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What Drives Online Redistribution Behavior: A Behavioral Decision-Making Model Based on Environmental Value Perception and Subjective Norms

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Abstract. In today's rapidly developing human society with increasing productivity and population growth, encouraging redistribution behavior has emerged as a viable solution to reduce MSW generation at its source and achieve eco-friendly economic growth. In the current era of continuous digital technology advancements, online platforms have become a more convenient means of implementing redistribution behavior. Based on the Theory of Reasoned Action, this study investigated how users form intentions and engage in redistribution behavior under the influence of digital technology. Quantitative data were collected through questionnaires and analyzed using SmartPLS4, resulting in a behavioral decision-making model for users' online redistribution behavior. The findings reveal that Environmental Value Perception (EVP) and Subjective Norm (SN) contribute to forming users' attitudes and further shape their behavioral intentions. The study proposes relevant design strategies for online redistribution platforms. However, it was noted that EVP and SN can stimulate behavioral intentions but may not directly drive online redistribution behavior. Hence, the intention–behavior gap exists, indicating that behavioral intention is not the sole predictor of behavior. Although age factors somewhat bridge the intention–behavior gap, other influencing factors remain to be explored.

Keywords. Redistribution Behavior; Online Platforms; TRA; PLS-SEM; Decision-Making Model

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1. Introduction

In today's rapidly evolving society, municipal solid waste (MSW) has emerged as a significant concern. This issue not only brings about numerous environmental challenges but also results in the waste of valuable resources [1]. In 2020, more than 2.1 billion metric tons of waste were generated in the European Union, equating to approximately 4.8 metric tons per capita [2]. To deal with these issues, recycling is considered a common and feasible approach for waste management, and many researches have indicated the influencing factors [3, 4]. Another feasible approach to reducing waste from sources and achieving eco-friendly economic growth is redistribution behaviors [5]. Redistribution behaviors involve various product disposal methods, which typically comprise reselling, gifting, and donating. These methods facilitate the transfer of product ownership, allowing items to retain their value until the end of their lifecycle, thus mitigating waste generation [6].

Many previous studies always focused on specific motivations of a single type of redistribution behavior [6, 7]. It has been summarized in De Ferran's research [5]. However, these discussions of redistribution behavior are biased and scattered, which are not able to indicate sufficiently why consumers redistribute their items rather than throw them away. Recently, some studies have identified common factors that affect redistribution behavior as a whole. Hou and Sarigöllü studied the impact of redistribution behavior from the perspective of product attributes and value perception, providing recommendations for product design [8]; De Ferran pointed out that the factors that determine consumer participation in redistribution are more related to individual-specific factors than to product factors [5]. However, there was little literature to discuss the impact of digital technology on redistribution behaviors.

In recent years, digital technology advancements have led to increased information exchange efficiency, resulting in the emergence of various online platforms. In 2022, second-hand e-commerce transactions in China reached a staggering 480.2 billion yuan—a growth of 19.99% compared to the previous year [9]. This substantially reduces waste generation from an environmental perspective, effectively adding value to discarded items. Online data from Europe and the United States has been converted by an organization that concluded that in 2021, the purchasing and selling of second-hand items resulted in the saving of 20.7 million tons of carbon dioxide emissions, 1.2 million tons of plastic, 7.8 million tons of steel, and 0.7 million tons of aluminum [10].

Environmental Value Perception (EVP) and Subjective Norms (SN) are the main variables in this research. The Chinese government has progressively strengthened its support for environmental protection and related propagation and education in recent years [11]. With the Chinese government's escalating emphasis on ecological advocacy, does such propagation positively impact redistribution behavior by online platforms? If so, how does this influence manifest? On the other hand, people are more susceptible to the influence of attitude and behavior on online platforms. Therefore, it is necessary to add subjective norm into the research framework.

The Theory of Reasoned Action (TRA), a widely utilized social psychology and behavioral science framework, is a potent tool for explaining and predicting human behavior [12]. Based on the TRA, this study aimed to explore how EVP and SN influence users' engagement in online redistribution behavior, thereby providing a theoretical basis for the design of online redistribution platforms and making a theoretical contribution to the use of digital technology for environmental conservation.

2. Conceptual framework

According to the TRA [12], behavioral intention (BI) is pivotal in predicting actual behavior (BEH), with its core determinants being attitude (ATT) and subjective norms (SN). When an individual has a positive attitude toward a particular behavior and perceives significant social support for that behavior, they are more likely to have a solid intention to engage in it.

ATT is an individual's positive or negative evaluation of an object, behavior, or concept, which can impact an individual's behavior and decisions. SN refers to an individual's perception of how their behavior aligns with social expectations or receives support from others, which elucidates how individuals respond to societal pressures and expectations and how these factors influence their behavioral intentions and actions.

Sujata's research shows that subjective norm can somewhat predict recycling intention [13]. If everyone around an individual recommends or supports redistribution behavior, the evaluation of redistribution behavior will likely become more positive. Thus, we hypothesized that: SN will influence BI through ATT (Hypothesis 1).

EVP refers to users' perception and assessment of the environmental impact of redistribution behavior [13]. The most important indicator of EVP is whether consumers perceive that they can reduce waste generation through such behaviors. With the Chinese government's vigorous promotion of environmental protection, the EVP of consumers has been heightened, potentially offering new perspectives on evaluating redistribution behavior. Consequently, EVP might influence attitudes and, subsequently, impact behavioral intention. Thus, we hypothesize: EVP will influence BI through ATT (Hypothesis 2).

Based on the TRA's premise of behavioral intention predicting behavior, we extended our investigation to explore the impact of EVP and SN on actual behavior. Given that H1 and H2 have already assumed positive effects of EVP and SN on behavioral intention, we further hypothesized that: SN will influence BEH through BI (Hypothesis 3); EVP will influence BEH through BI (Hypothesis 4).

Another variable we examined is age. Compared to previous generations, the younger generations tend to have greater internet exposure, which offers them more avenues for participating in redistribution behavior. Moreover, if they encounter obstacles, they may have more solutions at their disposal. Thus, we hypothesize: age will negatively moderate the path from behavioral intention to behavior, meaning that younger consumers are more likely to translate intention into action (Hypothesis 5).

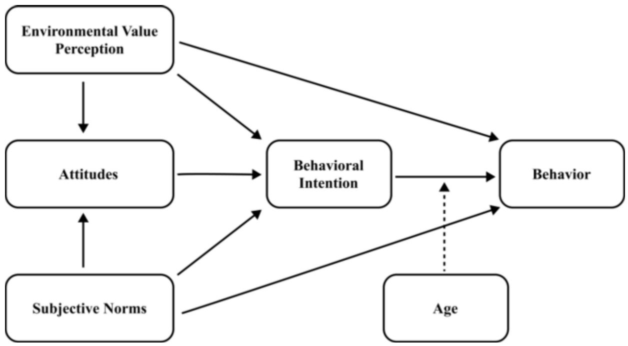

Figure 1. The research framework.

3. Method

We refined the questionnaire based on the existing literature to measure the required variables and applied it to our research context. Table 1 presents the questionnaire's design. EVP was measured by how consumers perceived whether they could reduce waste generation through redistribution behaviors [13]. ATT and SN were measured using two items adapted from Sujata and Ramayah's research questionnaires [13, 14]. Behavioral intention and actual behavior were measured using three items, encompassing the three common redistribution behaviors adopted by Hou and Sarigöllü's questionnaire [8]. All the measurement models were constructed using commonly used reflective measurement models. The seven-point Likert scale was used to measure these items, ranging from 1 (strongly disagree) to 7 (strongly agree). In addition, a 0-1 item," Have you ever used an online platform for redistribution behavior," was set to identify the users who redistribute online. Table 1 shows the complete list of the structure and corresponding items.

Table 1. Construct scales, mean, factor loadings, and VIF.

Construct	Items	Mean	Factor Loadings	VIF
Environmental value perception	● Redistribution participation can reduce the generation of waste.	5.530	1.000	1.000
Attitudes	● Redistribution participation is especially valuable for me.	5.576	0.932	2.206
	● I feel happy when I successfully redistribute my product	5.696	0.933	2.206
Subjective Norm	● My family agreed with me to redistribute my product	5.608	0.949	2.820
	● My friends and colleagues agreed with me to redistribute my product	5.548	0.950	2.820
Behavioral Intention	● I intend to resell my unused product	5.599	0.758	1.302
	● I intend to gift my unused product	5.369	0.881	2.142
	● I intend to donate my unused product to some organization to help people in need	5.585	0.841	2.044
Behavior	● How often do I resell the unused product	3.276	0.762	1.628
	● How often do I gift unused product	3.132	0.901	2.150
	● How often do I donate unused product	2.843	0.800	1.924

Table 2. Gender, age, income, and education.

Variable	Category	Frequency	Percentage (%)
Gender	male	88	40.6
	female	129	59.4
Age	below 30 years old	156	71.9
	between 30 and 40 years old	12	5.5
	between 40 and 50 years old	15	6.9
	Above 50 years old	6	2.8
	default	28	12.9
Income	below 5,000 RMB	60	27.6
	between 5,000 and 10,000 RMB	62	28.6
	between 10,000 and 20,000 RMB	36	16.6
	above 20,000 and 50,000 RMB	26	12.0
	default	33	15.2
Education	high school or below	31	14.3
	College	74	34.1
	bachelor's degree	45	20.7
	master's degree or higher	34	15.7
	default	33	15.2

The quantitative data were collected between March and May 2023 using a questionnaire distributed on the Wenjuanxing platform. In addition, some questionnaires were collected through offline interviews. In total, 386 questionnaires were collected, and then we deleted the samples who had never used online platforms to redistribute items and whose response time was less than 60 seconds. Finally, 217 questionnaires were selected, and descriptive statistics of samples are shown in Table 2.

Partial Least Squares Structural Equation Modeling (PLS-SEM) is a flexible method suitable for small sample studies; it can deliver efficient results even for small sample sizes. We thus chose the more flexible PLS-SEM for analysis [15]. To analyze and compute the research model, we analyzed the data using the SmartPLS 4.0 software, which can conduct PLS-SEM. Within SmartPLS 4.0, PLS-SEM algorithms were employed to output the values of factor loadings, discriminant validity (HTMT-ratio), construct validity, average variance extracted (AVE), and variance inflation factors (VIF) to assess the measurement model. Bootstrapping algorithms were employed to output t-values and evaluate the significance of the path model to validate the hypotheses and investigate the connections between the constructs. Table 4 presents the path coefficients for the various relationships. Table 5 displays the total effects, the direct effects, and the total indirect effects. And blindfolding algorithms were employed to output R^2 and Q^2. R^2 measures the proportion of variance explained by the model, indicating how well the variables in the model explain the variance in the data, and Q^2 is used to measure the predictive capability of a model by evaluating the predictive performance of the remaining variables after excluding certain variables from the model [8].

4. Result

For the reflective measurement model of this research, the factor loadings of each latent variable and Cronbach's alpha meet the standards commonly observed in previous studies, indicating good construct validity of the data [15, 16]. Next, CR and AVE were used to assess convergent validity. All the CR scores were above 0.7, and all the AVE values exceeded 0.5 [15, 16].

The Heterotrait-Monotrait Ratio (HTMT) was used to evaluate discriminant validity [15]. Considering that EVP, ATT, and SN conceptually resemble each other, involving subjective evaluations of certain concepts, a threshold of 0.90 was set based on reference [15]. All the HTMT values were found to be below 0.90, which validates the model (Table 3) [16]. Most of the variables' VIF were below 3.0, indicating that common method bias is not an issue in this model. Collectively, all these results demonstrate that the measurement model possesses good reliability and validity [15]. Table 3 presents the results in detail.

Table 3. Discriminant validity (HTMT-ratio), Construct validity, R^2, Q^2.

	ATT	BI	BEH	SN	EVP
ATT					
BI	0.689				
BEH	0.172	0.381			
SN	0.856	0.613	0.137		
EVP	0.898	0.587	0.225	0.659	
Cronbach's α	0.850	0.772	0.818	0.891	
CR	0.850	0.776	0.866	0.891	
AVE	0.949	0.689	0.727	0.870	
R^2	0.772	0.339	0.145		
Q^2	0.665	0.216	0.094		

The accuracy of the PLS-SEM model is typically evaluated using two statistical indicators: R^2 and Q^2. Table 3 presents the R^2 values. The model, it was found, explains 77.2% of the variance in attitude ($R^2 = 0.772$), which is relatively high and effectively reflects attitude. Moreover, the model accounts for 33.9% of the variance in consumers' intentions for online redistribution ($R^2 = 0.339$), indicating a moderate predictive level. The explanation of the behavioral intention in redistribution behavior by EVP, ATT, and SN is acceptable. However, the R^2 for actual behavior was only 0.145, suggesting that relying solely on behavioral intention is insufficient to explain actual behavior adequately.

The Q^2 values are presented in Table 3. In this study, the Q^2 values of ATT, BI, and BEH are 0.665, 0.216, and 0.094, respectively. These findings indicate that our model exhibits excellent predictive ability in forecasting consumers' attitudes towards online redistribution behavior and acceptable predictive capability for behavioral intentions. However, the model's predictive power for actual behavior is limited.

Table 4. Structural analysis.

Path	β	Standard Deviation	t-Value	p-Value
EVP→ATT	0.595	0.066	8.967	0.000
EVP→BI	0.169	0.088	1.919	0.055
EVP→BEH	-0.028	0.074	0.381	0.703
SN→ATT	0.375	0.069	5.449	0.000
SN→BI	0.209	0.093	2.150	0.032
SN→BEH	0.155	0.072	2.249	0.011
ATT→BI	0.261	0.122	2.132	0.033
BI→BEH	0.247	0.065	3.814	0.000
EVP→ATT→BI	0.155	0.152	2.041	0.041
SN→ATT→BI	0.098	0.097	2.015	0.044
EVP→BI→BEH	0.042	0.043	1.646	0.100
SN→BI→BEH	0.052	0.055	1.694	0.090
Age*BI→BEH	-0.161	0.074	2.176	0.030

Table 5. Total Effects, direct effects, and total indirect effects.

	Total effect		Direct effect		Indirect effect	
	β	p-Value	β	p-Value	β	p-Value
EVP→BI	0.325	0.000	0.169	0.055	0.155	0.041
EVP→BEH	0.052	0.504	0.028	0.703	0.080	0.005
SN→BI	0.307	0.001	0.209	0.025	0.098	0.044
SN→BEH	0.231	0.001	0.155	0.032	0.044	0.025

We initially examined the mediating effect of ATT in the model. The indirect effect of SN→BI, as well as the specific indirect path SN→ATT→BI, had path coefficients of 0.209 and 0.098, respectively, with p-values all below 0.05. Consequently, hypothesis 1 was confirmed.

Subsequently, we evaluated the impact of EVP on BI through the mediating variable ATT. The path coefficients EVP→BI and the specific indirect path EVP→ATT→BI were 0.033 and 0.155, respectively. The p-values for the first two paths were below 0.05, indicating their significance. Hence, hypothesis 2 was also confirmed.

Next, we examined the indirect and total effects of EVP and SN on actual behavior (BEH). The direct effect of EVP→BEH was not significant, and the specific indirect path EVP→BI→BEH was also insignificant. However, the total effect of EVP→BEH was significant. The direct effect of SN→BEH was significant, while the specific indirect path SN→BI→BEH was not. However, the total effect of SN→BEH was significant. These results suggest that, although EVP and SN significantly influenced BEH, BI was not a mediating variable for EVP's effect on BEH. Therefore, hypotheses 3 and hypotheses 4 were rejected.

The moderating effect of age on the relationship between BI and BEH was then examined. The result is shown in Table 5. The table indicates that age negatively moderates the relationship between BI and BEH, implying that older consumers are less willing to translate their intentions into actions. Consequently, hypothesis 5 was confirmed.

5. Discussion

Firstly, the findings demonstrate the model's effectiveness in predicting behavioral intention. The R^2 value for behavioral intention reached 0.339, indicating that the explanatory power of EVP, SN, and ATT toward behavioral intention was moderate. This suggests that these variables adequately reflected the formation of ATT.

It was found that EVP and SN significantly influenced BI formation, and this effect was achieved through their influence on ATT. The R^2 value for ATT reached 0.772, indicating the high explanatory power of EVP and SN toward ATT. This suggests that the awareness of the environmental significance and the influence of others play vital roles in consumers' evaluation of online redistribution behavior, thus driving the formation of behavioral intention.

Consequently, EVP is a significant influencer of consumer engagement in redistribution behavior within online platforms. Boosted by solid governmental support in China, consumer environmental consciousness has markedly increased, becoming a critical influence on purchasing decisions. According to our findings, these platforms should enhance their promotion of environmental values to attract more consumers to participate in redistribution practices. However, more than a simple promotional approach is required. For instance, consumers could be shown how a single resale or donation could reduce landfill waste. Such a message can resonate positively with consumers.

Subjective norm is another significant factor. Online redistribution platforms could design features that facilitate sharing and collaborative activities, such as attractive sharing posters or community-based environmental initiatives. These measures could leverage the power of SN and encourage more people to participate in online redistribution behavior.

However, our study revealed limitations in predicting actual behavior. Although the BI→BEH path was significant, the examined variables explained only 14.9% of the variance in actual behavior. This relatively low figure indicates that the model's explanatory power regarding BEH is somewhat inadequate. In the mediation test, where BI was the mediating variable and EVP and SN were the independent variables, the mediating effect of BI was insignificant, indicating that BI is not the sole variable influencing actual behavior. This suggests that an intention–behavior gap exists in the decision-making process for consumers engaging in online redistribution, which refers to consumers having intentions but failing to take action.

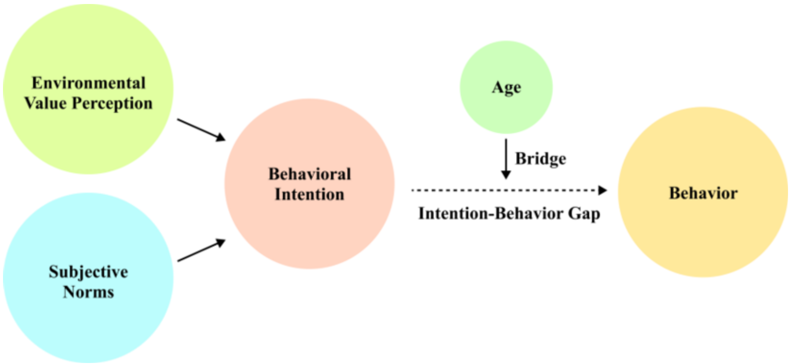

Figure 2. The decision-making model.

Moreover, examining the moderating effect of age on online redistribution behavior, we found that age does moderate the relationship between behavioral intention and actual behavior, thus partially explaining the intention–behavior gap. Younger consumers are more willing to translate their intentions into actions. We therefore recommend that, when promoting online redistribution behavior, younger audiences should be targeted using youthful and energetic. Moreover, in platform designs, aesthetics that resonate with younger individuals and exude vibrancy should be considered.

6. Conclusion and limitation

This study aims to understand better the factors influencing people's intentions and participation in online redistribution behavior. The contributions are shown as follows: (1) For the first time, it proposes a decision-making model that reveals how EVP and SN impact behavioral intention and actual behavior in the context of e-commerce; (2) It indicates the intention-behavior gap existed in online redistribution, and points out that age is a moderating factor of the gap; (3) Some targeted suggestions could be proposed for designing online platforms and policy-making based on this model. Subsequent studies should explore more critical factors that bridge this gap in online redistribution behavior, further propelling the advancement of this behavior and allowing digital technology to better contribute to environmental protection.

This study also has some limitations. Some respondents were unwilling to disclose relevant information in the offline collection, resulting in default values in this study's demographic statistics. Consequently, the demographic profile of the sample is not fully revealed. In addition, it has limitations regarding the explanatory power of the examined factors on behavior. In future research, these shortcomings should be improved to enhance the sample collection procedures and acceptance criteria, thereby improving the sample's reliability and the credibility of the research findings.

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