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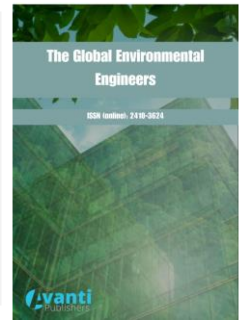

Decoding Key Drivers of Information-Sensitive Waste Electrical and Electronic Equipment Recycling in China Using a DEMATEL-BP Neural Network Approach

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ABSTRACT

At the intersection of environmental sustainability and personal data security, the recycling of information-sensitive waste electrical and electronic equipment (WEEE), such as smartphones and laptops, presents the dual challenges of low formal recycling rates and data security risks. Existing research often overlooks the specific dynamics of information-sensitive WEEE and the complex, interdependent factors influencing residents' recycling decisions from a holistic stakeholder perspective. The novelty of this study lies in integrating stakeholder theory with a hybrid analytical approach combining the Decision-making Trial and Evaluation Laboratory (DEMATEL) model and a back-propagation (BP) neural network model. This method first clarifies causal relationships among key factors and then examines their non-linear impacts on recycling intentions. The findings reveal three primary insights: (i) the cost of information cleaning has the greatest impact on the size of the recycling market. (ii) Economic benefits have the greatest impact on competition within informal recycling channels, residents' awareness of information protection and preference for recycling channels. (iii) Incentive publicity has the greatest impact on residents' environmental awareness. In conclusion, this study contributes a stakeholder-focused framework and demonstrates the efficacy of combining DEMATEL and BP neural network to decipher complex behavioral influences. The results underscore the necessity for integrated policies that simultaneously address economic incentives, cost barriers, and awareness campaigns to effectively promote the recycling of information-sensitive WEEE.

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1. Introduction

The rapid growth of waste electrical and electronic equipment (WEEE) has become a global environmental and resource challenge. Taking smartphones as an example, rapid technological iteration and marketing strategies have shortened replacement cycles, leading to the premature disposal of large quantities of fully functional devices. If improperly managed, the hazardous substances they contain—such as lead, mercury, cadmium, and brominated flame retardants—can cause lasting harm to the ecological environment [1, 2]. At the same time, they are rich in rare earth elements, lithium, cobalt, and other high-value materials such as copper and aluminum, making effective recycling crucial for balancing pollution control and resource circulation [3]. Household appliances also constitute a significant portion of WEEE. As the world's largest producer and consumer of household appliances, China generated 5.3 million tons of waste appliances in 2020. By 2030, the nation's total WEEE volume is projected to climb to 28.4 million tons [4, 5]. Therefore, advancing the effective management and resource utilization of WEEE is an urgent priority [6-8].

Currently, China's WEEE recycling system still faces a situation where formal and informal channels coexist. Due to features such as service convenience and high flexibility, large quantities of WEEE flow into informal recycling channels [9]. These channels often employ outdated and highly polluting treatment technologies, exacerbating environmental risks [10]. Particular attention should be paid to information-sensitive WEEE, such as smartphones, tablets, and laptops. Beyond the environmental challenges common to general WEEE, their recycling and processing pose additional unique information security risks [11]. This study defines such devices as electronic equipment that stores or processes personal privacy, financial accounts, or sensitive biometric information. If data leakage occurs during recycling, it could directly cause substantial harm to users' property, privacy, and even public safety. Consequently, the logic governing their recycling significantly differs from that of traditional WEEE. Conventional economic incentives and convenience factors often prove ineffective or distorted when confronted with the core concern of “privacy security.” This stark reality underscores the urgency for independent research. According to 2024 statistics from the China Circular Economy Association, China has generated over 400 million discarded mobile phones annually in the past five years. Among these, only approximately 5% are properly processed through formal recycling platforms or innovative channels like trade-in programs [12]. It is evident that the recycling of information-sensitive WEEE involves not only environmental and resource concerns but also the collaborative governance of multiple stakeholders. Based on stakeholder theory, this study will focus on the key factors influencing consumers' recycling decisions.

Existing research has made some progress in the field of WEEE management, such as revealing industry governance focal points through policy coherence analysis [13] or conducting surveys from the perspective of public awareness and behavioral willingness [14, 15]. Additionally, scholars have explored multiple influencing factors including personal responsibility [16], consequence awareness [17], price sensitivity [18]. However, existing research exhibits significant limitations that provide entry points for this study: (1) most current studies focus on e-waste management from a public, policy or regional perspective, but few comprehensively analyse the various factors affecting e-waste recycling from a holistic stakeholder perspective. (2) Although some studies have looked at e-waste recycling management, they often do not look in depth at specific types of e-waste. Information sensitive WEEE has its own particularities and its recycling process requires more attention and detailed research. (3) While current research methods are effective in revealing public attitudes and policy consistency, they often overlook the complex relationships between data and potential non-linear effects, limiting in-depth and comprehensive exploration of factors influencing e-waste recycling. Therefore, the purpose of this study is to identify the key factors affecting the recycling of information-sensitive WEEE based on the Stakeholder Theory (ST) and prioritize the key factors in order to successfully carry back the information-sensitive WEEE.

To address the aforementioned gap, this study adopts a stakeholder theory framework, focusing on information-sensitive WEEE. It integrates the Decision-Making Laboratory Method (DEMATEL) with a back-propagation neural network (BP) to construct an analytical model. DEMATEL effectively identifies causal structures and association strengths among factors [19], while BP neural networks excel at capturing nonlinear mapping relationships between variables [20]. Their combination enables systematic analysis of the composite effects of multiple factors on recycling behavior [21]. Compared to traditional structural equation modeling, this approach is better suited for scenarios involving multiple variables and complex relationships. This study aims to: First, systematically identify key factors influencing residents' recycling willingness; Second, clarify the causal structure and interaction intensity among these factors; Third, quantify the nonlinear impact of key factors on recycling behavior. Theoretically, it provides a systematic research framework integrating stakeholder perspectives with mixed-methods approaches. Practically, its findings offer empirical support for designing comprehensive governance policies that synergize incentives, mitigate costs, and build trust, thereby advancing WEEE recycling systems toward greater efficiency, safety, and sustainability. The framework of this study and its steps are shown in Fig. (**1**).

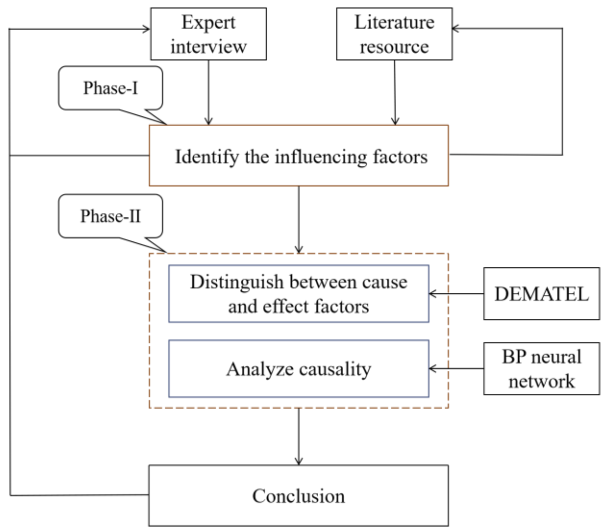

Figure 1: Research framework and the steps.

2. Identification of Influencing Factors

In 1983, Freeman, an American economist, provided a broad definition of a stakeholder. He defined a stakeholder as an individual or group who can influence the achievement of an organization's objectives or who can be affected by the process of achieving those objectives [22]. In the context of WEEE recycling, a stakeholder refers to any group or individual that can influence or is affected by the recycling process [23]. According to the Mitchell scale [24] and the characteristics of the WEEE recycling chain, in order to be considered a key stakeholder, one must possess at least one of the following three attributes: (1) initiative, which indicates a direct interest in identifying stakeholders within the WEEE recycling chain; (2) importance, which demonstrates the stakeholder’s impact on and direct influence on the development of the WEEE recycling industry; (3) urgency, which means that the absence of a stakeholder could lead to the failure of the entire stakeholder network [25]. The stakeholders involved in WEEE recycling in China can be summarised into five main categories, namely producers, residents, recyclers, disposers and the government [23] (Fig. **A1**).

The recycling of WEEE is closely linked to the product itself. This requires manufacturers to select safe raw materials during the manufacturing process, to take on the obligation to provide environmental information and safety notices about their products to citizens, and to set up a recycling and disposal system when citizens choose products and services. Residents are the suppliers of WEEE and their willingness and attitudes towards recycling have a significant impact on the WEEE recycling process. Without the active cooperation of residents, recycling efforts will be more difficult. Recyclers are a key stakeholder group, bridging the gap between residents and processors. They can be formal or informal; formal recycling typically includes e-commerce platforms, equipment stores, equipment manufacturers’ after-sales service centres and professional recycling platforms, while informal recycling includes individual sellers, second-hand resale, gifting, direct disposal and other processing methods. Disposers can extend the life of products by technical means and increase the reuse rate of recycled products by dismantling them. Government acts as a regulator of the recycling industry. Through measures such as taxation, bans and penalties, it is guiding China’s e-waste recycling management towards standardised development. At the same time, it increases subsidies and other measures to encourage residents to recycle [26].

In order to identify the key factors influencing the development of information-sensitive WEEE recycling, this study analyses the main stakeholders and identifies the influencing factors from different dimensions. From the government perspective, the factors influencing WEEE recycling include regulatory measures [27, 28], incentive systems [29], and financial subsidies. From a business perspective, the main actors are producers, recyclers and disposers. Factors affecting WEEE recycling include the cost of cleaning information [30], information clearing technologies [31], competition in informal recycling channels [32], size of the recycling market [33], economic benefits [34], disassembly and reuse technologies [34], and taking responsibility for recycling [8]. From the perspective of residents, factors affecting WEEE recycling include attitudes towards recycling, environmental awareness [35], recycling prices [36], recycling channel preferences [37, 38], and information sensitivity [36]. This study collects factors that may affect the development of the information-sensitive WEEE recycling industry from the dimensions of government, enterprises, and residents [39].

Through surveys and interviews with experts and academics, the similarities and rationality of these factors are explored. First, a preliminary list of potential factors was compiled through a systematic literature review. Subsequently, we invited three experts with deep expertise in the field to participate in interviews. These experts independently scored and commented on the necessity, clarity, and mutual exclusivity of the initial factors. Based on the experts' suggestions, unnecessary or additional relevant factors are removed, resulting in the identification of 13 influencing factors (Table **B1**), namely: regulatory measures, incentive systems, cost of cleaning up information, information cleansing technology, competition in informal recycling channels, the size of the recycling market, economic benefits, disassembly and reuse technology, take responsibility for recycling, recycling price, environmental awareness, information sensitivity and recycling channel preference.

3. Distinguish between Cause and Effect Factors

3.1. Identification Process

The DEMATEL model is used to identify the important factors affecting the recycling of information-sensitive WEEE. The DEMATEL model can effectively analyse the logical relationship between various factors of complex and difficult problems in the real world. It is a method for analyzing system elements using graph theory and matrix tools. It was first proposed by Gabus and Fontela of Battelle Laboratory in the United States at the Geneva Conference in 1971 [40]. In recent years, the DEMATEL method has been recognized by many scientists as a powerful tool for identifying and analyzing the relationships between different factors. It is one of the most widely used impact factor identification algorithms and is applied in mathematics, economics, computer science and other fields. The information-sensitive WEEE recycling system involves the interaction of multidimensional factors including technology, economics, behavior, and policy, falling precisely within the realm of complex causal network analysis—an area where the DEMATEL method excels. Applying this method helps transcend simple factor enumeration to reveal intrinsic influence pathways and priority levels. Based on these considerations, this study concludes that DEMATEL is an effective tool for revealing the systemic structure of factors influencing information-sensitive WEEE recycling. The main steps of its implementation are the following:

Step 1: Set the influence factor to $B = \{B_i \mid i = 1,2,\dots,n\}$, $n = 13$.

Step 2: To quantify the relationship between the elements, a direct impact matrix needs to be built. A team of experts in WEEE recycling was invited to compare factors i and factors j in a relational matrix which the direct influence matrix is obtained $A = (a_{ij})_{n\times n}$, a_{ij} which stands for the influence of i factor on j factor. The experts were scored on the following criteria: 0 for no impact, 1 for small impact, 2 for moderate impact, 3 for large impact, and 4 for very large impact (Table **B2**).

Step 3: Normalization directly affects the matrix to get the standard matrix. Take the maximum of the sum of the elements of the rows of matrix ***A***, then divide the maximum by matrix ***A*** to get the standardized influence matrix$X = (x_{ij})_{n\times n}$. The calculation is shown in Formula (1):

$$X = A / \max_{1\le i\le n} \sum_{j=1}^{n} a_{ij} \quad (1)$$

Step 4: Calculate the composite impact matrix. The comprehensive influence matrix is $T = (t_{ij})_{n\times n}$, and the main purpose of this step is to obtain the total influence relation value of each set of attributes. The comprehensive influence matrix as shown in Formula (2):

$$T = \sum_{n=1}^{\infty} X^n = X(E - X)^{-1} \quad (2)$$

In Formula (2), E denotes the identity matrix.

Step 5: According to the data of the comprehensive influence matrix, calculate the influence degree, affected degree, center degree, and reason degree of each factor. In the comprehensive influence matrix T, each row of factors adds up to the degree of influence D_i, and each row of factors in the matrix T adds up to the degree of influenceC_i. the calculation is shown in Formula (3)(4) :

$$D_i = \sum_{j=1}^{n} t_{ij}\ (i = 1,2,\dots,n) \quad (3)$$

$$C_j = \sum_{i=1}^{n} t_{ij}\ (j = 1,2,\dots,n) \quad (4)$$

The centrality M_i of the$i$influencing factor is calculated as shown in Formula (5):

$$M_i = D_i + C_j (i = j = 1,2,\dots,n) \quad (5)$$

The cause R_i of the$i$influencing factor is calculated as shown in Formula (6):

$$R_i = D_i - C_j (i = j = 1,2,\dots,n) \quad (6)$$

3.2. Data Analysis

To analyse the drivers of information-sensitive WEEE recycling from a multi-stakeholder perspective, we conducted interviews with three experts and academics with over ten years of experience in the recycling and disposal aspects of the WEEE industry.

Expert 1 (Institute of Electrical Recycling Technology, China Household Electrical Appliances Research Institute): A consulting expert who has been involved in research on laws, regulations, policies, standards and technologies related to the recycling and recovery of discarded household appliances and electronic products both domestically and internationally since 1998. This expert has conducted several national-level research projects and participated in the formulation of policies and related standards, such as China's "Regulations on the Recycling and Disposal of Discarded Electrical and Electronic Products". They have a comprehensive understanding of the market for the recycling of discarded WEEE in China and an in-depth knowledge of the relevant national laws, regulations and policies.

Expert 2 (Electronic Waste Research Centre, Shanghai Second Polytechnic University) A researcher who joined the Research Center for Electronic Waste (Shanghai Collaborative Innovation Center for Recycling of Electronic Waste) at Shanghai Second Polytechnic University in 2013 to engage in teaching and research. This expert, who is also the deputy director of the Institute of Lifecycle Management, has led and participated in several related research projects and construction planning, and has extensive knowledge and expertise in the field of WEEE recycling and disposal.

Expert 3 (Shaanxi Beikong Renewable Resources Co., Ltd.): The general manager with many years of practical experience in the recycling and disposal of electronic waste, who has an in-depth understanding of the state of WEEE recycling. Established on 18 May 2010, the company serves as a demonstration project for the recycling and recovery of waste electrical and electronic products in Shaanxi Province. It is registered with the Xianyang Municipal Development and Reform Commission and is listed as a supported project in the 2011 Industrial Restructuring Directory.

Based on various factors from the relevant literature that may influence the development of the information-sensitive WEEE recycling industry, experts analyzed the similarity and rationality of these factors. Finally, 13 relevant influencing factors were identified and a direct impact matrix ***A*** was constructed, as shown in Fig. (**2**).

Figure 2: Direct impact matrix heat map.

Normalize the matrix ***A*** and obtain the standardized impact matrix (Table **B3**) using formula (1). Then calculate the comprehensive impact matrix ***T*** (Table **B4**) using formula (2). Based on the comprehensive impact matrix, derive the impact, affected, centrality and causal factors (Table **B5**). Centrality indicates the relative importance of different influencing factors within the overall system impact. According to Table **B5**, the recycling price emerges as the most important influencing factor with a centrality value of 6.075, while the centrality of information sensitivity is the lowest with 3.136. Causal groups are distinguished on the basis of the degree of causality values; factors with a degree of causality greater than zero are considered to be causal factors, and those with a degree of causality less than zero are considered to be outcome factors.

The causal effects of the main criteria are shown in Fig. (**3**). It can be concluded that regulatory measures, incentive promotion, assumed recycling responsibilities, information cleaning costs, information cleaning technologies, economic benefits, dismantling and reuse technologies and recycling prices act as causal factors. On the other hand, the size of the recycling market, competition in informal recycling channels, environmental awareness, information sensitivity and preference for recycling channels are the outcome factors.

4. Analyze Causality

4.1. Identification Process

The BP neural network, proposed in 1986, is a multi-layer feed-forward network characterized by its training via the error back-propagation algorithm [22]. It is one of the most widely used neural network models today. The main advantages of the BP neural network are its strong fault tolerance, generalization and non-linear mapping capabilities. The BP algorithm consists of two processes: forward computation of the data stream (forward propagation) and backward propagation of error signals. In forward propagation, data flows from the input layer to the hidden layer and then to the output layer. The state of each layer only affects the following layer. If the desired output is not achieved in the output layer, the process switches to backward error propagation. By alternating these two processes, the gradient descent strategy for the error function is implemented in the weight vector space. This dynamic search for a set of weight vectors minimizes the error function of the network, thus completing the process of information extraction and storage.

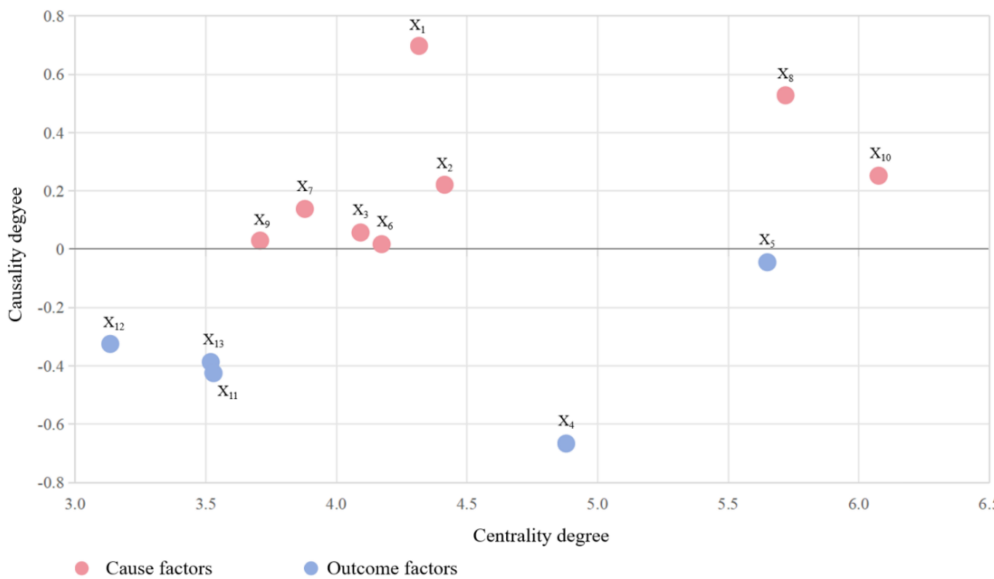

Figure 3: Centrality cause graph relationship.

As shown in Fig. (**A2**), the input layer has n nodes, the hidden layer has v nodes, and the output layer has m nodes. The weight between the input layer and the hidden layer is $w1_{ki}(i = 1,2,\cdots,n; k = 1,2,\cdots,v)$, and the weight between the hidden layer and the output layer is $w2_{jk}(j = 1,2,\cdots,m; k = 1,2,\cdots,v)$. The activation function of the hidden layer is $f_1(*)$, and the activation function of the output layer is $f_2(*)$. The input of the hidden layer node is $hi_k = \sum_{i=0}^{n} w1_{ki}\, x_i$, the output of the hidden layer node is $ho_k = f1(hi_k)$, the input of the output layer node is $yi_j = \sum_{k=0}^{m} w2_{jk}\, h_k$, the output of the output layer node is $yo_j = f_2(yi_j)$, and the output of d_j is expected. The specific implementation steps are as follows [41]:

Step 1: Define the error function. Enter s training samples represented by $x_1^s, x_2^s, \dots, x_n^s$. After the sample s is input into the network, the output yo_j^s is obtained. The global error E and error e_s of sample s are obtained by using the square error function.

$$e_s = \frac{1}{2}\sum_{j=1}^{m}\left(d_j^s - yo_j^s\right) \tag{7}$$

$$E = \frac{1}{2}\sum_{s=1}^{s}\sum_{j=1}^{m}\left(d_j^s - yo_j^s\right) = \sum_{s=1}^{s} e_s \tag{8}$$

Step 2: Calculate the weight change between the hidden layer and the output layer. The cumulative error BP algorithm is used to adjust $w2_{jk}$ to reduce the global error E, and the adjustment ratio is $\Delta w2_{jk}$, where η is the learning rate.

$$\Delta w2_{jk} = -\eta \frac{\partial E}{\partial w2_{jk}} = \sum_{s=1}^{s}\left(-\eta \frac{\partial e_s}{\partial w2_{jk}}\right) \tag{9}$$

The error signal is defined as:

$$\delta_{yo_j} = -\frac{\partial e_s}{\partial yi_j} = \sum_{j=1}^{m}\left(d_j^s - yo_j^s\right) f_2'\left(yi_j\right) \tag{10}$$

The weight between the hidden layer and the output layer changes as follows:

$$\Delta w2_{jk} = \sum_{s=1}^{s}\sum_{j=1}^{m}\left(d_j^s - yo_j^s\right) f_2'\left(yi_j\right) \cdot ho_k \tag{11}$$

The weight between the hidden layer and the output layer should be changed as follows:

$$w2_{jk}(t+1) = w2_{jk}(t) + \Delta w2_{jk} \tag{12}$$

Step 3: Calculate the weight change between the input layer and the hidden layer.

$$\Delta w1_{ki} = -\eta \frac{\partial E}{\partial w1_{ki}} = \sum_{s=1}^{S} \left(-\eta \frac{\partial e_s}{\partial w1_{ki}}\right) \tag{13}$$

The error signal is defined as:

$$\delta_{ho_k} = -\frac{\partial e_s}{\partial hi_k} = \sum_{j=1}^{m} \left(d_j^s - yo_j^s\right) f_2'\left(yi_j\right) w2_{jk} f_1'(hi_k) \tag{14}$$

The weight values between the hidden layer and the input layer change as follows:

$$\Delta w1_{ki} = \sum_{s=1}^{S} \sum_{j=1}^{m} \eta \left(d_j^s - yo_j^s\right) f_2'\left(yi_j\right) w2_{jk} f_1'(hi_k) x_i \tag{15}$$

The weight between the hidden layer and the input layer is modified as follows:

$$w1_{ki}(t+1) = w1_{ki}(t) + \Delta w1_{ki} \tag{16}$$

Step 4: Calculate the decision weights of input layer variables on output layer variables [42].

Calculate the correlation significance coefficient,

$$r_{ij} = \sum_{k=1}^{v} W_{ki} \,(1 - e^{-x})/(1 + e^{-x}) \tag{17}$$

$$x = w_{jk} \tag{18}$$

Calculate the relevant index,

$$R_{ij} = \left|\frac{(1-e^{-y})}{(1+e^{-y})}\right| \tag{19}$$

$$y = r_{ij} \tag{20}$$

Calculate the absolute influence coefficient, which is the decision weight of each influencing factor,

$$S_{ij} = R_{ij} / \sum_{i=1}^{n} R_{ij} \tag{21}$$

4.2. Data Analysis

The DEMATEL data analysis was used to identify the causal and outcome factors influencing the recycling of household information-sensitive WEEE. The causal factors were used as input layer variables for the BP neural network, while the outcome factors were used as output layer variables. Specifically, regulatory measures, incentive systems, cost of cleaning up information, the size of the recycling market, economic benefits, disassembly and reuse technology, take responsibility for recycling and recycling price served as input layer variables. In contrast, information cleansing technology, competition in informal recycling channels, environmental awareness, information sensitivity and recycling channel preference were designated as output layer variables. Therefore, the BP neural network model has 8 nodes in the input layer and 5 nodes in the output layer.

Data was collected through questionnaires for the purpose of analyzing a BP neural network model. The questionnaires were randomly distributed to online residents to capture their true opinions. A total of 237 questionnaires were distributed, and after excluding those with identical answers and short response times, 232 valid questionnaires remained, giving a response rate of 97%. Fig. (**4**) provides a detailed overview of the respondents. Based on 232 valid questionnaire responses, the study constructed a BP neural network model to analyze the nonlinear mapping relationships among influencing factors. Model parameters were configured according to the research framework and data characteristics. The specific parameters are detailed in Table **B6**. The number of hidden layer nodes is initially determined within a range based on empirical formulas, then optimized through trial-and-error methods. Initially, the number of hidden layer nodes was selected within the range of 4 to 12 based on common empirical rules. Subsequently, multiple rounds of network training and testing were conducted within this range, using mean squared error (MSE) and coefficient of determination (R^2) as evaluation metrics. Results revealed that when the number of hidden layer nodes was set to 4, the model achieved optimal fitting performance and minimal generalization error on the validation set, without exhibiting significant overfitting.

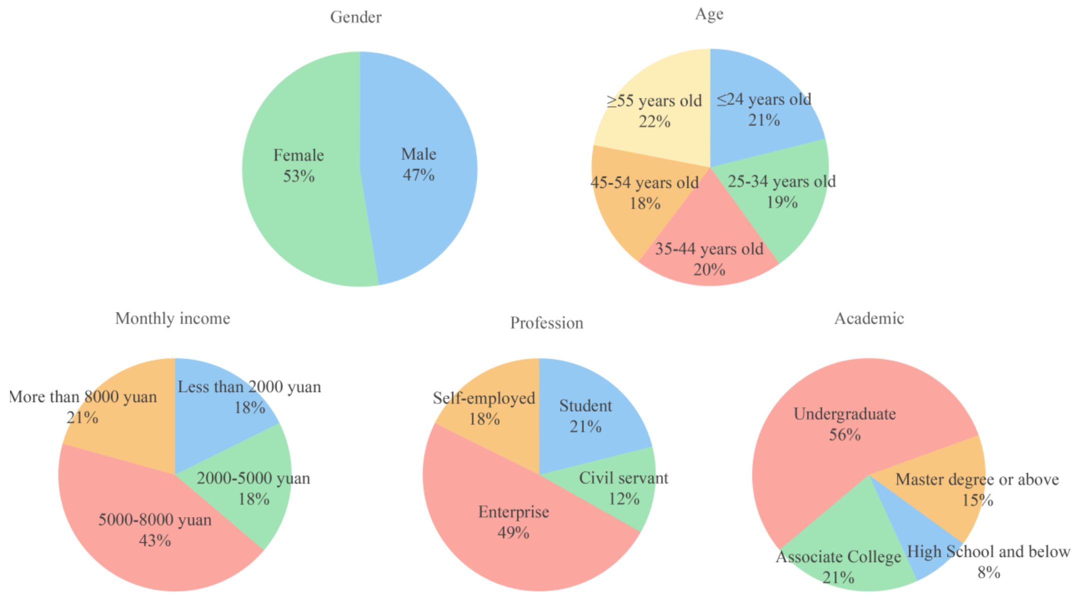

Figure 4: Detailed overview of respondents.

After the training of the BP neural network model is completed, the final weight results of the BP neural network training are obtained (Table **B7** and Table **B8**). Substituting the data from Table **B7** and Table **B8** into Formula (17) to obtain r_{ij}, R_{ij}, and S_{ij}, the calculation results are shown in Table **B9**, Table **B10**, and Table **1**. The decision weight represents the degree to which the input layer variable *i* influences the output layer variable *j*. From Fig. (**5**), it can be seen that the cost of information cleaning has the largest impact on the size of the recycling market with 0.241. The recycling price, the dismantling and reuse technology and the incentive promotion have a large impact on the size of the recycling market with 0.197, 0.173 and 0.155 respectively. Economic benefits have the smallest impact on the size of the recycling market with 0.021; economic benefits have the largest impact on competition from informal recycling channels with 0.259.

Table 1: Decision weight.

Weight	X_4	X_5	X_{11}	X_{12}	X_{13}
X_1	0.055	0.081	0.004	0.132	0.090
X_2	0.155	0.156	0.214	0.095	0.132
X_3	0.055	0.113	0.119	0.066	0.083
X_6	0.241	0.093	0.197	0.096	0.150
X_7	0.103	0.064	0.107	0.075	0.084
X_8	0.021	0.259	0.201	0.223	0.224
X_9	0.173	0.197	0.071	0.154	0.137
X_{10}	0.197	0.035	0.088	0.158	0.128

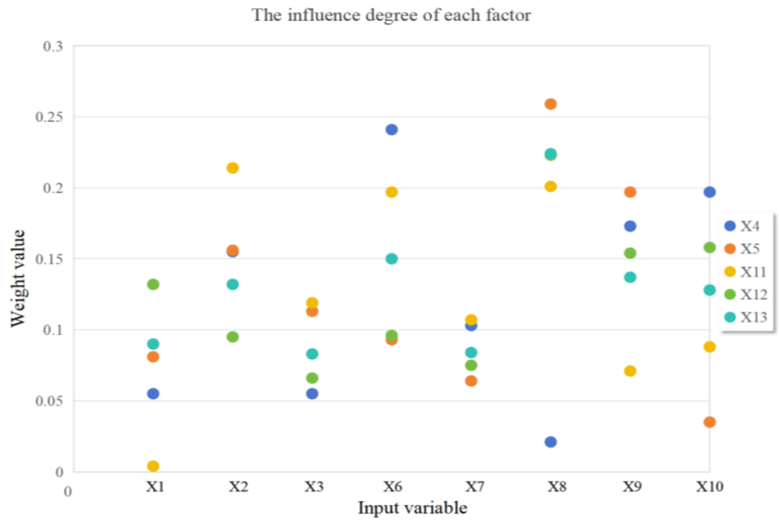

Figure 5: The influence degree of each factor.

Disassembly and reuse technology and incentive promotion have a greater impact on competition in informal recycling channels, with 0.197 and 0.156 respectively. The recycling price has the smallest effect on competition in informal recycling channels with 0.035; incentive promotion has the largest effect on environmental awareness with 0.214, while economic benefits and information cleaning costs have a larger effect on environmental awareness with 0.201 and 0.197 respectively. Regulatory measures have the smallest impact on environmental awareness with 0.004; economic benefits have the largest impact on information sensitivity with 0.223. The recycling price and the dismantling and reuse technology have a significant impact on information sensitivity with 0.158 and 0.154 respectively. The responsibility for recycling has the smallest effect on information sensitivity, 0.066; the economic benefits have the largest effect on the preference for recycling channels, 0.224, while the responsibility for recycling has the smallest effect on the preference for recycling channels, 0.083. The relationship between the input layer variables and the output layer variables is shown in Fig. (**6**).

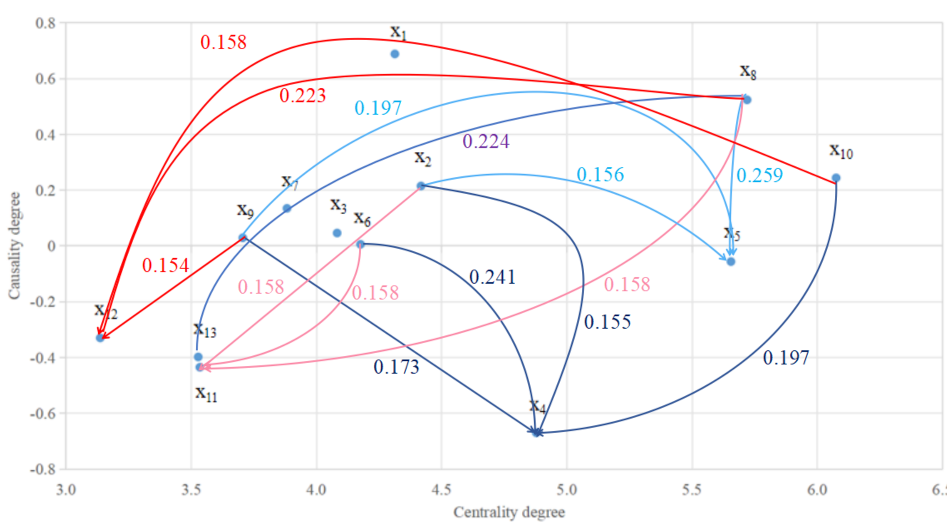

Figure 6: Diagram of the relationship between input layer variables and output layer variables.

5. Results and Discussions

5.1. Results

After extensive analysis and careful consideration using the DEMTEL model (Table **B5**), the following conclusions can be drawn:

(1) The causal factors influencing the recycling and treatment of information-sensitive WEEE are, in descending order of importance: regulatory measures, disassembly and re-use technology, recycling price, incentive systems, economic benefits, cost of cleaning information, take responsibility for recycling, size of the recycling market. These factors have a significant influence on other factors and are not easy to change. Among these, regulatory measures stand out as the most important causal factor. That is, government regulatory measures taken in accordance with the law in response to information leakage incidents during the recycling and treatment of information-sensitive WEEE will have a significant impact on other influencing factors. This highlights the government as a key stakeholder whose mandatory regulations serve as the foundational lever for initiating systemic change. From a stakeholder perspective, this finding demonstrates that governmental regulatory actions can directly alter the compliance cost structure of enterprises (recyclers/processors) and, through signaling effects, influence residents' risk perceptions regarding recycling safety. Consequently, this systematically drives the market toward greater standardization. Therefore, based on the existing laws and regulations on the recycling and treatment of WEEE, the government must further refine the relevant laws and regulations, strengthen the supervision of informal recycling enterprises, and reduce the occurrence of information leakage in the recycling of information-sensitive WEEE. This, in turn, will increase the willingness of residents to participate in formal recycling, strengthen the competitiveness of formal recycling enterprises, and promote the standardization of the recycling market.

(2) The resultant factors influencing the recycling and treatment of information-sensitive WEEE are, in descending order of importance: competition in informal recycling channels, information sensitivity, recycling channel preference, environmental awareness, information cleansing technology. These factors indicate that they are susceptible to influence by other factors and are relatively easy to change in the context of decision making related to the recycling and treatment of information-sensitive WEEE. Among these, competition in informal recycling channels is the most important outcome factor. The existence of informal recycling channels is mainly attributed to two reasons: firstly, inadequate government laws and regulations, coupled with a lack of supervision; secondly, weak awareness of information protection among residents, this reveals that the key to governance lies in simultaneously regulating the incentives of multiple stakeholders [43]. Therefore, in addition to improving laws and regulations, the government should strictly crack down on illegal recycling and dismantling of information-sensitive WEEE. At the same time, it should actively promote awareness of the environmental impact and personal losses caused by improper disposal of information-sensitive WEEE, thereby raising residents' information protection awareness and promoting the recycling of information-sensitive WEEE.

(3) The comprehensive influencing factors on the recycling and treatment of information-sensitive WEEE, in descending order of importance, are: recycling price, disassembly and reuse technology, competition in informal recycling, information cleansing technology, incentive systems, regulatory measures, the size of the recycling market, cost of cleaning up information, economic benefits, take responsibility for recycling, environmental awareness, recycling channel preference, information sensitivity. Among the wide range of influencing factors, recycling price is the most important, this finding is consistent with most research conclusions on traditional WEEE [44, 45]. However, this study further reveals that in the context of information-sensitive WEEE, the mechanism of price factors is more complex. It serves not only as an economic incentive but also as a critical factor in residents' weighing of "economic benefits" against "privacy risks." Higher recycling prices can, to a certain extent, increase the enthusiasm of citizens to recycle information-sensitive WEEE and thus influence the size of the recycling market for recyclers and processors. However, excessively high recycling prices can increase the recycling costs for recyclers and reduce their recycling profits. At the same time, it may trigger vicious competition among informal recycling channels, leading to an imbalance in the recycling market. Therefore, the government also needs to strictly monitor recycling prices in the WEEE recycling market and promote consumer recycling within a reasonable range while ensuring the healthy and sustainable development of the recycling market.

5.2. Discussions

By using the BP neural network model to examine the interaction between causal and outcome factors (Table **1**), the following conclusions were derived:

(1) The cost of cleaning information has the greatest impact on the size of the recycling market. Residents believe that increasing the cost of information cleaning can ensure data security and privacy protection, and therefore they are willing to bear the additional cost. Therefore, companies should intensify their research and application of data security technologies to encourage citizens to recycle information-sensitive WEEE. This will not only improve the ability of enterprises to handle information-sensitive WEEE, but also help to expand the size of the recycling market [46].

(2) Economic benefits have the greatest impact on competition in informal recycling channels. Informal recyclers attract residents with higher economic returns through their cost advantages. This exposes the limitations of relying solely on government bans, indicating that governance must acknowledge the fundamental role of economic incentives. Crucially, policies should empower formal enterprises to enhance their economic competitiveness through technological innovation and model optimization. This enables them to offer market alternatives that combine high returns with high safety, thereby guiding a fundamental shift in residents' preferences.

(3) Incentive systems have the greatest impact on environmental awareness. Governments can guide the behaviour of residents through incentive-based promotions by providing information on the environmental hazards of information-sensitive WEEE and related recycling details to residents through various channels. By formulating and implementing more environmentally friendly policies and regulations, promoting awareness of environmental issues and needs, and increasing residents' attention and concern about environmental problems, governments can increase residents' environmental awareness [47].

(4) Economic benefits have the greatest influence on recycling channel preference. These enterprises provide more convenient and professional recycling services, such as door-to-door collection and fast processing, which can meet residents' needs, improve their satisfaction, and encourage them to choose these enterprises as their recycling channels. When choosing a recycling channel, residents usually consider the credibility and sense of responsibility of the company [48]. Companies that take responsibility for recycling must adopt safer and more environmentally friendly measures to handle information-sensitive WEEE, such as data erasure and recycling of environmentally friendly materials. If companies can take on this recycling responsibility, their brand influence will also grow, and citizens will be more likely to choose these companies as their recycling channels.

(5) The market recycling scale has the most significant impact on information cleansing technology. When a significant number of residents choose a particular company to recycle information-sensitive WEEE, the company's recycling market expands, providing it with economies of scale and potentially increasing profit margins. At the same time, as the recycling market grows, so does the demand for higher standards of information erasure. To process these products better and more efficiently, companies can invest more in advanced information erasure technologies.

Based on the above research conclusions, it is evident that the process of recycling information-sensitive WEEE necessitates each stakeholder to jointly shoulder their responsibilities and make contributions towards sustainable development:

(1) As the regulatory authority, the government should pay more attention to the recycling of information-sensitive WEEE. Specific measures include: First, formulate or revise regulations and policies specifically targeting the recycling of information-sensitive WEEE, clearly defining technical levels for data erasure and audit certification requirements. Simultaneously, establish a dynamic “whitelist” system for formal recycling enterprises to provide clear guidance to the public. Second, design direct economic incentive tools, such as offering fixed subsidies for equipment compliantly processed by “whitelisted” enterprises or providing tax credits for their investments in data security equipment. This will substantially reduce compliance costs for formal channels and enhance their market competitiveness. Third, spearhead public awareness campaigns on the secure recycling of information-sensitive WEEE. Conduct risk education through case studies and collaborate with enterprises to promote the security guarantees of formal channels, systematically enhancing public risk awareness and trust levels [41].

(2) Manufacturers, recyclers, and processors play crucial roles in every stage of the recycling process. First, manufacturers must effectively implement Extended Producer Responsibility (EPR) by establishing convenient, free official recycling and data erasure services through existing networks, transforming recycling accessibility into a core brand responsibility [49]. Second, recycling processors must invest in internationally/nationally certified data destruction technologies and equipment, providing users with proof of critical disposal milestones via traceable platforms—converting technical capability into verifiable trust assets. Finally, industry leaders should spearhead the formation of an industrial alliance to share processing facilities, jointly develop technical solutions, and standardize service protocols. By leveraging economies of scale and collective action to reduce compliance costs, they can collectively enhance the overall efficiency and appeal of the formal recycling system [50].

(3) Residents should recognize the importance of recycling information-sensitive WEEE and actively participate in recycling activities [51]. Consumer choices and behaviors are the ultimate driving force behind market transformation. First, individuals should proactively use trusted software to perform basic data wiping on devices before recycling, fulfilling their responsibility for personal data management. Second, when recycling, they should actively seek out and prioritize government "whitelisted" or brand-authorized channels, using their purchasing power to incentivize the growth of legitimate markets. Third, they should actively provide feedback on experiences and report unlicensed recycling or environmental pollution through consumer platforms and environmental hotlines, becoming a social oversight force that drives industry standardization.

6. Concluding Remarks and Future Scope

6.1. Conclusion

This study first examines the factors influencing the recycling of information-sensitive WEEE generated by households, using the DEMATEL model to analyze the prioritization of the selected influencing factors. The BP neural network is then used to determine the impact of these causal factors on the corresponding outcome variables. Finally, the study presents recommendations from the perspective of the government, businesses and residents.

A comprehensive review of the existing literature and expert interviews was conducted to identify the 13 factors influencing resident information-sensitive WEEE. Utilizing the DEMATEL method, the interrelationships between these factors were elucidated, and causal maps were generated. The results of this study indicate that regulatory measures, incentive promotion, recycling responsibilities undertaken, information cleaning costs, information cleaning technologies, economic benefits, dismantling and reusing technologies, and recycling prices function as causal factors. Conversely, the size of the recycling market, competition in informal recycling channels, environmental awareness, information sensitivity, and preference for recycling channels are identified as outcome factors. The employment of a BP neural network model to calculate the weight of the causal factors reveals that the cost of information cleaning is the most significant factor in the recycling market size, that environmental awareness is the most influenced by incentive propaganda, that the economic benefit is the most influential factor in informal recycling channel competition, and that economic benefits play a leading role in shaping recycling channel preference. In light of these conclusions, the paper puts forward recommendations for the government, enterprises, and residents, with the aim of promoting the recycling of information-sensitive WEEE.

6.2. Limitations and Perspectives

The study was subject to certain limitations. First, regarding data samples, the questionnaire survey sample size is limited, with constraints in both geographical coverage and demographic diversity, which may affect the generalizability of the findings. Second, regarding methodology, the DEMATEL model relies on expert judgment, making its scoring inherently subjective. Meanwhile, the performance of the BP neural network is highly sensitive to parameter settings and data quality. Although combining these two approaches has proven to be an effective complementary strategy in complex system analysis, the robustness of results obtained through this hybrid method requires further empirical validation across different contexts. Third, regarding research perspective, this study primarily constructs the influencing factor system from the resident viewpoint, failing to fully incorporate first-hand data from other core stakeholders such as recycling enterprises, manufacturers, and policymakers. Future research could enhance the comprehensiveness of conclusions through multi-source data triangulation.

Given the aforementioned limitations, future research could be further deepened in the following directions: First, sample sizes could be expanded to conduct cross-regional and cross-cultural comparative studies; Second, explore integrating large-scale survey data with expert judgments to calibrate relationship strengths within DEMATEL; Third, refine the analysis of recycling behavior determinants for different categories of information-sensitive WEEE—such as smartphones, laptops, and smart wearables—to provide precise evidence for differentiated management strategies.

Conflict of Interest

The authors declare that they have no conflict of interest.

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Appendix A

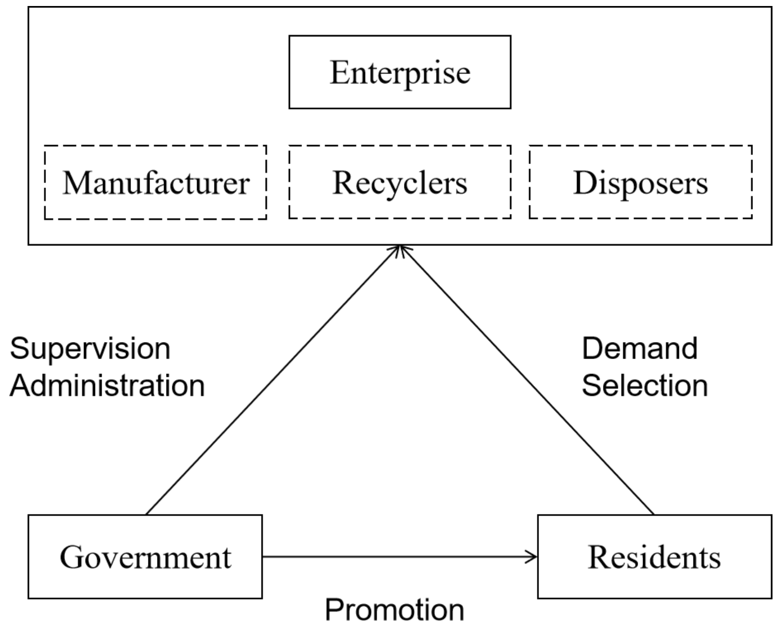

Figure A1: Stakeholder relations.

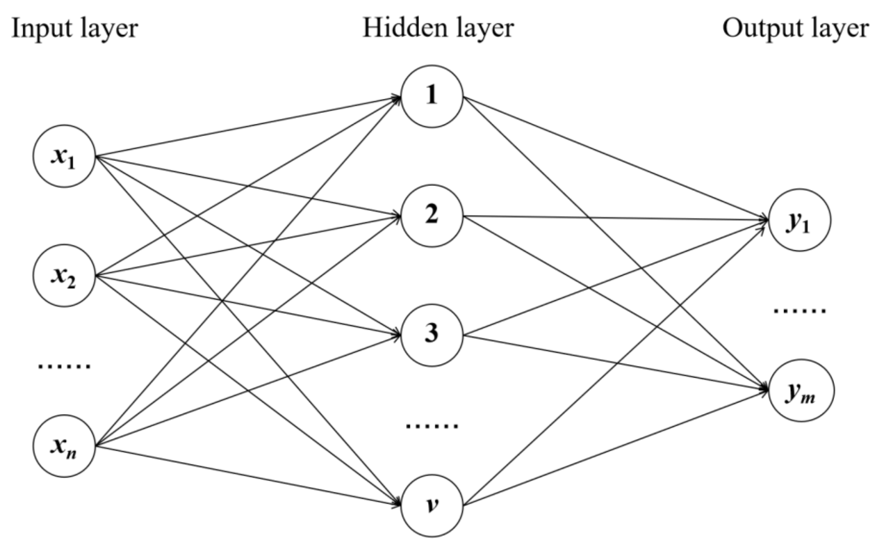

Figure A2: BP neural network model structure.

Appendix B

Table B1: Factors and explanations of WEEE recycling.

Dimension		Factor	Explain	Reference
Government		X_1: Regulatory measures	In the process of recycling information-sensitive WEEE, the informal enterprise divulges the personal information of residents, and the government carries on the supervision and punishment according to the law.	[24, 25]
		X_2: Incentive Systems	Government publicity helps to raise environmental awareness among residents, increase their willingness to recycle, and popularize formal recycling practices.	[26]
Enter prise	Recyclers	X_3: Cost of cleaning up information	Regular recyclers use the international ACI Data Destruction Standard to cover the resident personal information of information-sensitive WEEE several times to completely remove the data, informal recyclers use data format and other ways to carry out simple data cleaning.	[27]
		X_4: Information cleansing technology	The cleaning technology and method of resident personal data in information-sensitive WEEE by recycling enterprises affect the privacy and security of resident data.	[28]
		X_5: Competition in informal recycling channels	The competition of informal recycling channels makes regular recyclers lack of long-term stable sources of information-sensitive WEEE.	[29]
		X_6: The size of the recycling market	The amount of information-sensitive WEEE recovered from residents.	[30]
	Disposers	X_7: Economic benefits	Enterprises can gain profits by disassembling information-sensitive WEEE.	[31]
		X_8: Disassembly and reuse technology	The dismantling and reusing technology of the enterprise determines the reuse rate of the electronic waste components.	[31]
	Manufact urers	X_9: Take responsibility for recycling	From the point of view of corporate social responsibility, environmental responsibility producers to bear the recycling. The Extended Producers Responsibility (EPR) requires that the producer's responsibility for resources and environment extends from the production to the whole life cycle of product design, circulation, consumption, recycling, waste disposal, and so on.	[10]
Residents		X_{10}: Recycling Price	The price paid to residents by enterprises when residents Recycle information-sensitive WEEE.	[33]
		X_{11}: Environmental awareness	residents' perception of environmental hazards of information-sensitive WEEE. The higher the awareness of environmental protection, the higher the willingness of residents to recycle, and the more inclined to choose formal channels for recycling.	[32]
		X_{12}: Information sensitivity	After residents recall information-sensitive WEEE, they worry that information security can not be guaranteed. The higher the awareness of information protection, the more inclined to choose regular channels for recycling or refuse to recycle.	[41]
		X_{13}: Recycling channel preference	Due to the differences of residents, there are different degrees of preference for different recycling channels, such as online recycling channel preference.	[34, 35]

Table B2: Score scale.

Grading Criteria	Points
no impact	0
small impact	1
moderate impact	2
large impact	3
very large impact	4

Table B3: Standardized impact matrix.

Factor	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}
X_1	0.000	0.063	0.095	0.095	0.084	0.053	0.053	0.063	0.063	0.074	0.063	0.032	0.032
X_2	0.063	0.000	0.053	0.063	0.095	0.032	0.032	0.084	0.032	0.084	0.063	0.042	0.053
X_3	0.053	0.063	0.000	0.074	0.063	0.042	0.042	0.053	0.042	0.063	0.063	0.032	0.042
X_4	0.032	0.032	0.063	0.000	0.074	0.053	0.042	0.095	0.042	0.084	0.032	0.032	0.042
X_5	0.105	0.095	0.063	0.084	0.000	0.042	0.032	0.105	0.053	0.116	0.042	0.042	0.063
X_6	0.021	0.032	0.042	0.063	0.074	0.000	0.074	0.084	0.053	0.084	0.032	0.032	0.032
X_7	0.032	0.021	0.032	0.063	0.074	0.074	0.000	0.063	0.063	0.053	0.032	0.063	0.053
X_8	0.063	0.084	0.074	0.095	0.116	0.105	0.095	0.000	0.095	0.105	0.053	0.053	0.032
X_9	0.042	0.032	0.032	0.053	0.063	0.053	0.053	0.063	0.000	0.053	0.042	0.053	0.032
X_{10}	0.063	0.084	0.074	0.105	0.116	0.095	0.074	0.095	0.053	0.000	0.095	0.053	0.095
X_{11}	0.021	0.053	0.021	0.053	0.053	0.021	0.021	0.032	0.032	0.063	0.000	0.053	0.053
X_{12}	0.021	0.032	0.032	0.063	0.032	0.042	0.021	0.021	0.021	0.042	0.042	0.000	0.074
X_{13}	0.021	0.042	0.032	0.053	0.042	0.021	0.032	0.032	0.011	0.084	0.053	0.053	0.000

Table B4: Comprehensive impact matrix T.

Factor	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}
X_1	0.115	0.191	0.214	0.260	0.256	0.180	0.166	0.223	0.174	0.250	0.182	0.137	0.152
X_2	0.167	0.125	0.168	0.221	0.253	0.152	0.139	0.229	0.137	0.248	0.175	0.139	0.163
X_3	0.144	0.168	0.104	0.211	0.206	0.147	0.136	0.184	0.134	0.209	0.161	0.119	0.141
X_4	0.128	0.144	0.167	0.147	0.220	0.162	0.141	0.225	0.139	0.232	0.135	0.121	0.143
X_5	0.226	0.237	0.204	0.273	0.203	0.188	0.163	0.280	0.179	0.310	0.181	0.159	0.195
X_6	0.117	0.141	0.146	0.204	0.219	0.112	0.169	0.216	0.148	0.230	0.133	0.121	0.133
X_7	0.121	0.125	0.131	0.197	0.210	0.174	0.094	0.189	0.152	0.195	0.128	0.146	0.147
X_8	0.202	0.241	0.226	0.302	0.329	0.260	0.234	0.206	0.232	0.322	0.202	0.183	0.183
X_9	0.125	0.128	0.124	0.178	0.192	0.148	0.138	0.180	0.086	0.185	0.131	0.130	0.121
X_{10}	0.202	0.243	0.227	0.313	0.329	0.249	0.215	0.292	0.194	0.231	0.241	0.185	0.240
X_{11}	0.091	0.131	0.098	0.156	0.159	0.100	0.091	0.131	0.099	0.171	0.077	0.117	0.127
X_{12}	0.082	0.103	0.100	0.154	0.128	0.111	0.085	0.111	0.082	0.142	0.109	0.060	0.138
X_{13}	0.091	0.123	0.109	0.158	0.151	0.102	0.102	0.132	0.081	0.191	0.128	0.117	0.079

Table B5: DEMATEL calculates indicator values.

Factor	Impact D	Affected C	Centrality D+C	Causality D-C
X_1	2.501	1.812	4.313	0.688
X_2	2.316	2.101	4.417	0.215
X_3	2.064	2.018	4.083	0.046
X_4	2.104	2.774	4.878	-0.670
X_5	2.800	2.856	5.655	-0.056
X_6	2.091	2.085	4.176	0.006
X_7	2.009	1.874	3.882	0.135
X_8	3.122	2.598	5.720	0.524
X_9	1.867	1.838	3.706	0.029
X_{10}	3.160	2.915	6.075	0.244
X_{11}	1.549	1.985	3.534	-0.435
X_{12}	1.403	1.733	3.136	-0.330
X_{13}	1.565	1.963	3.528	-0.398

Table B6: BP neural network model parameter settings.

Model Parameter	Value
Number of input layer nodes	8
Number of output layer nodes	5
Number of hidden layer nodes	4
Training set: Test set	7:3
Model normalization	Maximum minimum normalization method
Maximum Number Of Iterations	1000
Learning rate	0.01
Activation function	tang, Lansing
Training function	Levenberg-Marquardt('trainlm')
Objective function	Mean Squared Error('MSE')

Table B7: Input layer - hidden layer weight coefficients.

Nodes	X_1	X_2	X_3	X_6	X_7	X_8	X_9	X_{10}
1	1.0748	-0.9143	-0.2227	-0.4058	0.4749	-0.0757	-0.6543	-1.3139
2	-1.158	0.2553	-0.2399	0.4719	-0.2831	-1.0717	-0.9473	0.4127
3	0.9397	-0.4939	0.0772	-0.1323	0.4217	0.1673	-0.6702	-1.1653
4	0.815	1.2811	0.8672	1.0281	-0.6833	2.1756	1.4131	-0.8945

Table B8: Hidden layer - output layer weight coefficient.

Nodes	X_4	X_5	X_{11}	X_{12}	X_{13}
1	0.052	-0.2231	0.2871	-1.3085	-0.1827
2	0.483	-0.1229	-0.2594	-0.1071	-0.0881
3	0.2205	0.1319	-0.3582	1.0506	0.1349
4	0.2359	0.1856	-0.3513	-1.085	-0.3597

Table B9: Correlation significance coefficient.

Coefficient	X_4	X_5	X_{11}	X_{12}	X_{13}
X_1	-0.048	0.089	-0.006	-0.506	-0.129
X_2	0.133	0.172	-0.298	-0.360	-0.189
X_3	0.048	0.125	-0.165	-0.251	-0.118
X_6	0.207	0.103	-0.274	-0.365	-0.176
X_7	-0.089	-0.071	0.148	0.284	0.119
X_8	0.018	0.287	-0.280	-0.895	-0.322
X_9	-0.149	0.217	-0.098	-0.596	-0.195
X_{10}	-0.169	-0.039	0.121	0.614	0.182

Table B10: Correlation index.

Index	X_4	X_5	X_{11}	X_{12}	X_{13}
X_1	0.024	0.044	0.003	0.248	0.064
X_2	0.066	0.086	0.148	0.178	0.094
X_3	0.024	0.062	0.082	0.125	0.059
X_6	0.103	0.051	0.136	0.180	0.088
X_7	0.044	0.035	0.074	0.141	0.060
X_8	0.009	0.142	0.139	0.420	0.160
X_9	0.074	0.108	0.049	0.289	0.097
X_{10}	0.084	0.019	0.061	0.298	0.091