sustainability

MDPI

Article

Do Green Information and Communication Technologies (ICT) and Smart Urbanization Reduce Environmental Pollution in China?

Shiping Xu [1] and Lili Wang [2,*]

[1] School of Public Administration, China University of Geosciences, Wuhan 430074, China; shpxu@126.com
[2] Institute of Railway Technology, Lanzhou Jiaotong University, Lanzhou 730070, China
* Correspondence: wanglili@mail.lzjtu.cn

Abstract: Due to rapid urbanization and industrialization, China faces numerous environmental challenges, including air and water pollution, resource depletion, and climate change. Adopting green ICT and smart urbanization is a critical strategy to address these challenges. At the heart of this study lies the question: Do green ICT adoption and smart urbanization contribute positively to environmental pollution reduction? Therefore, this study intends to scrutinize the influence of green ICT and smart urbanization on environmental pollution in China, focusing on the period from 1996 to 2021. The most up-to-date method of structural modeling, partial least squares structural equation modeling (PLS-SEM), was used to estimate the quantitative connection between green ICT, smart urbanization, and environmental pollution. The findings of the structural model show that only the path coefficient between smart urbanization and environmental pollution is significant and negative. Renewable energy consumption directly and negatively influences environmental pollution, whereas smart urbanization directly and positively affects renewable energy consumption and green ICT. Consequently, renewable energy consumption and green ICT negatively influence environmental pollution. Based on the findings, the study proposes targeted public policy recommendations aimed at fostering the development of green ICT and smart urbanization initiatives in China.

Keywords: green ICT; smart urbanization; environmental pollution

check for updates

Citation: Xu, S.; Wang, L. Do Green Information and Communication Technologies (ICT) and Smart Urbanization Reduce Environmental Pollution in China? *Sustainability* **2023**, *15*, 14492. https://doi.org/10.3390/su151914492

Academic Editor: Wen-Hsien Tsai

Received: 17 August 2023
Revised: 9 September 2023
Accepted: 21 September 2023
Published: 5 October 2023

1. Introduction

In recent years, the rapid growth of urbanization and technological advancements has given rise to an era of unprecedented transformation, with profound implications for both the environment and human societies [1]. This paradigm shift has led to the emergence of concepts such as green ICT and smart urbanization, which hold the promise of revolutionizing the way we interact with our surroundings [2]. At the forefront of this global movement stands China, a nation of remarkable dynamism and innovation, where the interplay between green ICT and smart urbanization is shaping a new trajectory toward environmental quality. China's trajectory is of particular significance due to its unique blend of challenges and opportunities. With a colossal population and burgeoning urbanization, the country faces intricate challenges in balancing economic growth with ecological conservation [3]. The rise of China as a global economic powerhouse has been meteoric, accompanied by a swift and profound urban revolution. With a population exceeding 1.4 billion and a relentless migration to urban centers, urbanization has become a crucible of challenges for environmental quality [4]. The imperatives of sustaining economic growth, improving quality of life, and safeguarding the natural world have catalyzed a quest for innovative solutions—a quest that finds its essence in the transformative potential of green ICT and smart urbanization [5].

Green ICT, encompassing sustainable practices in the realm of information technology, and smart urbanization and characterized by intelligent infrastructure and data-driven urban planning, have emerged as twin pillars of China's strategy to navigate the complex terrain of development while minimizing its ecological footprint [6]. This synergy transcends mere technological integration; it is a manifestation of a collective ambition to forge a path that balances human needs with the imperatives of a resilient environment. By harmonizing these imperatives, China seeks to recalibrate its growth trajectory, redefining resource consumption patterns, waste management practices, energy efficiency standards, and emissions control mechanisms [7].

Green ICT, as highlighted in the existing literature, play a crucial role in significantly reducing environmental pollution [8]. They achieve this through the promotion of energy-efficient hardware, software, and practices, enabling organizations to design power-efficient electronic devices, data centers, and networks that curtail energy consumption. These energy savings translate to lower operational costs, a substantial portion of ICT-related expenses while concurrently mitigating the environmental impact linked to energy production and consumption [9]. Additionally, green ICT foster efficient resource utilization, exemplified by practices such as virtualization and cloud computing, which optimize resource usage. This results in reduced hardware requirements, lower equipment purchasing costs, and a notable reduction in electronic waste generation [10]. The economic benefits extend to prolonging the lifespan of existing infrastructure and reducing the necessity for frequent hardware upgrades, thus further contributing to the reduction of electronic waste and environmental pollution [8–11].

Green ICT play a pivotal role in reducing environmental pollution by enabling remote work and telecommuting through advanced communication and collaboration tools. This leads to decreased commuting, resulting in reduced traffic congestion, lower fuel consumption, and decreased greenhouse gas emissions [12]. Additionally, green ICT facilitate the development of smart grids and advanced energy management systems, optimizing energy distribution and consumption while allowing for real-time monitoring and control of energy flows [13]. This reduction in energy wastage improves operational efficiency for utilities and helps avoid costly infrastructure upgrades. Consumers, in turn, benefit from more stable energy prices and reduced electricity bills [14]. Notably, the adoption of green ICT strategies offers economic advantages by optimizing resource use, reducing energy consumption, and enhancing operational efficiency [15]. These economic benefits, in turn, contribute to environmental quality by curbing emissions, minimizing resource depletion, and fostering responsible technology practices [16].

A bulk of the literature demonstrates that smart urbanization exerts a profound influence on environmental quality [17]. Smart urbanization emphasizes efficient resource utilization through technologies such as smart grids, efficient waste management systems, and sustainable water management. By optimizing resource distribution and consumption, cities reduce operational costs over the long term by reducing environmental pollution [18]. Smart urbanization promotes sustainable transportation solutions, such as electric vehicles, bike-sharing programs, and integrated public transit systems. These initiatives reduce traffic congestion, decrease fuel consumption, and lower pollution emissions. As a result, residents spend less on transportation costs, and the city benefits from reduced environmental pollution-related health expenses and infrastructure maintenance [19]. Smart urbanization strategically aligns economic prosperity with environmental well-being by optimizing resource use, reducing operational costs, and enhancing the overall quality of life while simultaneously mitigating environmental pollution [20,21]. Smart urbanization relies on data analytics and real-time information to optimize city planning and governance. This data-driven approach improves efficiency in areas such as traffic management, waste collection, and public service delivery, directly contributing to the reduction of environmental pollution. Efficient services translate to lower operational costs for the city, potentially leading to reduced taxes or better allocation of funds to other sustainability initiatives aimed at combatting environmental pollution [22]. Smart urbanization fosters innovation hubs and a conducive environment for technology start-ups, driving economic growth and job creation while encouraging the development of sustainable technologies and solutions that combat environmental pollution [23]. As innovation flourishes, cities become more capable of addressing environmental challenges and implementing economically viable green solutions to tackle environmental pollution [23]. While the upfront investment in smart urbanization technologies and infrastructure is substantial, the long-term benefits often outweigh the costs by preventing environmental degradation, avoiding health-related expenses, and minimizing the impact of climate change, all of which contribute significantly to the reduction of environmental pollution and result in significant savings for the city and its residents over time [24].

The interconnections among green ICT, smart urbanization, and environmental pollution have yet to be thoroughly explored in empirical research. The research gap lies in the insufficient attention given to the intersection of green ICT, smart urbanization, and environmental pollution, despite their potential significance. Similarly, some research has indicated the positive influence of ICT implementation in urban transportation on environmental preservation. However, these prior investigations have failed to explicitly address the holistic impact of green ICT and smart urbanization on environmental pollution. In light of these gaps, this paper seeks to delve into the intricate connections between green ICT, smart urbanization, and environmental pollution in the context of China from 1996 to 2021. This study endeavors to shed light on the following pivotal questions: (i) Does the adoption of green ICT have a positive impact on reducing environmental pollution? (ii) Can the implementation of smart urbanization lead to a reduction in environmental pollution?

This study contributes novel insights through five distinct avenues. First, it pioneers an examination of the influence of green ICT on environmental pollution within the Chinese context. Second, it delves into the environmental consequences of smart urbanization efforts in China. Third, it advances the environmental literature by concurrently investigating the combined impacts of both green ICT and smart urbanization on environmental pollution. Fourth, the study employs the PLS-SEM method to scrutinize the intricate relationships between green ICT, smart urbanization, and environmental pollution. The validity of the measurement model is meticulously assessed through three key indicators: construct reliability, convergent validity, and discriminant validity. Lastly, to affirm the robustness of the findings, the study incorporates a vector autoregression (VAR) approach. Based on the comprehensive findings, this study not only advances our understanding of the interplay between green ICT, smart urbanization, and environmental pollution, but it also proposes targeted public policy recommendations aimed at fostering the development of green ICT and smart urbanization initiatives in China.

2. Literature Review

The major ecological danger to human wellbeing and survival now is the rise in carbon footprints [25]. The ICT revolution, it is believed, played a role in the renowned phenomena of global warming resulting from greater carbon emissions while ushering in a new age of economic prosperity amongst nations. The International Energy Agency [26] estimates that the ICT industry produces 2% of global CO_2 emissions while ICT goods account for 15% of all private power use globally. ICT dissemination is thus crucial while concentrating on environmental quality.

The ICT industry drains energy; in 2007, it produced 830 MtCO2e in carbon emissions. Notably, these carbon emissions are almost equivalent to the ones the aviation industry released in 2007 [27]. Additionally, it is anticipated that the ICT sector's release of carbon dioxide will rise by a mean of 6% per year until 2020 [28]. As a result, CO_2 is often utilized in the ICT literature as a stand-in for ecological damage. The literature on the relationship between ICT and carbon emissions can be divided into two groups [29].

The first group [30,31] makes the case that ICT and CO_2 emission are positively correlated. Trade and foreign direct investments will expand as a result of ICT. Industrialization and scale economies will benefit. Through the consumption of energy (such as fossil fuels) for electricity and the operation of mechanical frameworks, a growth in economic activity will result in a boost in carbon emissions. Thus, Avom et al. [30] argue that ICT mostly cause a rise in CO_2 emissions due to commerce, financial growth, and energy usage. Nevertheless, the sort of energy used will determine CO_2 emissions. Renewable energy really reduces CO_2 emissions, but non-renewable energy actually increases them [32]. Additionally, trade openness encourages economic integration and global value chains, which have recently been shown to be the primary contributors to CO_2 emissions [33].

According to the second group of academics [34,35], ICT are thought to have a negative correlation with the release of CO_2. As a consequence, ICT increases reduce the impact of CO_2 emissions. ICT considerably lessen the influence of carbon footprints only at lower quantiles, but economic expansion and financial growth lead to carbon emissions across all quantiles [36]. The usage of many conventional commodities has decreased as a result of advancements in ICT and the widespread use of electronic products and services, including online conferences, distance learning, e (electronic) books, online banking, and e-commerce. For example, virtual conferences have mostly supplanted conventional meetings. Additionally, the necessity for travel has decreased thanks to e-commerce while conventional books have been switched to e-books, and letters have been similarly supplanted by e-mails. The massive substitution of conventional goods with new ones minimizes the use of resources and, therefore, the procedures associated with that consumption that contribute to the deterioration of the environment. Additionally, the ICT revolution has prompted the embrace of contemporary modes of transportation and the installation of contemporary traffic-control software, resulting in decreased energy use and emissions [37]. As a result, ICT have improved electronic commerce as a substitute for previous trading systems, lowering human interaction, transportation, and use of energy, which are the primary sources of CO_2 emissions.

In addition to the aforementioned linear impacts, other research groups have emphasized non-linear correlations between ICT and CO_2 emission [35,38]. ICT might be a factor in the rising levels of CO_2 emissions if they are used to produce ICT equipment, use energy, and recycle electronic trash. ICT are also expected to help reduce CO_2 emissions globally if they are geared toward the creation of smarter cities, transportation networks, electrical grids, and industrial processes. These two influences create an inverted-U nexus between CO_2 emissions and ICT, which are discernible in opposing directions [39]. Through a scale effect, ICT adoption by businesses may boost productivity and raise emissions. The manufacturing procedure is optimized, and energy efficiency is realized with the ICT capital in place, decreasing pollutants via the technical impact. ICT, according to some scholars, have little impact on the environment. According to Asongu et al. [34], ICT by means of mobile phones do not significantly affect CO_2 emissions on their own, but the entire impact within the scope of an interaction regression produces net positive and negative effects dependent on the CO_2 trends.

Numerous impacts of urbanization on the condition of the environment have been discovered in empirical research. Numerous empirical studies for various developed and developing economies across different periods confirmed that urbanization boosts carbon footprints. For instance, Majeed and Tauqir [40] and Nathaniel et al. [41] analyzed the urbanization–environment nexus for South Asian economies from 1983 to 2013 and Caribbean nations from 1990 to 2017. On the other hand, several studies have shown beneficial effects of the urbanization–environment nexus, such as for 19 developing countries from 1990 to 2013 [42] and 55 middle-income nations from 1992 to 2012 [43]. Likewise, Chatti and Majeed [44] conducted an analysis covering the years 1998 to 2016, encompassing both developing and developed nations. Their findings indicated that smart urbanization has the potential to enhance environmental quality in both types of economies.

According to some researchers, the relationship between urbanization and the environment has little bearing on how much urbanization affects the environment in either a good or bad way. Cole and Neumayer [45] estimated a negligible effect of urbanization on carbon footprints for 86 nations between 1975 and 1998 while Sadorsky [46] indicated an insignificant effect for 16 countries between 1971 and 2009. Other research projects show that urbanization will have variable and/or asymmetrical environmental effects. Luo et al. [47] produced contradictory data on the relationship between urbanization and the ecosystem, showing that urbanization has a detrimental impact on the environment in China. Wei et al. [48] examined belt and road initiative nations regarding various income brackets and found that although urbanization generally results in more pollution, it has little effect on carbon footprints across different income brackets. Urban environmental issues have prompted research to pay more consideration to applying cutting-edge technology in urban settings. ICT infrastructure in urban environments is commonly recognized as being important. At this point, smart and green urbanization are critical demands.

3. Materials and Methods

In the last few decades, the covariance-based structural equation modeling (CB-SEM) approach, which scrutinizes complicated associations between recognizable and latent variables, has been the primary choice of researchers [49]. In comparison to CB-SEM, the studies published in the past few years employing PLS-SEM have significantly matured [50]. Indeed, PLS-SEM is now frequently used in a variety of social science fields [51]. Many researchers find the PLS-SEM approach to be highly attractive. It allows them to calculate bulky models with numerous structures, indicator factors, and structural routes without putting distributive presumptions on the data. Nevertheless, PLS-SEM is a causal-predictive strategy for SEM that stresses anticipation in generating statistical frameworks whose structures are intended to give causal explanations [52]. This makes it more significant. The method, therefore, resolves the seeming opposition between description and prediction, which is the foundation for creating managerial effects and is often stressed in scientific studies [53]. In addition, there are simple-to-use software programs that usually demand little technical understanding of the methodology, such as PLS-Graph [54] and Smart PLS [55], as well as more sophisticated programs for statistical computing settings, such as R, that are capable of running PLS-SEM. More thorough justifications and explanations of whether to implement and when not to employ PLS-SEM are provided by Richter et al. [56].

PLS-SEM is known as variance-based since it considers the whole variance and utilizes it for estimating parameters [50]. PLS-SEM use in various circumstances has been hotly contested over the last ten years. The following are the justifications for selecting the PLS-SEM approach over the CB-SEM method. First, PLS-SEM differs from CB-SEM in that it does not need the data to have a normal distribution and be large. Second, PLS-SEM provides greater statistical features for data than CB-SEM and can more naturally express the relevance of data. Third, PLS-SEM is better suited to investigating and constructing mathematical models. It may also be used to validate previously investigated causal links. The system will experience several effects when there is a multiple collinearity issue. For instance, the multicollinearity would raise the predicted variance of the regression estimates, and the reliability is quite bad. The crucial point is that separating each regressor's unique impact on the dependent variable is challenging. Therefore, the multicollinearity issue must be solved. In comparison to other approaches, including the standard "least squares method, principal component analysis, and ridge regression", the approach known as partial least squares (PLS) is more adequately equipped to address the issue of multicollinearity. This helped the study accomplish its research goal. This study selected a structural equation model (SEM) in accordance with partial least squares (PLS) by integrating the criteria mentioned above.

3.1. Measurement Model

In this scenario, we considered *J* series of observable variables, each group consisting of p_j variables. These observable variables, denoted as X_j (X_{j1}, X_{j2}, . . ., X_{jpj}) for j = 1, 2, . . ., J, are often represented from n different perspectives, and each variable is intensive. Each series of observable variables is associated with a corresponding latent variable, standardized to have a mean of 0 and a variance of 1. This standardization creates a measurement model, also known as an outer model. The relationship between observable variables and latent variables is explored using two methods in the outer model. The first method is the reflective measurement, where each observable variable X_{jh} (j = 1, 2, . . ., J; h = 1, 2, . . ., p_j) is correlated with a single latent variable. Following Hair et al. [57], the relationship between the j groups of observable variable X_{jh} and its latent variable can be expressed through a linear regression equation as follows:

$$X_{jh} = \lambda_{jh}\xi_{jh} + \varepsilon_{jh} \tag{1}$$

ε_{jh} represents the stochastic error term in the equation. The aforementioned equation fulfills the specified assumptions:

$$E\left(X_{jh}/\xi_j\right) = \lambda_{jh}\xi_j \tag{2}$$

The hypothesis suggests that the residual mean is 0, showing no association with the latent variable, known as the forecast-appointed condition. Reflective measurement indicates a causal relationship between latent and observable variables, and SmartPLS3 software offers three methods to investigate this relationship: principal component analysis, Cronbach's Coefficient α, and Dillon Goldstein's rho coefficient ρ. When observable variables do not meet the examination criteria, certain variables can be excluded or separated within the group to meet the necessary conditions. Formative measurement indicates that the latent variable ξ_j is a linear combination of all variables in its observable variable group [58].

$$\xi_j = \sum_{h=1}^{p_j} WX_{jh} + \delta_j \tag{3}$$

δ_j serves as the stochastic error term in the equation. Equation (4) is expected to fulfill the forecast-appointed condition:

$$E\left(\xi/x_1, x_2, \ldots, x_j\right) = \sum_{h=1}^{p_j} WX_{jh} \tag{4}$$

We can infer that the residual δ_j has a mean of 0 and is independent of the observable variable X_{jh}.

3.2. Structure Model

Structural models describe implicit variables with distinct causal connections and are typically represented using linear equations [59]. The linear equation is expressed as:

$$\xi_j = \sum_{i \neq j} \beta_{ij}\xi_i + \zeta_j \tag{5}$$

In the above equation, ζ_j is the stochastic error term that adheres to the forecast appointed condition, ensuring the residual averages to 0 and is unrelated to ξ_j. Equation (5) indicates the existence of interdependence relationships between significant variables, forming a causal association model that must be a causal chain, i.e., no circular relationships within the causal model. Thus, the causal association of the structural model can be depicted using a 0/1 square matrix with dimensions equivalent to the number of latent variables. When latent variable j influences latent variable i, the corresponding component in the matrix is assigned the value 1; otherwise, it remains 0. This matrix is commonly known as the internal design matrix.

3.3. Model Estimation

PLS primarily employs an iterative method to estimate latent variables. There are two approaches to performing this estimation. First, it involves computing the latent variables based on the relationship between observable variables and latent variables, which is also known as outer estimation. The latent variable ξ_j can be assessed by considering the linear combination of observable variables X_{jh} (j = 1, 2, . . ., J; h = 1, 2, . . ., p_j), and the resulting value is denoted as Y_j. Since the supposed latent variable ξ_j is normalized, the expression becomes:

$$Y_j = \left(\sum_{h=1}^{p_j} W_{jh} X_{jh}\right)^* = \left(X_j W_j\right)^* \tag{6}$$

In the above equation, W_j represents the weight vector, and the asterisk signifies normalization for the assessment. On the contrary, it is computed through the interconnections among latent variables, also known as inner estimation [60]. This method is employed to evaluate latent variables ξ_j and other related latent variables, represented as Z_j:

$$Z_j = \left(\sum_{i,\beta_{ij}} e_{ij} Y_i\right)^* \tag{7}$$

The coefficient in Equation (7) is denoted as β_{ij}, and e_{ji} represents the inner weight, which is calculated using Equation (8):

$$e_{ji} = sign\left(r\left(Y_j, Y_i\right)\right) = \begin{cases} 1, \left(r\left(Y_j, Y_i\right) > 0\right) \\ 0, \left(r\left(Y_j, Y_i\right) = 0\right) \\ -1, \left(r\left(Y_j, Y_i\right) < 0\right) \end{cases} \tag{8}$$

The "Sign" denotes the sign function, whereas $r(Y_j, Y_i)$ represents the relevant coefficient of the outer weight assessment for Y_j and Y_i. The formula for Model 1 is as follows:

$$W_j = \frac{1}{n} X_j^T Z_j \tag{9}$$

In these conditions, the weight vector W_j represents the relevant variable or variance of X_j and Z_j. Specifically, for normalized variables, W_j corresponds to the weight of the first component in Z_j's PLS to X_j, which is equivalent to the first axis vector of the PLS. The formula for Model 2 is as follows:

$$W_j = \left(X_j^T Z_j\right)^{-1} X_j^T Z_j \tag{10}$$

In light of these circumstances, W_j represents the coefficient in the equation obtained through normal least square regression for Z_j. Reflective measurement and formative measurement employ Model 1 and Model 2, respectively, to calculate the weights [61]. PLS effectively addresses multicollinearity. This paper utilized reflective measurement, and due to the observable variables' high correlation, Model 1 aligned better with PLS-SEM calculations. The iterative method was applied to compute the latent variables in the PLS-SEM model. The measurement model and structural model were subsequently derived using the estimated values of the latent variables.

3.4. Vector Autoregression

We applied vector autoregression (VAR) to check the robustness of our PLS-SEM results. It was used to examine the dynamic connections between several time series variables. It belongs to the larger field of time series analysis and is especially well-suited for examining the relationships and dependencies that develop over time between various variables [62]. In a VAR model, each variable in the system is regressed on its own lagged values as well as the lagged values of all other variables. This model assumes that the previous values of each variable and the past values of other variables in the system influence its current value. Consequently, researchers can examine the short-term dynamics and feedback loops among the variables [63].

4. Data

This study is to investigate the impact of green ICT and smart urbanization on environmental pollution in China between 1996 and 2021. Using China as the focus for this study offers several compelling reasons: (i) As the world's most populous country and one of the largest economies, China plays a crucial role in contributing to global environmental challenges. (ii) China has extensive data available on green ICT and smart urbanization. (iii) China has been actively implementing policies and initiatives related to green ICT and smart urbanization to address environmental issues. Four indicators are taken for the measurement of environmental pollution. These are CO_2 emissions in kilotons (CO_2), methane emissions in kilotons of CO_2 equivalent (CH4), nitrous oxide emissions in terms of thousand metric tons of CO_2 equivalent (NO2), and SF6 gas emissions in thousand metric tons of CO_2 equivalent (SF6). Green ICT diffusion (ICT) and smart urbanization (SU) are two focused variables. Whereas, the indicators of green ICT diffusion are climate change mitigation in information and communication technologies (CCM) and enabling smart technologies in transport (GT). Three indicators for smart urbanization and two indicators for green ICT diffusion are used in our model. The indicators of smart urbanization are internet users in urban areas as % of the total population (IU), access to clean fuels and technologies for cooking as % of the urban population (CT), and energy efficiency in urban buildings (SB). Renewable energy consumption (REC) is the control variable in our model. Three indicators are used for REC. These are wind energy consumption in megawatts (Wind), biofuels energy consumption in petajoules (Biomass), and hydroelectricity energy consumption in Exajoules (Hydro). Table 1 provides a comprehensive overview of each variable.

Table 1. Variables and abbreviations.

Variables	Description	Abbreviation	Sources
Environmental pollution (E)	CO_2 emissions (kt)	CO_2	WDI
	Methane emissions (kt of CO_2 equivalent)	CH4	WDI
	Nitrous oxide emissions (thousand metric tons of CO_2 equivalent)	NO2	WDI
	SF6 gas emissions (thousand metric tons of CO_2 equivalent)	SF6	WDI
Green ICT diffusion (ICT)	Climate change mitigation in information and communication technologies (ICT)	CCM	OECD
	Enabling smart technologies in transport	GT	OECD
Smart urbanization (SU)	Internet users in urban areas (% of total)	IU	WDI
	Access to clean fuels and technologies for cooking, urban (% of urban population)	CT	WDI
	Energy efficiency in urban buildings	SB	OECD
Renewable energy consumption (REC)	Solar energy consumption (Megawatts)	Solar	BP
	Wind energy consumption (Megawatts)	Wind	BP
	Biofuels energy consumption (Petajoules)	Biomass	BP
	Hydroelectricity energy consumption (Exajoules (input-equivalent))	Hydro	BP

5. Results and Discussion

In the current study, PLS-SEM evaluated both the measurement model (Figure 1) and the structural model (Figure 2). The study discovered both convergent and discriminant validity procedures as viable methods for estimating the measurement model. All of these metrics meet the standards for this study, which are shown in Table 2. The values for factor loadings, AVE, and CR should correspondingly be higher than 0.50, 0.50, and 0.60. Cronbach's alpha must be greater than 0.60 claims. In Table 2, it is shown that the AVE scores are greater than 0.50 while the CR scores exceed 0.60. Cronbach's alpha value is also greater than the prescribed threshold of 0.60, which is greater than 0.60. Table 3 shows, however, that the current study fits the requirements for discriminant validity, as is clear from the results. Table 3 illustrates the results of Fornell and Larcker's and reports that diagonal higher values are greater than alternative related data in identical columns and rows.

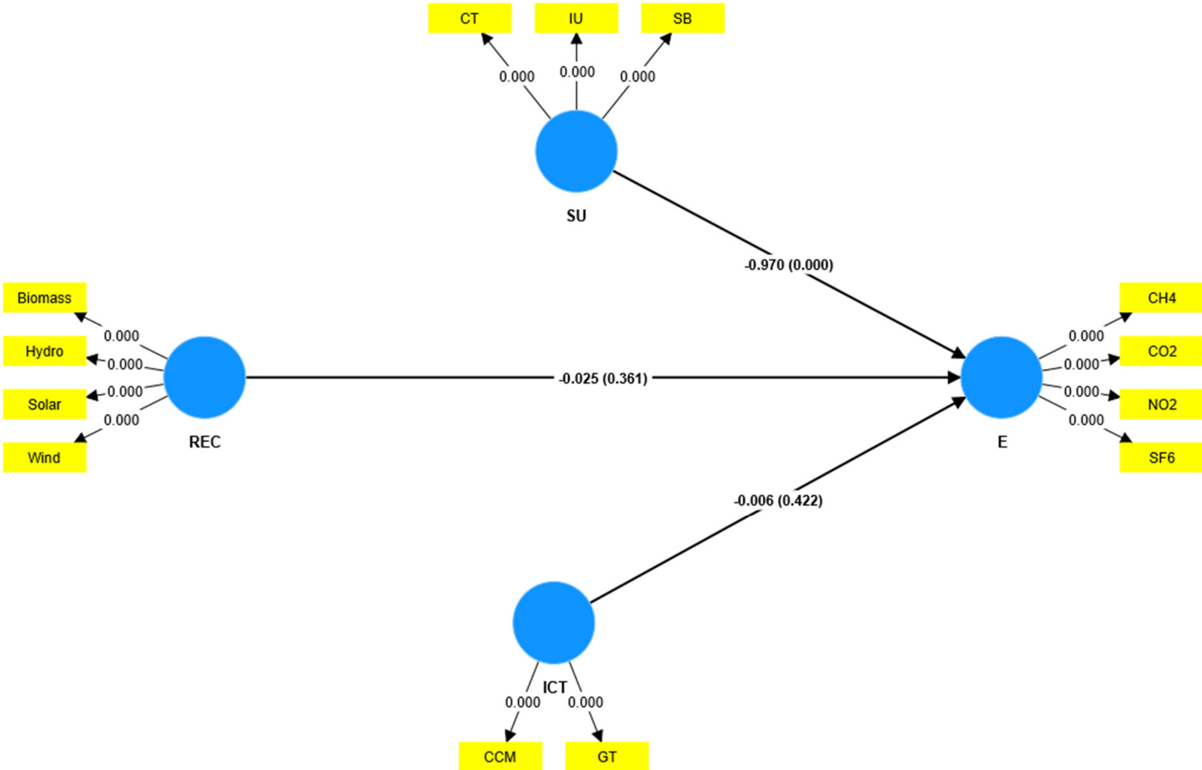

Figure 1. Measurement model.

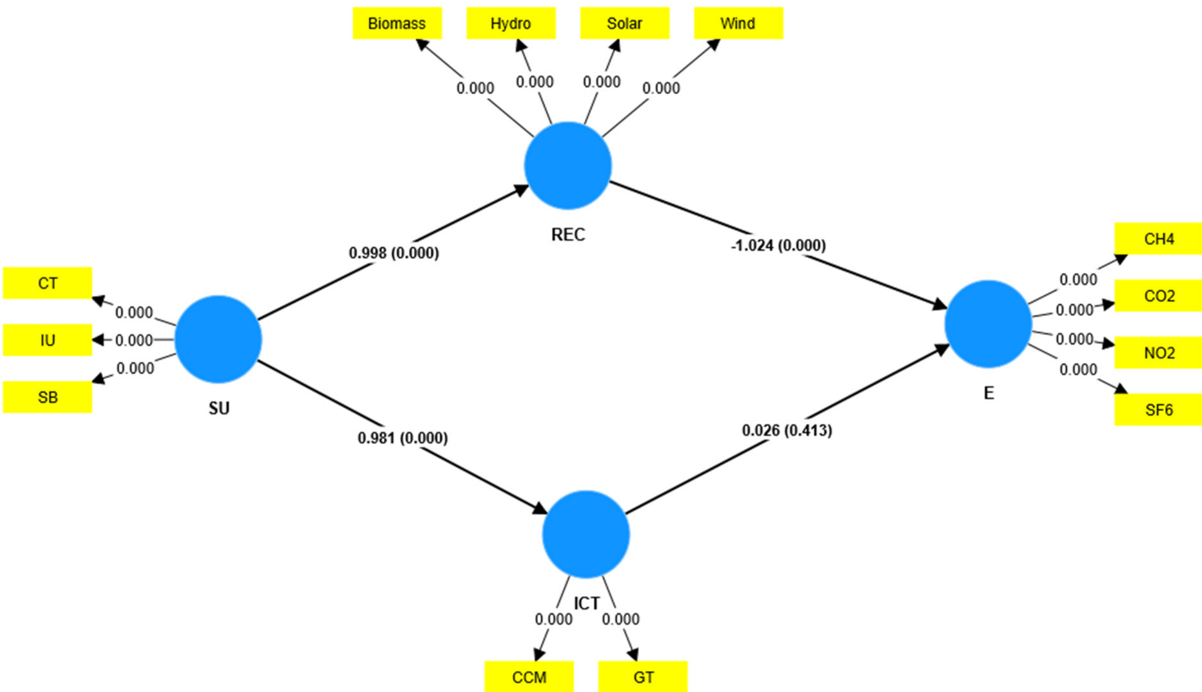

Figure 2. Structural model.

Table 2. Constructs' reliability and convergent validity.

	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
E	1	1	1	1
ICT	0.987	0.987	0.994	0.987
REC	0.996	0.996	0.997	0.989
SU	1	1	1	1

Note: Environmental pollution (E), Green ICT diffusion (ICT), Smart urbanization (SU), Renewable energy consumption (REC).

Table 3. Fornell–Larcker for discriminant validity.

	E	ICT	REC	SU
E	1			
ICT	−0.781	0.994		
REC	−0.858	0.564	0.994	
SU	−0.812	0.651	0.798	1

Note: Environmental pollution (E), Green ICT diffusion (ICT), Smart urbanization (SU), Renewable energy consumption (REC).

Tables 4 and 5 estimated the path coefficients between the variables and the direct and indirect influence of green ICT diffusion (ICT), smart urbanization (SU), and renewable energy consumption (REC) on environmental pollution (E). Table 4 shows that path coefficients between SU and environmental pollution, ICT and environmental pollution, and REC and environmental pollution are 0.970, 0.006, and 0.025, respectively. Only the path coefficient between smart urbanization and environmental pollution is negatively significant while the path coefficients between ICT and environmental pollution and renewable energy consumption and environmental pollution are negative but insignificant. This result implies that only smart urbanization helps reduce the environmental burden; however, ICT and renewable energy consumption do not significantly impact environmental pollution. This finding is backed by Guo et al. [64], who reported that smart urbanization increases energy-efficient technologies. These technologies help to reduce energy consumption and greenhouse gas emissions, thereby mitigating the negative impacts of urbanization on the environment. Similarly, Xu et al. [65] inferred that smart urbanization contains the implementation of intelligent transportation systems, such as smart traffic management and electric vehicles. These technologies reduce traffic congestion and air pollution in urban areas, thereby reducing greenhouse gas emissions. Moreover, smart urbanization also improves waste management practices in cities through the use of advanced technologies, such as smart bins and waste-to-energy systems. These technologies help to reduce the amount of waste generated and improve the efficiency of waste disposal, thereby reducing pollution and environmental degradation. Some studies have also reported a positive impact of smart urbanization on environmental pollution, which contradicts our findings. Li [66] revealed that smart urbanization involves the deployment of energy-efficient technologies, but it leads to increased energy consumption due to the growing demand for electricity and other energy services, thus enhancing environmental pollution. This finding is also contradicted by Qi et al. [67], who reported a positive association between smart urbanization and environmental pollution. They also reported that smart transportation increases greenhouse gas emissions by increasing overall energy consumption.

Table 4. Path coefficients.

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (∣O/STDEV∣)	*p* Values
SU → E	−0.970 ***	−0.961	0.058	16.76	0.000
ICT → E	−0.006	−0.009	0.029	0.197	0.422
REC → E	−0.025	−0.031	0.069	0.356	0.361
SU → E	−0.970 ***	−0.961	0.058	16.76	0.000

Note: Environmental pollution (E), Green ICT diffusion (ICT), Smart urbanization (SU), Renewable energy consumption (REC). *** $p < 0.01$.

Table 5. Direct and indirect effects.

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (∣O/STDEV∣)	*p* Values
REC → E	−1.024 ***	−0.998	0.119	8.579	0.000
SU → ICT	0.981 ***	0.982	0.156	6.288	0.000
SU → REC	0.998 ***	0.998	0.123	8.113	0.000
ICT → E	0.026	0.002	0.121	0.219	0.413
SU → ICT → E	−0.006 ***	−0.009	0.002	3.001	0.006
SU → REC → E	−0.025 ***	−0.030	0.004	4.166	0.003

Note: Environmental pollution (E), Green ICT diffusion (ICT), Smart urbanization (SU), Renewable energy consumption (REC). *** $p < 0.01$.

From Table 5, we can see the direct influence of REC on environmental pollution is negatively significant, with a coefficient value of 1.024. Smart urbanization positively affects ICT (0.981) and renewable energy consumption (0.998). However, smart urbanization does not directly influence environmental pollution, but smart urbanization indirectly impacts environmental pollution via ICT and renewable energy consumption. The indirect impact of smart urbanization helps reduce environmental pollution by 0.006% and 0.025%. The direct impact of ICT on environmental pollution is insignificant while it significantly and negatively impacts environmental pollution when ICT are driven by smart urbanization. In support of our findings, Wu et al. [68] described that green ICT promote energy-efficient practices and technologies. By reducing energy consumption, organizations lower their electricity bills, leading to direct cost savings. Additionally, decreased energy usage translates into reduced demand for fossil fuels, which are a major source of pollution emissions. This means that green ICT encourage virtualization and cloud computing, enabling multiple applications to run on fewer physical servers. This leads to reduced hardware requirements, lower maintenance costs, and a smaller physical footprint, which can contribute to less electronic waste and a decrease in pollution resulting from manufacturing, disposal, and resource extraction. These empirical inferences are also supported by Usman et al. [69], who described that green ICT emphasize responsible disposal and recycling of electronic waste. Proper e-waste management reduces the release of hazardous materials and pollutants into the environment. Effective e-waste recycling recovers valuable metals and components, reducing the need for resource extraction and contributing to a circular economy, which minimizes waste and conserves resources. Moreover, green ICT help in tracking and optimizing supply chains, ensuring that materials are sourced responsibly and sustainably. This reduces the environmental impact of resource extraction and transportation, leading to lower pollution levels. The economic benefit comes from reduced regulatory compliance costs, reputation enhancement, and long-term resource cost stability. Raihan [70] inferred that green ICT raise awareness about environmental issues through digital platforms. Educated individuals and businesses are more likely to adopt sustainable behaviors, such as reduced energy consumption and responsible waste disposal. The economic impact stems from reduced pollution-related health costs and improved public perception of environmentally conscious businesses. Contrary to our findings, certain studies have indicated a positive impact of green ICT on environmental pollution. Raheem et al. [71] revealed that green ICT components require significant energy inputs during their manufacturing processes. The energy-intensive production of these components results in increased greenhouse gas emissions and contributes to climate change. This finding is also contradicted by Avom et al. [30], who reported a positive nexus between green ICT and environmental pollution. The study described that green ICT initiatives encourage frequent hardware and software upgrades. This leads to a faster turnover of electronic devices, resulting in more e-waste. Additionally, the disposal of older devices may not be managed sustainably, contributing to pollution and resource depletion.

VAR-Robustness Results

Table 6 presents the results of the VAR model for robustness. The findings indicate significant relationships for China between E, ICT, SU, and REC in the E equation. Specifically, the first lags of E exhibit a positive correlation while ICT, SU, and REC demonstrate a negative correlation with E, implying that an increase in ICT, SU, and REC leads to a decline in the current level of E. However, E, ICT, and REC are statistically significant at second lags, showing a negative correlation with E. Moving on to the ICT equation, the results show that E, ICT, and SU are statistically significant at first lags, and their initial values positively correlate with the current level of ICT. Similarly, at second lags, ICT and SU maintain positive correlations with the current level of ICT, indicating that an increase in their initial values induces an upsurge in the current level of ICT.

Table 6. VAR results.

	E	ICT	SU	REC
E(−1)	1.810 ***	0.648 *	0.882 *	0.759 *
	[6.241]	[1.814]	[1.799]	[1.946]
E(−2)	−0.796 **	0.565	0.103	0.564
	[−2.437]	[0.163]	[0.184]	[0.373]
ICT(−1)	−0.081 **	0.041 **	0.016 **	0.055 **
	[−2.061]	[2.078]	[2.063]	[2.212]
ICT(−2)	−0.056 **	0.019 **	0.011 *	0.028
	[−1.979]	[2.033]	[1.909]	[0.737]
SU(−1)	−0.504 *	1.818 *	0.571 **	1.079 ***
	[−1.692]	[2.502]	[2.195]	[2.752]
SU(−2)	−0.211	0.544 *	0.206 *	0.249 **
	[−1.542]	[1.776]	[1.859]	[2.055]
REC(−1)	−0.080 ***	0.019	0.044	0.845 *
	[−2.858]	[0.013]	[0.288]	[1.837]
REC(−2)	−0.042 **	0.698	0.219	0.316 *
	[−2.457]	[0.713]	[1.371]	[1.733]

Note: Environmental pollution (E), Green ICT diffusion (ICT), Smart urbanization (SU), Renewable energy consumption (REC). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Regarding the SU equation, E, ICT, and SU are statistically significant at first lags, with their initial values positively influencing the current level of SU. At second lags, ICT and SU continue to be statistically significant and positively correlated with the current level of SU, suggesting that an increase in their initial values leads to a rise in the current level of SU. Lastly, the REC equation shows that E, ICT, SU, and REC at first lags are statistically significant and positively correlated with the current level of REC, indicating that an increase in their initial values results in an upswing in the current level of REC. At second lags, SU and REC are statistically significant and positively correlated with the current level of REC, inferring that an increase in their initial values induces a rise in the current level of REC.

The results of impulse response functions are depicted in Figures 3 and 4. In Figure 3, the findings reveal interesting patterns regarding the impact of one standard deviation shock in green ICT on various aspects of China. Regarding environmental pollution, the immediate effect of the shock was observed to be zero. However, from year 1 to year 2, a positive impact was evident, which gradually decreased until year 3. Interestingly, there was a subsequent increase from year 3 to year 4, followed by fluctuations from year 5 to year 8, and finally a persistent decline from year 8 to year 10. Similarly, when examining smart urbanization, the shock's immediate effect was positive. It then displayed an increasing trend from year 1 to year 2, but subsequently declined until year 3, becoming insignificant from year 3 to year 4. Nevertheless, from year 4 to year 8, a significant upward trend was observed, followed by a decline from year 8 to year 10. Regarding renewable energy consumption, the shock's immediate effect was positive. However, there was a declining trend from the first year to year 3, which was then reversed with an increase from year 3 to year 4. Subsequently, there was a slight decline until year 5, followed by an upward trend from year 5 to year 8. However, there was an abrupt decline from year 8 to year 9, which was later followed by an increase until year 10. Overall, these results shed light on the complex and dynamic relationships between green ICT diffusion and environmental pollution, smart urbanization, and renewable energy consumption in China over the specified time period.

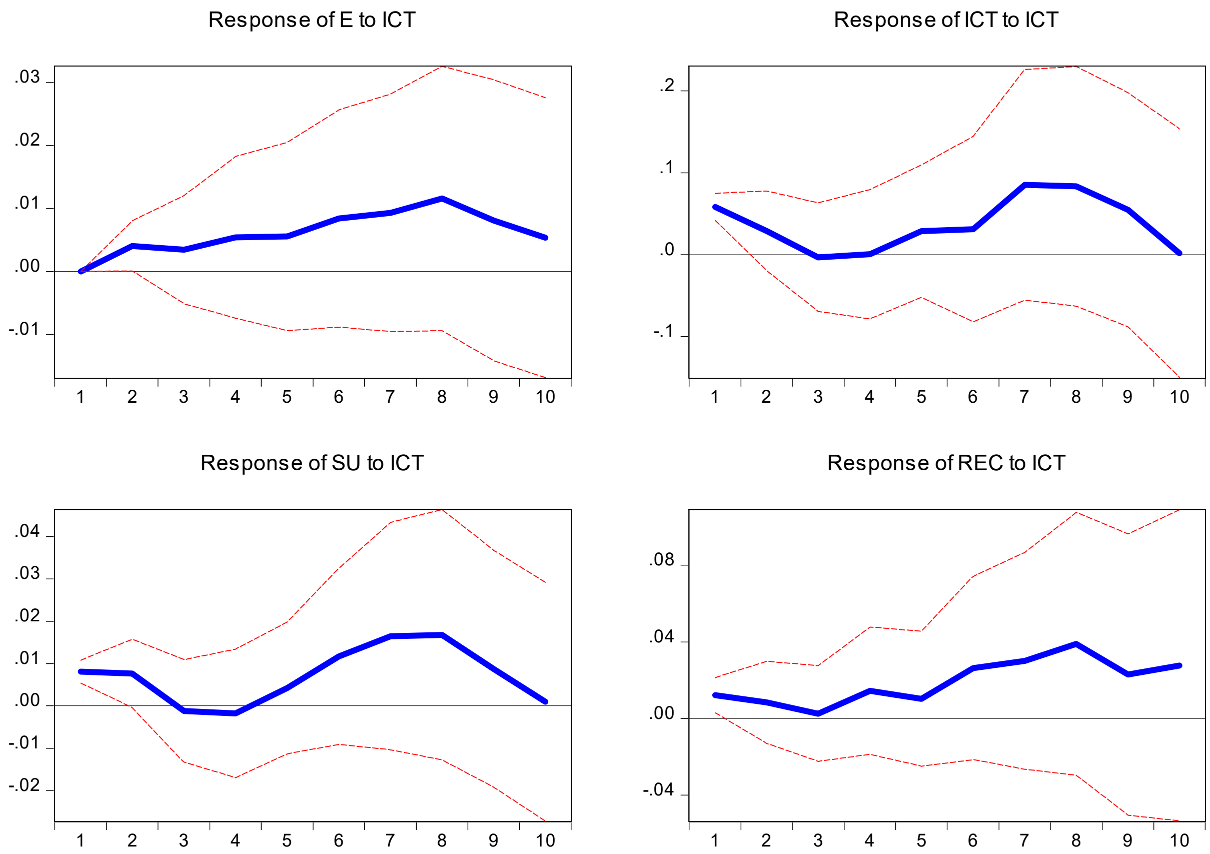

Figure 3. Impulse-response functions to a green ICT shock.

Figure 4 presents intriguing findings regarding the impact of a one-standard deviation shock in smart urbanization on various aspects of China. In terms of environmental pollution, the immediate effect of the shock was positive from year 1 to year 8. However, from year 8 to year 10, the impact showed a declining trend. When considering green ICT diffusion, the shock's immediate effect was positive. Nonetheless, it displayed a decline from year 2 to year 3, followed by a significant increase from year 3 to year 8. However, from year 8 to year 10, there was a subsequent decline. Regarding renewable energy consumption, the shock's immediate effect was also positive. However, there was a decline from the first year to year 2, followed by an increase from year 2 to year 7. Nevertheless, there was a decline again from year 7 to year 10. These results contribute valuable insights into the dynamic relationships between smart urbanization and its effects on environmental pollution, green ICT diffusion, and renewable energy consumption over the specified period in China.

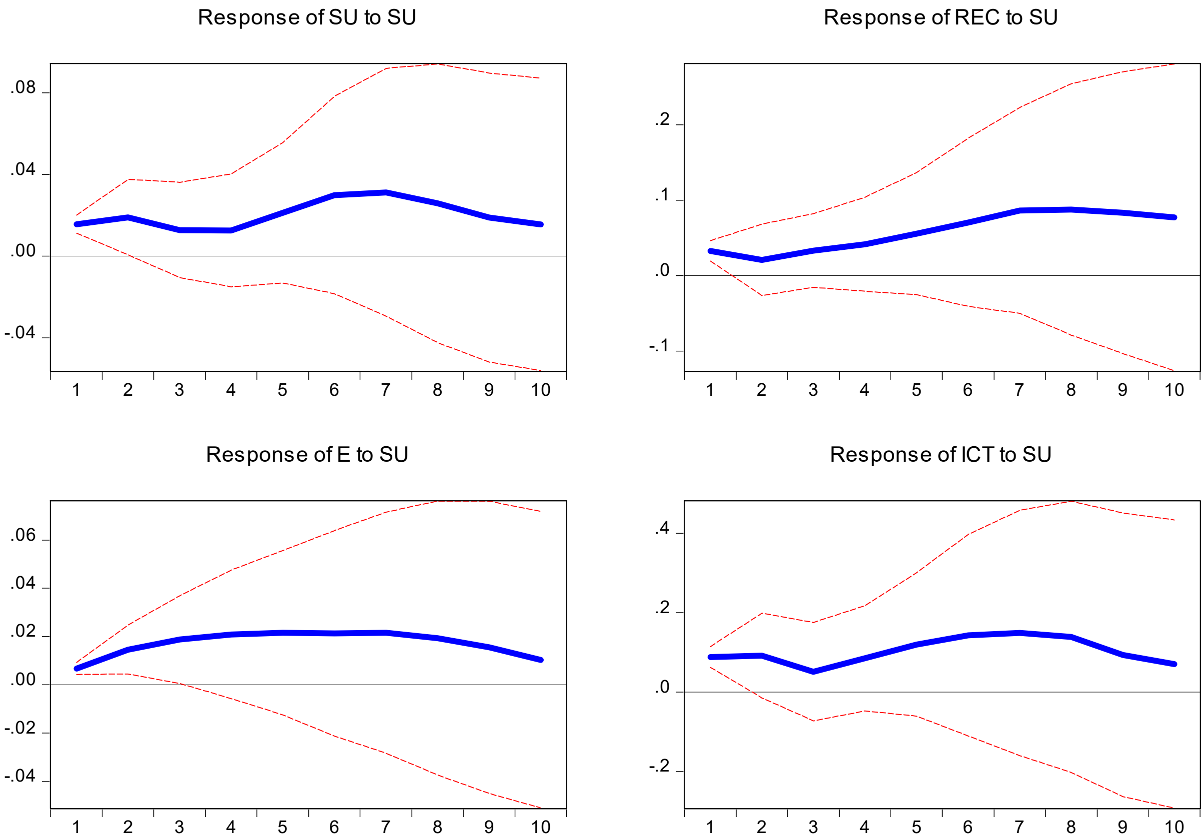

Figure 4. Impulse-response functions to a smart urbanization shock.

6. Conclusions and Implications

Environmental pollution is a critical challenge faced by many countries worldwide, as urbanization and economic development continue to accelerate, leading to increased environmental pollution and resource depletion. In this context, the adoption of green ICT and smart urbanization technologies has emerged as a promising strategy for promoting environmental quality. From this perspective, our study aims to explore the impact of green ICT and smart urbanization on environmental pollution in China, focusing on the period from 1996 to 2021. The main findings of the study are reported as follows. We have used the PLS-SEM method to examine the relationship between green ICT, smart urbanization, and environmental pollution. To evaluate the validity of the measurement model, three different indicators, construct reliability, convergent validity, and discriminant validity, are employed. These indicators are based on Cronbach's alpha, the composite reliability, and the average variance values, all matched or surpassed the conditions, confirming the validity of the measurement model. In addition, our study's model has acceptable discriminant validity. The findings of the structural model show that only the path coefficient between smart urbanization and environmental pollution is significant and negative. Renewable energy consumption directly and negatively influences environmental pollution, whereas smart urbanization directly and positively affects renewable energy consumption and green ICT. Consequently, renewable energy consumption and green ICT negatively influence environmental pollution.

The findings of our study have several policy implications for the government and other stakeholders. Our study suggests that the adoption of green ICT and smart urbanization can play a significant role in promoting environmental quality in China. Therefore, the government should continue to promote the deployment of these technologies in various sectors, such as energy, transportation, and waste management, to reduce environmental pollution. While green ICT and smart urbanization can contribute to reducing environmental pollution, their effectiveness depends on the behavior and consumption patterns of individuals and households. Therefore, the government should launch public awareness campaigns and provide incentives to encourage sustainable behavior and consumption, such as reducing energy waste, promoting public transportation, and reducing electronic waste. To ensure that green ICT and smart urbanization are deployed sustainably and effectively, the government should develop regulations and standards for their deployment and management. This includes developing standards for energy efficiency, electronic waste management, and green infrastructure development. The findings of our study suggest that there is a need for further research to understand the potential of green ICT and smart urbanization to promote environmental quality in China. Therefore, the government should invest in R and D to identify new technologies and solutions to reduce environmental pollution and promote sustainable development.

This study has several limitations that suggest potential directions for future research. First, our study only covers the period from 1996 to 2021. Future research could extend the analysis to cover a more extended period. Second, our study focuses exclusively on China, which limits its generalizability to other countries and contexts. Future research could expand the analysis to other countries and regions to compare the effectiveness of green ICT and smart urbanization in promoting environmental pollution. Third, our study examines the impact of green ICT and smart urbanization on environmental pollution, and additional factors could be considered in future studies that may affect environmental pollution, such as green growth, economic growth, IoT, renewable energy technology, climate policies, energy use, and green digital finance. Future research could consider these factors to develop a more comprehensive understanding of the drivers of environmental pollution and the role of green ICT and smart urbanization in addressing them.

Author Contributions: Conceptualization, Data curation, Writing the first draft, and Software: S.X.; Analysis, Writing the first draft, Reviewing and Supervision: L.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Hepburn, C.; Qi, Y.; Stern, N.; Ward, B.; Xie, C.; Zenghelis, D. Towards carbon neutrality and China's 14th Five-Year Plan: Clean energy transition, sustainable urban development, and investment priorities. *Environ. Sci. Ecotechnol.* **2021**, *8*, 100130. [CrossRef] [PubMed]
2. Mondejar, M.E.; Avtar, R.; Diaz, H.L.B.; Dubey, R.K.; Esteban, J.; Gómez-Morales, A.; Hallam, B.; Mbungu, N.T.; Okolo, C.C.; Garcia-Segura, S.; et al. Digitalization to achieve sustainable development goals: Steps towards a Smart Green Planet. *Sci. Total Environ.* **2021**, *794*, 148539. [CrossRef] [PubMed]
3. Wu, J.; Zhao, H. Research on Urbanization and Low-Carbon Development in China. In *China's Resources, Energy and Sustainable Development: 2020*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 35–61.
4. Ahouga, Y. The local turn in migration management: The IOM and the engagement of local authorities. *J. Ethn. Migr. Stud.* **2018**, *44*, 1523–1540. [CrossRef]
5. Cheshmehzangi, A.; Dawodu, A.; Sharifi, A. *Sustainable Urbanism in China*; Routledge: Oxford, UK, 2021.
6. Bibri, S.E.; Krogstie, J. The emerging data–driven Smart City and its innovative applied solutions for sustainability: The cases of London and Barcelona. *Energy Inform.* **2020**, *3*, 5. [CrossRef]
7. Yanzhe, F.; Ullah, S. Energy regulation, energy innovation, and carbon intensity nexus in China: A nonlinear perspective. *Energy Environ.* **2023**, 0958305X231188745. [CrossRef]
8. Akman, I.; Mishra, A. Sector diversity in green information technology practices: Technology acceptance model perspective. *Comput. Hum. Behav.* **2015**, *49*, 477–486. [CrossRef]

9. Benzidia, S.; Makaoui, N.; Bentahar, O. The impact of big data analytics and artificial intelligence on green supply chain process integration and hospital environmental performance. *Technol. Forecast. Soc. Change* **2021**, *165*, 120557. [CrossRef]
10. Xu, L.; Ullah, S. Evaluating the impacts of digitalization, financial efficiency, and education on renewable energy consumption: New evidence from China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 53538–53547. [CrossRef]
11. Powell, S.; Kara, E.C.; Sevlian, R.; Cezar, G.V.; Kiliccote, S.; Rajagopal, R. Controlled workplace charging of electric vehicles: The impact of rate schedules on transformer aging. *Appl. Energy* **2020**, *276*, 115352. [CrossRef]
12. Massar, M.; Reza, I.; Rahman, S.M.; Abdullah, S.M.H.; Jamal, A.; Al-Ismail, F.S. Impacts of autonomous vehicles on greenhouse gas emissions—Positive or negative? *Int. J. Environ. Res. Public Health* **2021**, *18*, 5567. [CrossRef]
13. Hashmi, S.A.; Ali, C.F.; Zafar, S. Internet of things and cloud computing-based energy management system for demand side management in smart grid. *Int. J. Energy Res.* **2021**, *45*, 1007–1022. [CrossRef]
14. Pawar, P. Design and development of advanced smart energy management system integrated with IoT framework in smart grid environment. *J. Energy Storage* **2019**, *25*, 100846. [CrossRef]
15. Saleem, M.U.; Shakir, M.; Usman, M.R.; Bajwa, M.H.T.; Shabbir, N.; Shams Ghahfarokhi, P.; Daniel, K. Integrating Smart Energy Management System with Internet of Things and Cloud Computing for Efficient Demand Side Management in Smart Grids. *Energies* **2023**, *16*, 4835. [CrossRef]
16. Jafri, M.A.H.; Liu, H.; Ullah, S.; Majeed, M.T.; Anwar, S.; Mustafa, S. Designing a clean environmental framework for Pakistan: Analyzing the nonlinear impact of aggregate demand drivers on CO_2 emissions. *Environ. Sci. Pollut. Res.* **2023**, *30*, 19292–19303. [CrossRef] [PubMed]
17. Usman, A.; Ozturk, I.; Ullah, S.; Hassan, A. Does ICT have symmetric or asymmetric effects on CO_2 emissions? Evidence from selected Asian economies. *Technol. Soc.* **2021**, *67*, 101692. [CrossRef]
18. Hafeez, M.; Rehman, S.U.; Faisal, C.N.; Yang, J.; Ullah, S.; Kaium, M.A.; Malik, M.Y. Financial efficiency and its impact on renewable energy demand and CO_2 emissions: Do eco-innovations matter for highly polluted Asian economies? *Sustainability* **2022**, *14*, 10950. [CrossRef]
19. Liu, F.; Zhao, F.; Liu, Z.; Hao, H. Can autonomous vehicle reduce greenhouse gas emissions? A country-level evaluation. *Energy Policy* **2019**, *132*, 462–473. [CrossRef]
20. Sitati, C.N.; Oludhe, C.; Oyake, L.; Mbandi, A.M. A street-level assessment of greenhouse gas emissions associated with traffic congestion in the city of Nairobi, Kenya. *Clean Air J.* **2022**, *32*, 1–12. [CrossRef]
21. Caratù, M.; Pigliautile, I.; Piselli, C.; Fabiani, C. A perspective on managing cities and citizens' well-being through smart sensing data. *Environ. Sci. Policy* **2023**, *147*, 169–176. [CrossRef]
22. Zhang, P.; Li, Z.; Ghardallou, W.; Xin, Y.; Cao, J. Nexus of institutional quality and technological innovation on renewable energy development: Moderating role of green finance. *Renew. Energy* **2023**, *214*, 233–241. [CrossRef]
23. Wu, S. Smart cities and urban household carbon emissions: A perspective on smart city development policy in China. *J. Clean. Prod.* **2022**, *373*, 133877. [CrossRef]
24. Liu, K.; Meng, C.; Tan, J.; Zhang, G. Do smart cities promote a green economy? Evidence from a quasi-experiment of 253 cities in China. *Environ. Impact Assess. Rev.* **2023**, *99*, 107009. [CrossRef]
25. Dong, H.; Xue, M.; Xiao, Y.; Liu, Y. Do carbon emissions impact the health of residents? Considering China's industrialization and urbanization. *Sci. Total Environ.* **2021**, *758*, 143688. [CrossRef]
26. IEA. *Gadgets and Gigabytes, Policies for Energy Efficient Electronics*; OECD/IEA, International Energy Agency: Paris, France, 2009.
27. Uddin, M.; Darabidarabkhani, Y.; Shah, A.; Memon, J. Evaluating power efficient algorithms for efficiency and carbon emissions in cloud data centers: A review. *Renew. Sustain. Energy Rev.* **2015**, *51*, 1553–1563. [CrossRef]
28. Salahuddin, M.; Alam, K.; Ozturk, I. The effects of Internet usage and economic growth on CO_2 emissions in OECD countries: A panel investigation. *Renew. Sustain. Energy Rev.* **2015**, *62*, 1226–1235. [CrossRef]
29. Khan, F.N.; Sana, A.; Arif, U. Information and communication technology (ICT) and environmental sustainability: A panel data analysis. *Environ. Sci. Pollut. Res.* **2020**, *27*, 36718–36731. [CrossRef] [PubMed]
30. Avom, D.; Nkengfack, H.; Fotio, H.K.; Totouom, A. ICT and environmental quality in Sub-Saharan Africa: Effects and transmission channels. *Technol. Forecast. Soc. Change* **2020**, *155*, 120028. [CrossRef]
31. Liu, J.; Yu, Q.; Chen, Y.; Liu, J. The impact of digital technology development on carbon emissions: A spatial effect analysis for China. *Resour. Conserv. Recycl.* **2022**, *185*, 106445. [CrossRef]
32. Dogan, E.; Seker, F. The influence of real output, renewable and non-renewable energy, trade and financial development on carbon emissions in the top renewable energy countries. *Renew. Sustain. Energy Rev.* **2016**, *60*, 1074–1085. [CrossRef]
33. Essandoh, O.K.; Islam, M.; Kakinaka, M. Linking international trade and foreign direct investment to CO_2 emissions: Any differences between developed and developing countries? *Sci. Total Environ.* **2020**, *712*, 136437. [CrossRef]
34. Asongu, S.A.; Le Roux, S.; Biekpe, N. Enhancing ICT for environmental sustainability in sub-Saharan Africa. *Technol. Forecast. Soc. Change* **2018**, *127*, 209–216. [CrossRef]
35. Usman, M.; Yaseen, M.R.; Kousar, R.; Makhdum, M.S.A. Modeling financial development, tourism, energy consumption, and environmental quality: Is there any discrepancy between developing and developed countries? *Environ. Sci. Pollut. Res.* **2021**, *28*, 58480–58501. [CrossRef] [PubMed]

36. Chien, F.; Anwar, A.; Hsu, C.C.; Sharif, A.; Razzaq, A.; Sinha, A. The role of information and communication technology in encountering environmental degradation: Proposing an SDG framework for the BRICS countries. *Technol. Soc.* **2021**, *65*, 101587. [CrossRef]
37. Lahouel, B.B.; Taleb, L.; Zaied, Y.B.; Managi, S. Does ICT change the relationship between total factor productivity and CO_2 emissions? Evidence based on a nonlinear model. *Energy Econ.* **2021**, *101*, 105406. [CrossRef]
38. Azam, A.; Rafiq, M.; Shafique, M.; Yuan, J. An empirical analysis of the non-linear effects of natural gas, nuclear energy, renewable energy and ICT-Trade in leading CO_2 emitter countries: Policy towards CO_2 mitigation and economic sustainability. *J. Environ. Manag.* **2021**, *286*, 112232. [CrossRef]
39. Zheng, R.; Wu, G.; Cheng, Y.; Liu, H.; Wang, Y.; Wang, X. How does digitalization drive carbon emissions? The inverted U-shaped effect in China. *Environ. Impact Assess. Rev.* **2023**, *102*, 107203. [CrossRef]
40. Majeed, M.T.; Tauqir, A. Effects of urbanization, industrialization, economic growth, energy consumption, financial development on carbon emissions: An extended STIRPAT model for heterogeneous income groups. *Pak. J. Commer. Soc. Sci.* **2020**, *14*, 652–681.
41. Nathaniel, S.P.; Nwulu, N.; Bekun, F. Natural resource, globalization, urbanization, human capital, and environmental degradation in Latin American and Caribbean countries. *Environ. Sci. Pollut. Res.* **2021**, *28*, 6207–6221. [CrossRef]
42. Saidi, K.; Mbarek, M.B. The impact of income, trade, urbanization, and financial development on CO_2 emissions in 19 emerging economies. *Environ. Sci. Pollut. Res.* **2017**, *24*, 12748–12757. [CrossRef]
43. Lv, Z.; Xu, T. Trade openness, urbanization and CO_2 emissions: Dynamic panel data analysis of middle-income countries. *J. Int. Trade Econ. Dev.* **2019**, *28*, 317–330. [CrossRef]
44. Chatti, W.; Majeed, M.T. Information communication technology (ICT), smart urbanization, and environmental quality: Evidence from a panel of developing and developed economies. *J. Clean. Prod.* **2022**, *366*, 132925. [CrossRef]
45. Cole, M.A.; Neumayer, E. Examining the impact of demographic factors on air pollution. *Popul. Environ.* **2004**, *26*, 5–21. [CrossRef]
46. Sadorsky, P. The effect of urbanization on CO_2 emissions in emerging economies. *Energy Econ.* **2014**, *41*, 147–153. [CrossRef]
47. Luo, Q.; Zhou, J.; Zhang, Y.; Yu, B.; Zhu, Z. What is the spatiotemporal relationship between urbanization and ecosystem services? A case from 110 cities in the Yangtze River Economic Belt, China. *J. Environ. Manag.* **2022**, *321*, 115709. [CrossRef]
48. Wei, G.; Bi, M.; Liu, X.; Zhang, Z.; He, B.J. Investigating the impact of multi-dimensional urbanization and FDI on carbon emissions in the belt and road initiative region: Direct and spillover effects. *J. Clean. Prod.* **2023**, *384*, 135608. [CrossRef]
49. Zhu, X.; Zhang, P.; Wei, Y.; Li, Y.; Zhao, H. Measuring the efficiency and driving factors of urban land use based on the DEA method and the PLS-SEM model—A case study of 35 large and medium-sized cities in China. *Sustain. Cities Soc.* **2019**, *50*, 101646. [CrossRef]
50. Hair, J.F., Jr.; Matthews, L.M.; Matthews, R.L.; Sarstedt, M. PLS-SEM or CB-SEM: Updated guidelines on which method to use. *Int. J. Multivar. Data Anal.* **2017**, *1*, 107–123. [CrossRef]
51. Wen, L.; Li, Z. Driving forces of national and regional CO_2 emissions in China combined IPAT-E and PLS-SEM model. *Sci. Total Environ.* **2019**, *690*, 237–247. [CrossRef]
52. Wei, Y.; Zhu, X.; Li, Y.; Yao, T.; Tao, Y. Influential factors of national and regional CO_2 emission in China based on combined model of DPSIR and PLS-SEM. *J. Clean. Prod.* **2019**, *212*, 698–712. [CrossRef]
53. Hair, J.F.; Sarstedt, M.; Ringle, C.M. Rethinking some of the rethinking of partial least squares. *Eur. J. Mark.* **2019**, *53*, 566–584. [CrossRef]
54. Chin, W.W. *PLS Graph 3.0*; Soft Modeling Inc.: Houston, TX, USA, 2003.
55. Ringle, C.; Da Silva, D.; Bido, D. Structural Equation Modeling with the Smart pls. *Braz. J. Mark.* **2014**, *13*, 56–73. [CrossRef]
56. Richter, N.F.; Sinkovics, R.R.; Ringle, C.M.; Schlägel, C. A critical look at the use of SEM in international business research. *Int. Mark. Rev.* **2016**, *33*, 376–404. [CrossRef]
57. Hair, J.F., Jr.; Hult, G.T.M.; Ringle, C.M.; Sarstedt, M.; Danks, N.P.; Ray, S. An introduction to structural equation modeling. In *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 1–29.
58. Rigdon, E.E.; Ringle, C.M.; Sarstedt, M. Structural modeling of heterogeneous data with partial least squares. *Rev. Mark. Res.* **2010**, *7*, 255–296.
59. Thakkar, J.J. *Structural Equation Modelling: Application for Research and Practice (with AMOS and R)*; Springer Nature: Berlin/Heidelberg, Germany, 2020; Volume 285.
60. Henseler, J.; Chin, W.W. A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling. *Struct. Equ. Model.* **2010**, *17*, 82–109. [CrossRef]
61. Danks, N.P.; Sharma, P.N.; Sarstedt, M. Model selection uncertainty and multimodel inference in partial least squares structural equation modeling (PLS-SEM). *J. Bus. Res.* **2020**, *113*, 13–24. [CrossRef]
62. Xu, B.; Lin, B. Assessing CO_2 emissions in China's iron and steel industry: A dynamic vector autoregression model. *Appl. Energy* **2016**, *161*, 375–386. [CrossRef]
63. Talbi, B. CO_2 emissions reduction in road transport sector in Tunisia. *Renew. Sustain. Energy Rev.* **2017**, *69*, 232–238. [CrossRef]
64. Guo, Q.; Wang, Y.; Dong, X. Effects of smart city construction on energy saving and CO_2 emission reduction: Evidence from China. *Appl. Energy* **2022**, *313*, 118879. [CrossRef]
65. Xu, A.; Wang, W.; Zhu, Y. Does smart city pilot policy reduce CO_2 emissions from industrial firms? Insights from China. *J. Innov. Knowl.* **2023**, *8*, 100367. [CrossRef]

66. Li, B. Effective energy utilization through economic development for sustainable management in smart cities. *Energy Rep.* **2022**, *8*, 4975–4987. [CrossRef]
67. Qi, G.; Che, J.; Wang, Z. Differential effects of urbanization on air pollution: Evidences from six air pollutants in mainland China. *Ecol. Indic.* **2023**, *146*, 109924. [CrossRef]
68. Wu, H.; Hao, Y.; Ren, S.; Yang, X.; Xie, G. Does internet development improve green total factor energy efficiency? Evidence from China. *Energy Policy* **2021**, *153*, 112247. [CrossRef]
69. Usman, A.; Ozturk, I.; Hassan, A.; Zafar, S.M.; Ullah, S. The effect of ICT on energy consumption and economic growth in South Asian economies: An empirical analysis. *Telemat. Inform.* **2021**, *58*, 101537. [CrossRef]
70. Raihan, A. Economy-energy-environment nexus: The role of information and communication technology towards green development in Malaysia. *Innov. Green Dev.* **2023**, *2*, 100085. [CrossRef]
71. Raheem, I.D.; Tiwari, A.K.; Balsalobre-Lorente, D. The role of ICT and financial development in CO_2 emissions and economic growth. *Environ. Sci. Pollut. Res.* **2020**, *27*, 1912–1922. [CrossRef]