to users. Improvements in HDL can enhance residents' environmental awareness, enabling families to truly understand the impact of their daily behaviors on the environment. This helps gradually correct misconceptions about environmental protection, transforming households' attitudes from passive and negative

to proactive and positive. Ultimately, this is associated with the adoption of concrete green and low-carbon lifestyles, forming a complete closed-loop cycle of "knowledge acquisition-attitude transformation-behavioral practice" [31]. Accordingly, this study proposes the following hypothesis:

H3: *HDL is linked to higher environmental awareness, which is positively associated with HGBI.*

Based on the above hypotheses, the mechanism diagram is shown in: Figure 1.

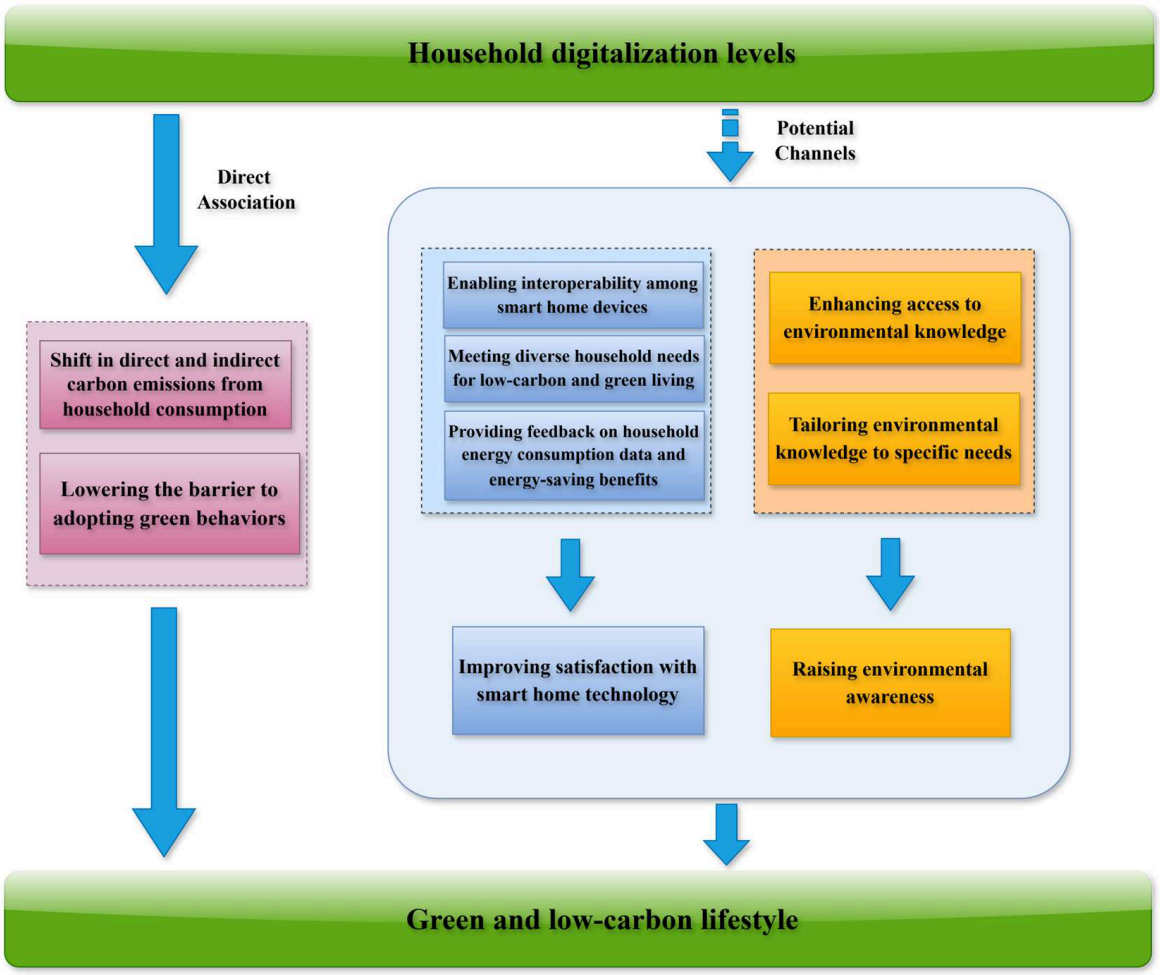


Figure 1. Potential Channels Linking HDL and Green and Low-Carbon Lifestyles.

4. Variables, Model Specifications, and Data Description

4.1. Variable Declaration

(1) Explained Variable: Household Green Behavior Index (HGBI). The green lifestyle behaviors of households in the questionnaire include: whether they prioritize public transportation such as buses, subways, bicycles, or walking over private cars; whether they frequently purchase locally produced food and goods to reduce carbon emissions from transportation; whether they try to choose products with minimal, recyclable packaging when shopping; whether they choose to buy secondhand items rather than always buying brand-new items; and whether they purchase or replace household appliances with more energy-efficient models. If a sample household engages in any of the above green behaviors, it is coded as 1; otherwise, it is coded as 0. This study aggregates the green and low-carbon lifestyle behavior indices across these different dimensions to ultimately derive the HGBI [32] Reliability and factor analysis results indicate that the five items are internally

consistent and reflect a common underlying factor, supporting the validity of the HGBI measure, as shown in Supplementary Materials.

(2) Explanatory Variable: Household Digitalization Level (HDL). The HDL is constructed using the entropy weighting method, with digital skills receiving relatively higher weight, consistent with studies on the second-level digital divide and human capital, which emphasize the role of skills in enabling effective use of digital technologies [33,34]. HDL is measured across five dimensions, including digital services, digital infrastructure and devices, digital literacy awareness, digital skills, and digital applications, providing a comprehensive framework that captures both access and capability beyond prior studies relying mainly on binary access indicators, as shown in Table 1. This approach is consistent with the study's focus on the environmental implications of overall household digitalization.

Since the original indicators differ in units and scales, all indicators are standardized before index construction. For household i and indicator j, the standardized value is calculated as:

$$X_{ij} = \frac{x_{ij} - x_{j,min}}{x_{j,max} - x_{j,min}} \tag{1}$$

where x_{ij} denotes the original value of indicator j for household i, and $x_{j,\min}$ and $x_{j,\max}$ represent the minimum and maximum values of indicator j, respectively. For reverse indicators, the standardization procedure is adjusted accordingly. All variables used in the construction of the HDL index are complete, with no missing observations in the final sample. Data cleaning procedures are conducted prior to analysis to ensure consistency and validity across all indicators.

After standardization, this study applies the entropy weight method to determine the objective weight of each indicator. The proportion of household i under indicator j is calculated as:

$$P_{ij} = \frac{X_{ij}}{\sum_{i=1}^{m} X_{ij}} \tag{2}$$

where n denotes the number of household observations. The entropy value of indicator j is then calculated as:

$$e_j = -\frac{1}{lnn}\sum_{i=1}^{n} P_{ij} \times \ln P_{ij} \tag{3}$$

The information redundancy of indicator j is:

$$d_j = 1 - e_j \tag{4}$$

The weight of indicator j is obtained as:

$$\varphi_j = \frac{d_j}{\sum_{j=1}^{k} d_j} \tag{5}$$

where k denotes the total number of indicators. Finally, HDL is calculated as the weighted sum of standardized indicators:

$$HDL_i = \sum_{j=1}^{k} \varphi_j \times X_{ij} \tag{6}$$

This procedure avoids subjective weighting and assigns weights based on the relative variation in indicators across households.

Table 1. Household Digitalization Indicator System.

First-Level Dimension	Second-Level Dimension	Third-Level Dimension	Specific Indicators
Digital Service	Digital Network Services (6.19%)	Network Access (6.19%)	Whether fixed broadband is installed at home
			Whether household internal products are managed through a unified control terminal
	Digital Infrastructure and Equipment (3.87%)	Infrastructure (2.08%)	Construction of digital infrastructure around residents
		Digital Equipment (1.79%)	Number of digital devices in use by residents
Digital Skills and Digital Usage	Digital Literacy Cognition (2.68%)	Digital Comprehension (2.68%)	Whether the concepts of digital family and smart family are heard of
	Digital Skills (41.93%)	Information Acquisition (2.89%)	Search skills, information evaluation, and content browsing
		Online Social Interaction and Communication (3.53%)	Instant messaging, email, and social media interaction
		Online Transactions and Consumption (5.39%)	Shopping platform operation, electronic payment operation
		Online Security and Protection (7.52%)	Account security management, personal privacy protection
		Tool and Application Operation (22.60%)	Browser usage, file download, and upload
Digital Skills and Digital Usage	Digital Application (45.34%)	Life Field (2.89%)	Watching videos, playing games, listening to music, and ticket purchasing
		Financial Field (3.69%)	Online mobile payment, online banking, deposits, and loans
		Office Field (2.91%)	Professional software office work, resource download, and storage
		Education Field (6.18%)	Online courses, e-book reading
		Health Field (9.40%)	Health management via online platforms
		Government Services (20.27%)	Online legal popularization and government dispute resolution

(3) $Control_{ir}$: This study includes seven control variables in the empirical model, specifically as follows: gender (gender) is measured as a dummy variable, coded 1 for male respondents and 0 for female ones; age (age) is measured by the actual age of the respondents; household size (scale) is gauged by the total number of household members; occupational type (career) is determined based on the respondents' actual occupational category; the assessment of household digitalization level (assessment) is measured by the respondents' satisfaction with the development of household digitalization; annual income level (income) is reflected by the respondents' actual annual income; and educational attainment (education) is recoded according to the respondents' educational background, with a value of 1 assigned for primary school or below, 2 for junior high school, 3 for senior high school, and 4 for college or above.

4.2. Model Setup

To examine the association between household digitalization levels and the Household Green Behavior Index, an ordered logit model was constructed, as shown in Equations (7) and (8).

$$Y_{ir}^{*} = \beta_0 + \beta_1 HDL_{ir} + \gamma \text{Control}_{ir} + \lambda_r + \varepsilon_{ir} \quad (7)$$

$$Y_{ir} = k \qquad if\ \mu_{k-1} < Y_{ir}^{*} \leq \mu_k \quad k = 0, 1, 2, 3, 4, 5 \tag{8}$$

In which i represents each household participating in the survey, and r represents the region to which they belong.Y_{ir} denotes the observed HGBI, while Y_{ir}^{*} represents the corresponding latent variable in the ordered logit model. HDL_{ir} stands for household digitalization level. Control_{ir} represents a vector of control variables that may influence household green and low-carbon lifestyle behaviors. λ_r denotes regional fixed effects, which are included to control for unobservable and time-invariant regional characteristics, such as geographical location and economic structure. ε_{ir} represents the random disturbance term. μ_k denotes the threshold parameters to be estimated in the ordered logit model.

To further explore the potential mechanisms underlying the relationship between household digitalization and green and low-carbon lifestyle behaviors, this study adopts a three-step mechanism analysis. Following the baseline regression in Equation (7), the second and third steps of the mechanism analysis are specified as follows:

$$M_{ir} = \beta_0 + \beta_1 HDL_{ir} + \gamma \text{Control}_{ir} + \lambda_r + \varepsilon_{ir} \tag{9}$$

$$Y_{ir}^{*} = \beta_0 + \beta_1 HDL_{ir} + \beta_2 M_{ir} + \gamma \text{Control}_{ir} + \lambda_r + \varepsilon_{ir} \tag{10}$$

Among these, M_{ir} represents the mechanism variable. All other variables are defined as in Equation (7).

4.3. Data Explanation and Descriptive Statistics

This study was conducted in 19 Digital Household Pilot Regions in China to examine the relationship between household digitalization and green and low-carbon lifestyles. The questionnaire was designed around the themes of household digitalization and green and low-carbon living, covering four major dimensions: household and individual characteristics, digital infrastructure and technology adoption, household energy consumption and expenditure, and environmental awareness and green consumption behaviors.

To control for regional heterogeneity, a stratified sampling framework was employed. Specifically, the 19 pilot regions were grouped into 3–4 relatively homogeneous strata according to key regional characteristics, including population size and gross domestic product (GDP), to improve comparability within each stratum. A stratified quota sampling design was then implemented based on demographic characteristics reported in the latest national population census, including age, gender, and occupation, to improve the alignment between the sample structure and the target population in the pilot regions.

The survey was conducted anonymously online, with voluntary participation and informed consent. This study met the criteria for exemption from formal ethics review. A total of 8120 questionnaires were distributed across the 19 pilot regions. After removing incomplete, inconsistent, duplicate, or abnormally fast responses, 6903 valid questionnaires were retained, yielding an effective response rate of 85.01%. Demographic quota controls were applied during sampling and data cleaning to reduce deviations between the sample structure and the target population. No post-stratification weighting or calibration weighting was applied. The reliability assessment indicated satisfactory measurement quality, with Cronbach's alpha coefficients exceeding the recommended threshold of 0.80. Descriptive statistics for the main variables are reported in Table 2. Details of the 19 Digital Household Pilot Regions and their corresponding sample sizes are reported in Supplementary Materials.

Table 2. Descriptive Statistics.

Variable	N	Mean	SD	Min	Max
HGBI	6903	3.97	1.510	0	5
HDL	6903	0.260	0.0900	0.0600	0.670
Total Carbon	6903	21,069.24	13,373.78	1529.154	69,708.66
gender	6903	0.510	0.500	0	1
age	6903	3.860	1.510	1	7
scale	6903	4.470	1.640	1	8
career	6903	4.800	2.130	1	9
assessment	6903	2.510	1.110	1	4
income	6903	84,532	44,590	25,000	180,000
education	6903	2.510	0.800	1	4

4.4. Spatial Distribution Characteristics of Digitalization and Carbon Emissions in Pilot Areas

Building upon the descriptive statistics presented above, this study further characterizes the development status of regions participating in the Digital Household Pilot Programs in China from both spatial and distributional perspectives.

As illustrated in Figure 2, the spatial pattern of household digitalization is largely consistent with pilot implementation performance. Higher digitalization levels are mainly concentrated in eastern coastal areas and several central urban nodes, where most "completed" pilot regions are located. These areas benefit from stronger digital infrastructure, mature industrial ecosystems, and better governance capacity, enabling more effective implementation of digital household scenarios.

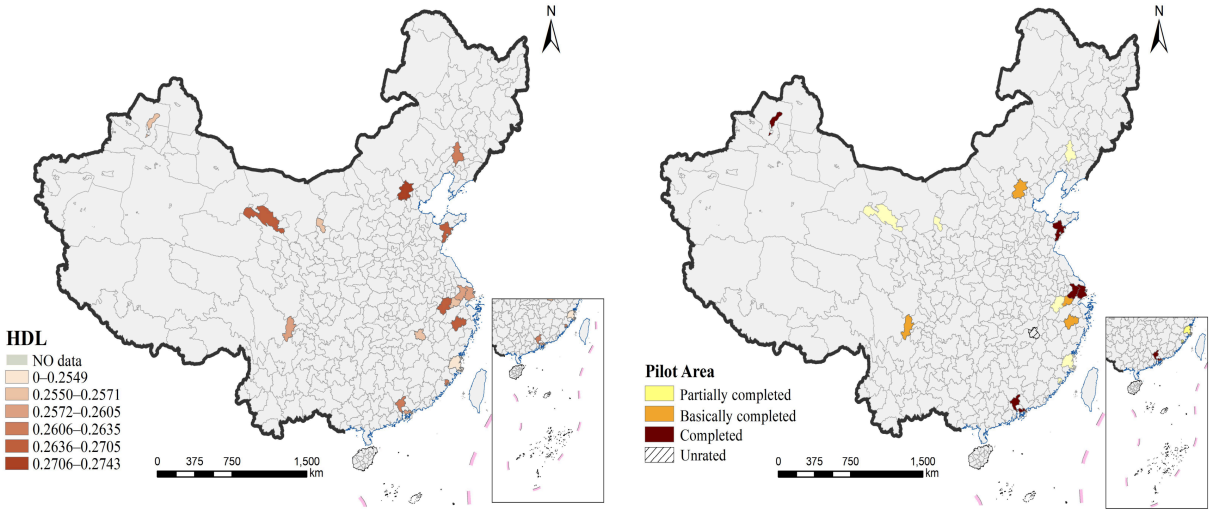


Figure 2. Spatial Pattern of HDL and Digital Family Pilot Classification in China. Note: The map was created using ArcGIS Desktop 10.8 software and standard maps with review number GS (2019) 1822 downloaded from the website of the Standard Map Service System of the Ministry of Natural Resources of China.

In contrast, western and less-developed regions generally show lower digitalization levels and weaker pilot progress, with gaps in infrastructure, applications, and operation. "Basically completed" regions are transitional, having built core infrastructure but still needing deeper applications and sustainable services.

From a distributional perspective in Figure 3, the violin plot shows that HDL is relatively concentrated, with most observations clustered around the middle range. This indicates that digital development in the pilot regions has generally reached a moderate

stage. However, the distribution still shows some dispersion and an extended upper range, suggesting that regional differences in household digitalization remain evident.

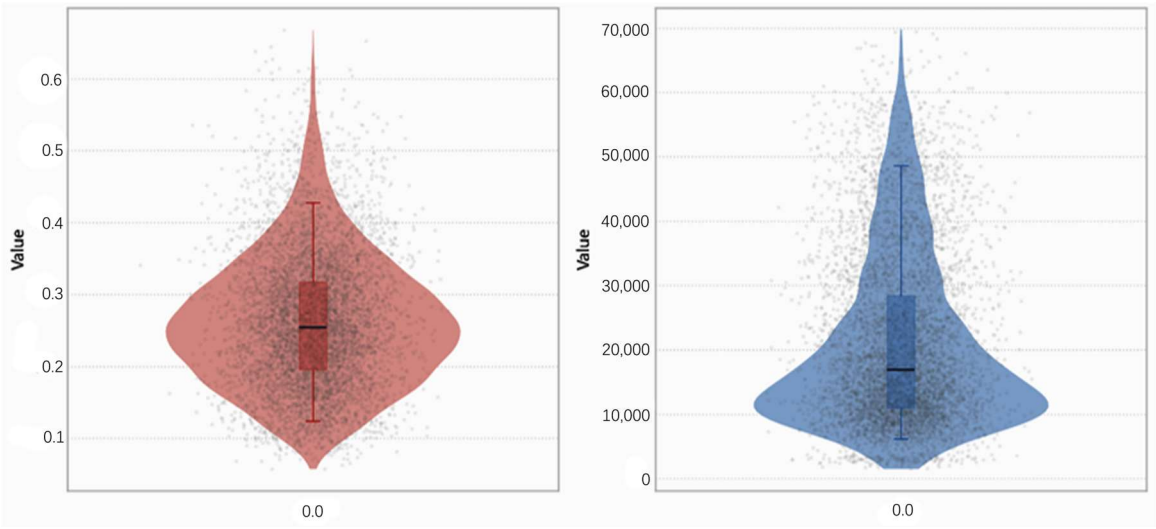


Figure 3. Violin Plots of HDL and Total Carbon Emissions.

In contrast, total carbon emissions show a wider and right-skewed distribution with a long upper tail, indicating substantial variation in household energy consumption and environmental outcomes across pilot regions (see Supplementary Materials for calculation details). Although total carbon emissions provide an objective measure of household environmental outcomes, this study focuses on green and low-carbon lifestyles as the primary dependent variable because lifestyle behaviors represent the behavioral foundation of household carbon reduction. Total carbon emissions are therefore used as a complementary descriptive indicator to characterize the environmental status of households across pilot regions.

Overall, the pilot regions do not exhibit a uniform development pattern, but rather show pronounced regional differentiation. Household digitalization remains at a moderate level on average, while substantial heterogeneity exists across regions. Differences in development foundations, pilot implementation progress, and total carbon emissions further reveal uneven digital and environmental conditions across the pilot regions. As an objective indicator of household environmental outcomes, total carbon emissions complement the descriptive evidence provided by HDL. Together, these patterns suggest considerable variation in both digital development and environmental performance, motivating the subsequent econometric analysis of the relationship between household digitalization and green low-carbon lifestyles.

5. Empirical Analysis and Results

5.1. Benchmark Regression

Table 3 presents the benchmark regression results examining the association between HDL and residents' adoption of green and low-carbon lifestyle behaviors. Model 1 includes only regional fixed effects. The coefficient of HDL is 0.732 and is statistically significant at the 1% level, suggesting a positive association between HDL and the HGBI. Model 2 further incorporates all control variables. The coefficient of HDL remains positive (0.664) and statistically significant at the 5% level. These results indicate that the positive association between household digitalization and green lifestyle behaviors remains robust after controlling for household characteristics and regional factors.

Table 3. Benchmark Regression Analysis.

	Model 1 **HGBI**	**Model 2** **HGBI**
HDL	0.732 ***	0.664 **
	(2.767)	(2.502)
gender		0.011
		(0.228)
age		0.036 **
		(2.142)
scale		0.059 ***
		(3.941)
career		0.010
		(0.866)
assessment		0.036 *
		(1.660)
income		0.000 ***
		(3.556)
education		0.034
		(1.071)
Regional fixed	YES	YES
N	6903	6903

z-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

To facilitate the interpretation of the ordered logit estimates, we further calculated the average marginal effects (AMEs) of HDL on HGBI categories. The results show that higher HDL is associated with a lower probability of being in lower HGBI categories and a higher probability of being in higher categories. Specifically, a one-unit increase in HDL decreases the probability of being in the lowest HGBI category by 4.29 percentage points and increases the probability of being in the highest category by 13.74 percentage points. The full AME estimates are reported in Supplementary Materials.

5.2. Robustness Test

To rule out potential confounding factors, this study conducts robustness tests using five methods. First, the HGBI was standardized to re-measure the level of green and low-carbon lifestyle behavior; the corresponding regression results are shown in Model 3 of Table 4, where there were no significant changes in the coefficients or their signs for HDL levels. Second, considering that the baseline model employs an Ordered Logit specification, we replace it with an Oprobit model. The results reported in Model 4 remain consistent with the baseline findings. Third, because municipalities directly under the central government have special administrative characteristics, this study excluded these samples from the regression analysis. Model 5 presents the regression results after this exclusion. The regression coefficient for HDL remains positive and is statistically significant at the 1% level, and the research conclusions remain unchanged. Fourth, by replacing the explanatory variable and recalculating the HDL index using the equal-weighting method (denoted as HDL_EW), the regression results are shown in Model 6, and the baseline hypothesis is once again validated. Fifth, to alleviate the potential influence of extreme values, the HDL index is winsorized at the 1% level. The regression results reported in Model 7 continue to support the baseline conclusion. Sixth, using the principal component analysis (PCA)-based HGBI as an alternative measure, Model 8 shows that the coefficient of HDL remains positive and significant at the 1% level. Seventh, after excluding weakly green-relevant indicators, we reconstruct the HDL index (r-HDL) and re-estimate the model. Specifically, r-HDL excludes gaming/entertainment, online legal information, and government dispute resolution. As reported in Model 9, the results remain consistent with the baseline findings, further supporting the robustness of the observed association between HDL and HGBI.

Table 4. Robustness Tests.

	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
	HGBI_std	Oprobit model	No Municipalities	EW for HDL	HDL (W1%)	PCA-HGBI	r-HDL
HDL	0.078 ***	0.389 **	0.919 ***		0.646 **	0.259 ***	0.502 **
	(2.599)	(2.564)	(3.215)		(2.395)	(2.606)	(2.187)
HDL_EW				1.122 ***			
				(4.787)			
Constant	0.644 ***					−0.495 ***	
	(32.446)					(−7.510)	
Controls	YES	YES	YES	YES	YES	YES	YES
Regional fixed	YES	YES	YES	YES	YES	YES	YES
N	6903	6903	5983	6903	6903	6903	6903

z-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$.

5.3. Supplementary Endogeneity Check via CMP Model

Considering that the observed association between HDL and HGBI may be affected by potential endogeneity arising from reverse causality and omitted variables, this study employs the Conditional Mixed Process (CMP) model as a supplementary analysis [35]. The CMP framework accommodates mixed-equation systems with different types of dependent variables and jointly estimates the first-stage and outcome equations. The significance of the Atanhrho statistic is used to indicate potential correlation between the error terms [36].

In this study, "Does the household head possess repair skills (RS)" is used as an instrumental variable within the CMP framework. RS may reflect an individual's familiarity with digital tools and technical capability, and is therefore expected to be positively associated with HDL. At the same time, the exclusion restriction cannot be directly verified and may be contestable, as RS may also be related to green and low-carbon behaviors through alternative channels independent of household digitalization. Given these potential alternative linkages, the validity of the instrument should be interpreted with caution. Accordingly, the CMP analysis is employed as a supplementary approach to examine whether the baseline association remains robust after accounting for potential endogeneity concerns, rather than to provide definitive causal identification.

The regression results are shown in Table 5. The results in column (1) of Model 10 show that RS is positively and significantly associated with HDL, supporting the relevance of the instrument. Column (2) reports the CMP estimation results. The Atanhrho statistic is significantly different from zero at the 1% level, suggesting the presence of endogeneity and supporting the use of the CMP model. After accounting for endogeneity, the coefficient of HDL remains positive and statistically significant, providing supplementary evidence that the positive association between HDL and HGBI is robust to potential endogeneity concerns.

Table 5. CMP Results for Endogeneity Correction.

	Model 10 (1)	Model 10 (2)
	HDL	HGBI
RS	0.013 ***	
	(9.96)	
HDL		7.051 ***
		(9.84)
Controls	YES	YES
Regional fixed	YES	YES
N	6903	6903
Atanhrho		−0.737 ***

z-statistics in parentheses. *** $p < 0.01$.

5.4. Exploratory Channel Analysis

To further explore the underlying channels linking HDL and HGBI, this study conducts an exploratory channel analysis; the results are shown in Table 6.

Table 6. Exploratory Channel Analysis.

	Model 11 (1)	**Model 11 (2)**	**Model 12 (1)**	**Model 12 (2)**
	DS Satisfaction	HGBI	Eco-consciousness	HGBI
HDL	0.045 **	0.512 *	0.867 **	0.563 **
	(2.169)	(1.880)	(2.008)	(2.106)
DS Satisfaction		5.415 ***		
		(33.084)		
Eco-consciousness				2.317 ***
				(23.042)
Constant	0.602 ***			
	(45.063)			
Controls	YES	YES	YES	YES
Regional fixed	YES	YES	YES	YES
N	6903	6903	6903	6903

z-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

To further explore the potential channels linking HDL and HGBI, this study conducts an exploratory channel analysis. The first step examines the association between HDL and HGBI, as reported in the baseline regression. The second step examines whether HDL is associated with the proposed channel variables. The third step incorporates each channel variable into the HGBI regression to assess whether it is associated with green and low-carbon lifestyle behaviors after controlling for HDL. Given the cross-sectional nature of the data, the results should be interpreted as suggestive evidence of potential channels rather than as definitive evidence of underlying pathways.

The digitization of households can enhance residents' satisfaction with smart home technology through technological innovation; higher satisfaction, in turn, strengthens residents' recognition of the eco-friendly nature of smart homes, and is associated with the realization of a greener lifestyle [37]. This study measures households' satisfaction with digital smart technology based on their overall satisfaction across four dimensions: satisfaction with the infrastructure currently provided by their community; overall satisfaction with the smart devices and systems currently in their homes; satisfaction with the ease of use of smart devices; and satisfaction with after-sales service for smart home systems [38]. As shown in Model 11 (1) of Table 6, HDL is positively associated with satisfaction with smart home technology. Model 11 (2) further includes both HDL and smart home technology satisfaction in the HGBI regression. The coefficient of satisfaction is significantly positive, indicating that smart home technology satisfaction is an important potential channel linking HDL and green and low-carbon lifestyle behaviors, consistent with H2.

As households become more digitally connected through HDL, residents can more easily access targeted and engaging environmental information. This enables families to gain a clear understanding of how their daily actions impact the environment, thereby raising environmental awareness and fostering green and low-carbon lifestyles. This study measures households' environmental awareness based on their views regarding the question: "Do individual daily consumption habits have a significant impact on global carbon emissions?" [39]. Although this measure captures an important aspect of environmental awareness, it is based on a single survey item and may not fully reflect the multidimen-

sional nature of environmental cognition. Results are shown in Model 12 (1) of Table 6. The regression coefficient is significantly positive, indicating that higher levels of household digitalization are associated with greater environmental awareness. Model 12 (2) further shows that environmental awareness is positively associated with HGBI after controlling for HDL, indicating that environmental awareness is another important potential channel linking HDL and HGBI, consistent with H3.

5.5. Heterogeneity Analysis

To further examine whether the relationship between HDL and the HGBI varies across individual and household characteristics and thus exhibits heterogeneity, this study conducted a heterogeneity analysis from the following three perspectives, as shown in Table 7.

Table 7. Heterogeneity Analysis.

	Model 13	**Model 14**	**Model 15**	**Model 16**	**Model 17**	**Model 18**
	Large family	Small family	Urban/Suburban	Rural area	E&D Cons	S Cons
HDL	1.002 ***	0.031	0.933 ***	−0.432	1.036 ***	0.238
	(3.125)	(0.066)	(3.111)	(−0.738)	(2.853)	(0.603)
Controls	YES	YES	YES	YES	YES	YES
Regional fixed	YES	YES	YES	YES	YES	YES
N	4762	2141	5387	1516	3751	3152
Pseudo R^2	0.093	0.132	0.080	0.232	0.077	0.142

z-statistics in parentheses. *** $p < 0.01$.

Initially, there is a correlation between household size and resource consumption patterns, which often vary depending on household size. These differing consumption patterns, in turn, lead to variations in how HDL influences the HGBI [40]. This study divides the sample into large-scale family and small-scale family based on the median number of household members. As shown in columns Model 13 and Model 14 of Table 7, the positive association between household digitalization and the HGBI is more pronounced in large-scale family. A possible reason is that small-scale family consume fewer resources overall and have relatively concentrated consumption patterns, resulting in weaker intrinsic motivation to use digital tools for energy conservation and waste reduction. In contrast, large-scale family consume significantly more resources and have more complex energy usage patterns; resource waste can substantially increase their living costs, leading to a stronger willingness to adopt environmentally friendly and energy-saving practices. These factors may help explain why the positive association between HDL and HGBI appears stronger among large households.

Furthermore, there is the urban–rural divide. Due to disparities in digital infrastructure and digital development between urban and rural areas, the relationship between HDL and HGBI may vary across regions. Classifying the sample into urban, suburban, and rural groups based on residential location, the regression results in columns Model 15 and Model 16 of Table 7 indicate that the positive association between household digitalization and the HGBI is more pronounced in urban areas. The reason is that urban areas have more developed digital infrastructure and broader network coverage, providing a solid hardware foundation and service guarantees for enabling green living through household digital technologies [41]. In comparison, rural areas suffer from underdeveloped digital infrastructure, unstable network conditions and much lower penetration of smart home equipment relative to cities. Rural residents also generally face insufficient digital literacy, and household digitalization is mostly applied to online shopping and consumption-focused digital services rather than green daily practices. Such consumption-biased digital development

easily triggers consumption rebound effects that partially offset the environmental gains of HDL. The estimated coefficient for rural households is not statistically significant and therefore does not provide evidence of a systematic association between HDL and HGBI in rural areas. These multi-layered urban–rural gaps may help explain the observed regional heterogeneity in the relationship between HDL and HGBI.

Finally, there are differences in consumption patterns. This study categorizes consumption patterns into subsistence, enjoyment, and development types. It constructs a consumption pattern index based on the proportion of the combined annual expenditure on enjoyment and development types relative to total annual household income [42]. Samples with values above the average consumption pattern index are classified as enjoyment and development-type consumption (denoted as E&D Cons), while those below the average are classified as subsistence-type consumption (denoted as S Cons). The regression results correspond to columns Model 17 and Model 18 in Table 7. Notably, in households where development-oriented consumption predominates, HDL shows a stronger association with green and low-carbon lifestyle behaviors. This is because the core needs of households where subsistence-oriented consumption predominates regarding digital tools lie in low cost and convenience; consequently, such households tend to use digital tools primarily to conveniently obtain necessities rather than to purchase higher-priced energy-efficient home products. For households focused primarily on enjoyment-oriented and development-oriented consumption, the core focus of their spending is no longer basic survival, but rather improving the quality of life for themselves and their families. The health and low-carbon benefits offered by digital green features align perfectly with the core aspirations of these households. Consequently, a stronger positive association between HDL and HGBI is observed among households characterized by enjoyment- and development-oriented consumption.

Results of the heterogeneity analysis are shown in Figure 4.

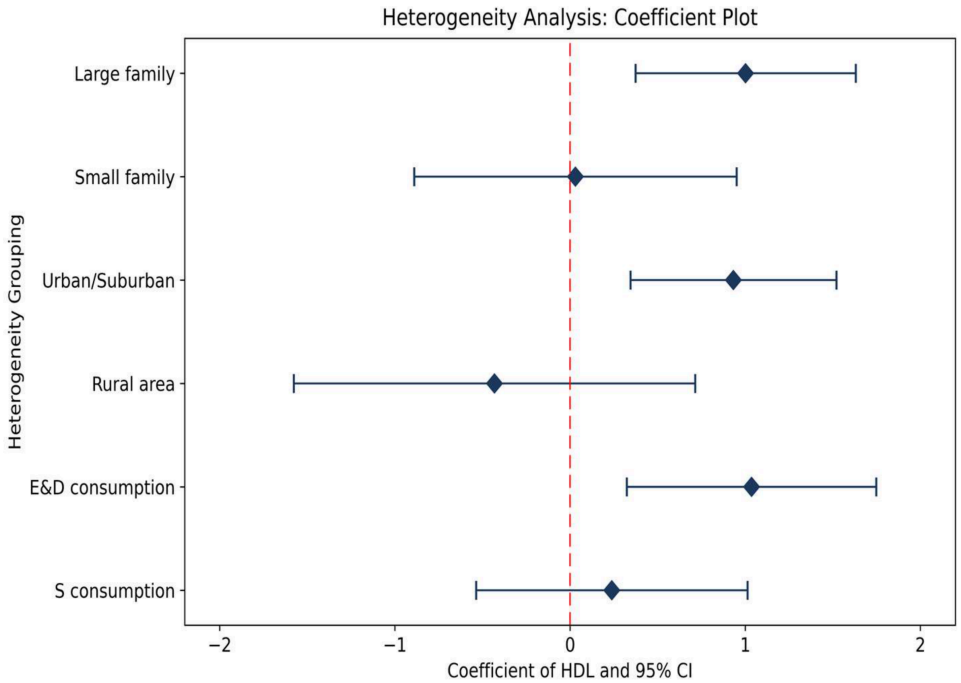


Figure 4. Analysis Chart of the Coefficient of Heterogeneity in Household Digitalization. Note: Diamonds indicate coefficient estimates, horizontal lines indicate 95% CIs, and the dashed vertical line indicates zero.

To further assess whether the estimated HDL coefficients differ across groups, bootstrap-based group-difference tests were conducted. The corresponding results are reported in Supplementary Materials.

6. Discussion

The findings of this study suggest that household digitalization is positively associated with the adoption of green and low-carbon lifestyles. This result is consistent with studies arguing that digital technologies can reduce information frictions, improve access to services, and facilitate the adoption of sustainable consumption practices. By lowering the costs of information acquisition and behavioral adjustment, digitalization may create favorable conditions for households to engage in green and low-carbon behaviors [43].

This study further finds that satisfaction with smart home technology and environmental awareness are important channels linking household digitalization and green lifestyles [44]. In addition, the relationship exhibits significant heterogeneity across household groups, with stronger associations observed among urban households, larger households, and households with higher consumption levels [45]. These findings suggest that digital access, digital capabilities, and household resources may influence the extent to which digitalization translates into green behavioral outcomes [46].

At the same time, the environmental implications of digitalization remain a subject of ongoing debate. While digital technologies may facilitate green lifestyles, they may also generate rebound effects through increased energy use, online consumption, and logistics activities [47]. The findings of this study indicate an overall positive association between household digitalization and green lifestyles, but future research could further examine these potential effects.

Several limitations of this study deserve discussion. First, the analysis relies on cross-sectional and self-reported survey data, which restricts this study to examining correlational relationships rather than identifying rigorous causal effects between household digitalization and green and low-carbon lifestyles. Second, while the composite HDL index captures the overall level of household digitalization as intended, some indicator components may be only indirectly connected to residents' green behaviors. This study addresses this concern through a supplementary sensitivity test that reconstructs a revised HDL index (r-HDL) after removing weakly green-relevant indicators. Even so, future studies could further decompose HDL into its subdimensions to identify which specific aspects of household digitalization are more closely associated with sustainable household lifestyles. Third, the CMP model results should be interpreted only as supplementary evidence for addressing potential endogeneity concerns and cannot provide definitive causal inference. Fourth, the online questionnaire survey was conducted in digital household pilot regions, and no post-stratification or calibration weighting was applied to adjust sample representativeness. Finally, the relatively small number of pilot regions should be considered when interpreting the statistical inference. This study employs heteroskedasticity-robust standard errors and regional fixed effects in the baseline specification. Nevertheless, because the data are drawn from 19 Digital Household Pilot Regions, the statistical inference should still be interpreted with caution. Future research could further expand the regional sample to examine the robustness of the findings. Overall, the findings provide useful pilot-based evidence for understanding the relationship between household digitalization and green and low-carbon lifestyle behaviors, although their applicability beyond the pilot contexts warrants further examination. Future research could further examine this relationship using longitudinal data, more refined HDL subdimensions, and direct measures of household carbon-emission outcomes.

7. Conclusions and Policy Recommendations

7.1. Conclusions

Using survey data from 6903 households in digital home pilot regions, this study examines the relationship between household digitalization and green and low-carbon lifestyles. The results show that household digitalization is positively associated with the adoption of green and low-carbon lifestyle behaviors, and this finding remains robust across multiple specifications. Exploratory channel analysis suggests that satisfaction with smart home technology and environmental awareness are important channels linking household digitalization and green lifestyles. In addition, the relationship exhibits significant heterogeneity across household groups.

Overall, this study provides household-level empirical evidence on the relationship between digitalization and sustainable lifestyles and offers useful implications for promoting the coordinated development of digital transformation and green transition.

7.2. Policy Recommendations

Considering the policy context of the digital home pilot program and the observed association between household digitalization and green and low-carbon lifestyles, the following policy implications are proposed.

(1) Integrating green and low-carbon orientation. The government may incorporate green and low-carbon lifestyle indicators into digital home policies. Support and resources can focus on energy-efficient appliances, household carbon management, and digital platforms for green consumption, while encouraging market actors to develop green smart products suited to household needs.

(2) Guiding digital platforms to support green practices. The government may guide digital platforms to provide low-carbon information, shared services, and green consumption options for households. It can also improve relevant standards for device usability, service quality, after-sales support, energy-use visualization, and carbon tracking, so that digital household services better support environmental awareness and routine green practices.

(3) Adapting policies to household heterogeneity for sustainable green transitions. The government may tailor policy measures to different household types. For rural households, priority should be given not only to improving digital infrastructure and service availability, but also to guiding digital tools toward green consumption rather than excessive online consumption. For small households, targeted subsidies and affordable green products may help reduce adoption barriers. For urban households and households with higher consumption levels, policies should encourage advanced digital green living scenarios while preventing convenience-driven overconsumption and rebound effects.

(4) Strengthening foundational safeguards for household green transitions. The government may consider raising household income levels through measures such as social welfare and employment support, thereby providing the material foundation for a green and low-carbon lifestyle; optimize the design of digital household products and services to better suit the needs of households of various sizes; and conduct comprehensive digital skills training in pilot regions, covering heads of households of all ages, to enhance their ability to operate digital devices and practice green living, enabling more families to share in the benefits of digital green development and jointly build a green lifestyle for households.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su18136539/s1. Supplementary Note S1: Reliability and factor analysis results for HGBI; Supplementary Note S2: Digital household pilot regions and sample sizes; Supplementary Note S3: Calculation of household total carbon emissions; Supplementary Note S4: Average marginal effects of HDL on HGBI categories; Supplementary Note S5: Bootstrap group-difference tests for heterogeneous associations; Tables S1–S7: detailed supplementary results.

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Institutional Review Board Statement: In alignment with China's Measures for the Ethical Review of Life Science and Medical Research Involving Human Subjects (2023), this study is exempt from ethical review. The research design and protocol are scientific, reasonable, fair and impartial, and will not cause obvious harm or risk to participants. The recruitment of participants follows the principles of voluntary and informed consent, and the research process can effectively protect the rights and privacy of participants. There is no conflict of interest or violation of ethics, laws and regulations in this research. According to the regulations of School of Economics, Qingdao University, ethics approval can be waived.

Informed Consent Statement: Informed consent for participation was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

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