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Research article

Influencing factors of urban residents' willingness to classify waste during COVID-19: The case of Hangzhou

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ABSTRACT

During COVID-19, the urban environment has faced more challenges, and household waste classification has become increasingly important. Based on the theory of planned behavior (TPB), this paper studies the key influencing factors and influence paths of urban residents' willingness to perform waste classification using a structural equation model. Based on the timing of two questionnaires, one before and one after the COVID-19 outbreak, we apply multigroup analysis to test the moderating role of the pandemic. We find that 1) social norms are the primary factor that directly affects residents' willingness to classify waste, followed by perceived behavior costs and behavior attitude. All factors show a positive effect, except for perceived behavior costs. We also find that 2) the results of multigroup analysis indicate that before and after the epidemic there are significant differences in the effect from three influencing paths, which verifies that during the epidemic, the influence paths of behavior attitude and perceived behavior costs on waste classification willingness have been strengthened, but the influence from social norms is weakened. Finally, we suggest that the government should keep playing an important role in waste classification in terms of promotion, reward and penalty, as well as improvement in laws, rules and waste classification facilities.

1. Introduction

It has been 30 years since China implemented its waste classification pilot project, which is an important symbol of urban civilization and even an important indicator of the quality of urban governance (UNDP, 2013) [1]. In 2000, Hangzhou was listed by the Ministry of Construction as one of the 8 pilot cities for waste classification in China. In 2015, Hangzhou issued the 'Hangzhou Municipal Waste Management Regulations'. However, there are still many problems, and the rate of participation has long remained low. In 2021, Hangzhou set a target of being a 'no-waste city', so this study can help with the establishment of a long-term mechanism for waste classification.

The outbreak of COVID-19 resulted in new challenges for waste classification. The first is the promotion difficulty. Due to the requirements of epidemic prevention and control, residents had to avoid gatherings and large-scale activities, including in-person activities held by the government and local community for waste classification. The second is the implementation difficulty. The reduction in outdoor activities led to a surge in waste, and the frequency of residents dealing with the waste was significantly reduced, which made it more difficult for individuals to engage in waste classification. Last, the epidemic put forward higher requirements on

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the living environment because waste classification needs to be traceable so that we can reduce the risk of virus transmission. Therefore, it is of great practical significance to explore the factors affecting residents' willingness to perform waste classification during the epidemic to raise residents' rate of participation in waste classification.

This paper uses a structural equation model to address the following research questions: what are the driving forces, key elements and influencing paths of urban residents' willingness to perform waste classification from the perspective of behavior psychology? The next section reviews the literature on behavior theory and waste classification. The third section presents the method and data. The fourth section is the analysis based on empirical results. The final section concludes.

2. Literature review

Ajzen (1991) [2] proposed the theory of planned behavior (TPB) that behavior intention is an important determinant of human behavior, while individual attitudes, subjective norms and perceived behavioral control profoundly affect behavior intention. This theory better explains the influencing factors of individual behaviors. It has been widely applied in many fields of human research. Numerous studies provide support for the predictive validity of the TPB framework (Armitage and Conner, 2001 [3]; Elliott et al., 2003 [4]), including studies of environmental behavior (Bamberg and Blöbaum, 2007 [5]; Ao et al., 2022 [6]).

According to Taylor et al. (1995) [7], perceived behavior costs can indirectly and directly affect waste management behavior. In Hong Kong, attitude is the main factor in the intention to use waste recycling containers (Chan, 1998) [8]. Regarding Malaysian students' willingness to recycle, behavioral perceptual control and subjective norms are the strongest predictor of behavior intention (Mahmud and Osman, 2010) [9]. Recently, a meta-analysis verified \ the application of the TPB framework in environmental behavior and found differences across countries and cultures (Morren and Grinstein, 2016) [10]. The novel coronavirus outbreak at the end of 2019 posed a new challenge to the promotion of waste classification. In China, when an outbreak occurs in a region, a series of strict local prevention and control measures are taken to contain the spread, and the shortage in resources and workforce caused by virus-prevention measures hinders the full implementation of sustainable waste management that was introduced and enforced in 2019 (Van Fan et al., 2021) [11]. It has also been suggested that waste classification and epidemic control are mutually reinforcing, as the promotion of community waste classification significantly contributes to the implementation of epidemic control, while epidemic control strengthens the organizational capacity of community work and raises residents' behavioral awareness (Yin et al., 2021) [12].

Overall, it can be seen from the above that residents' willingness to classify waste is a combined result of multiple factors. At present, research on the influencing factors of residents' participation in waste classification is still relatively scattered, and few studies have analyzed the relationship between the COVID-19 epidemic and residents' willingness to classify waste. By establishing a comprehensive and multilevel influencing factor analysis framework, we provide a new perspective on the willingness to classify waste, filling the research gap in the impact of the epidemic on the willingness to classify waste.

3. Methodology and data

3.1. Conceptual model and influencing factor

The conceptual model of the influencing factors of urban residents' willingness to classify waste is constructed in Fig. 1. However, data do not address the relationship between the willingness to classify waste and actual classification behavior, but this relationship seems settled. Experiments (Ajzen, 2012) [13] and longitudinal studies (Venkatesh et al., 2012) [14] have demonstrated the causal effects of willingness on behavior.

Behavior attitude reflects residents' perceptions of participating in waste classification and their expectations for the outcome. It has been verified that residents' attitudes towards waste classification have a significant positive effect on their willingness to classify waste (Tonglet et al., 2004) [15]. Therefore, we propose Hypothesis H1.

H1. Behavior attitude significantly and positively affects residents' willingness to classify waste.

Perceived behavior costs reflect the perceived difficulty of waste classification and the cognition that hinders waste classification behavior, such as required space, time, and walking distance. According to Rejonen et al. (2021) [16], perceived behavior costs include low behavioral costs, ease of gaining information and dealing with waste. When people realize that it is less difficult to perform waste classification, they are more willing to do so, and it is easier for the government to promote. Existing studies (Martin et al., 2006 [17];

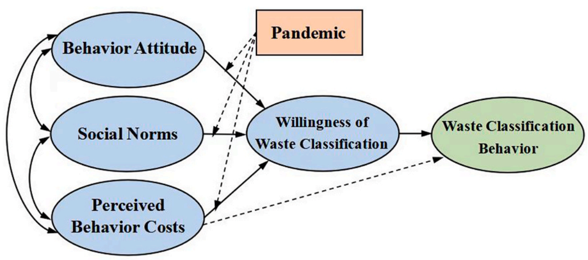

Fig. 1. Conceptual model of factors influencing waste classification willingness.

Zhang et al., 2017 [18]) have also verified that residents' perception of behavior is significantly and negatively correlated with their willingness to classify waste. Therefore, we propose Hypothesis H2.

H2. Perceived behavior costs significantly and negatively affect residents' willingness to classify waste.

Social norms are perceived behavioral rules within a certain group (Kirakozian, 2016 [19]). Individuals will be affected by their surroundings when making decisions, especially by people who are very important to them, such as relatives and friends (Pappas et al., 2019 [20]; Liu et al., 2019 [21]). Thus, social norms can encourage people to classify waste despite high behavioral costs. Therefore, we propose Hypothesis H3.

H3. Social norms significantly and positively affect residents' willingness to classify waste.

3.2. Variable selection

We select four latent variables to measure the scale of residents' willingness to classify waste in the survey questionnaires: behavior attitude, perceived behavior costs and social norms. Almost all the variables are borrowed from previous studies (Sherer et al., 1982 [22]; Xu et al., 2017 [23]), and they have corresponding observation variables in this paper. The scale (Likert scale) is a 5-level framework. That is, each variable in the table has five grades, from "strongly disagree" to "strongly agree", marked as 1 to 5, respectively.

3.3. Structural equation model

The variables above cannot be measured directly. It is difficult for scholars to use traditional analysis methods to obtain accurate results, while structural equation models can handle this issue very well. Therefore, we adopt the structural equation model.

The structural equation model includes two parts. (1) The measurement model is about the relationship between the latent variable and the observed variable. Observation variables can be measured by data obtained from measurement tools, such as scales or questionnaires. Latent variables cannot be directly measured, and we need data from several observed variables. (2) The structural model concerns the causal relationship among latent variables. The mathematical expression of the structural equation model in this paper is:

Measurement model:

$$y = \Lambda_{y\eta} + \varepsilon \tag{1}$$

$$x = \Lambda_{x\xi} + \delta \tag{2}$$

Structural model:

$$\eta = B\eta + \Gamma\xi + \varepsilon \tag{3}$$

The measurement equation model includes the measurement equation of endogenous latent variables and the measurement equation of exogenous latent variables. In the structural equation model, the exogenous latent variables are those not pointed to by other latent variables. Equation (1) is a measurement equation of endogenous latent variables composed of endogenous indicators, y is a $p \times 1$ vector of p endogenous indicators, η is a $m \times 1$ vector of m endogenous latent variables' factors, $\Lambda_{y\eta}$ is y's $p\times m$ factor loading matrix on η, and ε is a $p \times 1$ vector of measurement errors with p errors. The same applies to Equation (2).

In Equation (3),B is the $q \times n$ coefficient matrix, which describes the influence among the endogenous variables η, Γ is the $m\times n$ coefficient matrix, which describes the influence from the exogenous latent variables ξ on the endogenous latent variables η, and ε is a $m \times 1$ residual vector (Hou et al., 2004 [24]; Byrne, 2016 [25]).

3.4. Data sources

Data come from two survey questionnaires conducted by random sampling in May 2021 and February 2022. From 25 January to 5 February 2022, 114 new local cases were reported in Hangzhou, causing a new round of control over the COVID-19 epidemic. The second questionnaire was conducted to investigate whether the fear and sense of the epidemic have an impact on the willingness of Hangzhou residents to classify waste. Between May 2021 and February 2022, there were no new local cases in Hangzhou, so the selection of these two timings is appropriate.

We randomly selected nine residential communities with high occupancy rates in Hangzhou and distributed the questionnaire in person, covering all age groups as much as possible. In May 2021, the first questionnaire was conducted. A total of 350 questionnaires were distributed, 318 of which were valid, with an effective rate of 90.8%. In the valid questionnaires, males and females accounted for 53.5% and 46.5%, respectively, and the proportions were relatively balanced. Most of them are young people aged between 20 and 50, but there are fewer respondents under the age of 20 or over 50. In February 2022, the same scale was used to conduct a questionnaire on urban residents in Hangzhou again. The distribution sites of the two questionnaires were located in the same residential communities. A total of 180 questionnaires were distributed in the second round, 156 of which were valid, with an effective rate of 86.7%; the demographic distribution of the survey group was roughly the same as that in the first round. All paper-based questionnaires were distributed randomly at the entrance of the community. After screening the survey data, no individual participated in both surveys, so a total of 474 valid questionnaires in these two rounds (see Table 2er for details).

This study was approved by the Research Ethics Committee under the Academic Board of Zhejiang University of Science and Technology, and informed consent was obtained from all participants in this study.

However, cross-sectional data are used to study different individuals at the same time, and it is easier to provide spurious evidence (Armstrong, 2012 [26]; Venkatesh et al., 2012 [14]). Cross-sectional data often have greater differences among individuals and lack a time dimension to support causal inference.

4. Empirical analysis

4.1. Reliability and validity test (EFA)

There are 19 measurement questions in the questionnaire, corresponding to 19 observation variables in Table 1. The paper used SPSS 25.0 to test the reliability and validity of the questionnaire. The overall Cronbach's α coefficient of the questionnaire is 0.86, and every dimension's α coefficient is greater than 0.8, indicating that each observation variable in the questionnaire reflects the latent variables well and the reliability of the questionnaire data is high. In terms of validity, the KMO value is 0.842, and the significance level of Bartlett's test of sphericity is 0.000. The statistical test is significant, and it meets the conditions for factor analysis.

We further conduct exploratory factor analysis on the data of 19 questions. Through principal axis factoring and oblique rotation (Carpenter, 2018) [27], the factors with eigenvalues greater than 1 were selected as latent variables, and the cumulative contribution rate of the variance of the four main factors was 61.364% (Table 3).

Table 4 is the factor loading matrix after the oblique cross rotation. PBC6, SN5, SN6, and SN7 were excluded because of low loadings, and all remaining variables had loadings greater than 0.5. Thus, it passes the exploratory factor analysis and is consistent with the previously delineated dimensions, which means that the questionnaire used in this paper has structural validity.

4.2. Model fitting

With the hypothetical path of latent variables and 474 sample data, the structural equation model is fitted by Amos 24.0. In the estimation results of the initial model, the fitting outcome is not very good. To improve the fitness of the model, we modified the covariance correction index MI. According to the principle of modifying one parameter at a time until the optimal model is obtained, we modified several residuals, in turn, to raise the residual correlation and reduce the overall chi-square value of the model. The overall fitness of the modified model is shown in Table 5. After modification, most indicators are relatively ideal, and the overall fitness of the model is improved.

4.3. Confirmatory factor analysis

4.3.1. Convergent validity

Convergent validity measures internal consistency (Aibinu and Al-Lawati, 2010 [28]). When using multiple items to measure latent variables, researchers should pay attention not only to the reliability of individual measurements but also to the extent to which the measures demonstrate convergent validity (Hulland, 1999 [29]). According to Fornell and Larcker (1981) [30], we calculate the AVE values of four latent variables through standardized coefficients (see Table 6). These results demonstrate that there is convergent validity and good internal consistency in the measurement model (all AVE $>$0.5).

Table 1
The Selection of variables.

Latent variable	Observed variable	Expected symbol
Behavior Attitude	Waste classification is a good practice (BA1)	+
	Waste classification is an effective measure to protect the environment (BA2)	
	Waste classification reflects personal quality (BA3)	
Perceived Behavior Costs	Waste classification takes a lot of time (PBC1)	–
	Waste classification requires a lot of physical effort (PBC2)	
	The standard of waste classification is too complicated; I always get it wrong (PBC3)	
	My community has a bad waste classification system (PBC4)	
	My community has bad waste classification facilities (PBC5)	
	My community has no fixed or mobile waste collection stations (PBC6)	
Social Norms	I am influenced by my friends and family on waste classification (SN1)	+
	I am influenced by my neighbor on waste classification (SN2)	
	Government and community policies raise awareness of waste classification (SN3)	
	Government and community policies have taught me how to classify waste (SN4)	
	The government should take mandatory measures to implement waste classification (SN5)	
	The government should provide incentives for residents who implement waste classification (SN6)	
	The government should impose fines on residents who violate waste classification policies (SN7)	
Willingness to Classify Waste	I am willing to classify household waste every day (BE1)	
	I plan to dispose all kinds of rubbish every day from now on (BE2)	
	I decided to classify all kinds of waste every day in the future (BE3)	

Table 2
General characteristics of the data sample.

Factor	Feature	First Round	Second Round	Overall Proportion (%)
Gender	Male = 1	170	81	53.0
	Female = 2	148	75	47.0
Income	2000 yuan = 1	45	21	13.9
	2000-4000 yuan = 2	69	44	23.8
	4000-6000 yuan = 3	107	51	33.3
	6000 yuan = 4	97	40	29.0
Education	High school and below = 1	34	14	10.1
	Bachelor or College = 2	240	112	74.3
	Graduate and above = 3	44	30	15.6
Age	younger than 20	14	6	4.2
	20 to 30 = 2	198	116	66.7
	31 to 40 = 3	64	19	17.5
	41 to 50 = 4	36	11	9.9
	51 and elder = 5	6	2	1.7
No. of Family Members	1	20	3	4.9
	2	36	8	9.3
	3	152	92	51.5
	4 and above	110	53	34.4

Table 3
Total variance explained for principal axis factoring.

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.146	32.348	32.348	5.783	30.435	30.435
2	3.955	20.814	53.162	3.610	19.002	49.437
3	1.590	8.369	61.531	1.250	6.581	56.018
4	1.297	6.826	68.356	1.016	5.346	61.364
5	.812	4.275	72.631			

Table 4
Factor loading matrix.

Variables	Factor			
	1	2	3	4
BE1	−.038	−.033	.115	**.856**
BE2	−.026	.005	−.005	**.973**
BE3	.017	−.015	.010	**.929**
BA1	−.028	−.027	**.835**	.067
BA2	−.015	.032	**.824**	.096
BA3	.172	.029	**.651**	.084
PBC1	.040	**.847**	.094	−.005
PBC2	.213	**.850**	−.163	.052
PBC3	.059	**.748**	.031	−.097
PBC4	−.235	**.644**	.112	−.121
PBC5	−.239	**.540**	.000	.023
PBC6	−.543	.045	.254	−.200
SN1	**.712**	−.083	−.031	−.036
SN2	**.697**	.013	.006	.097
SN3	**.549**	.011	.276	.014
SN4	**.640**	−.042	.175	.083
SN5	.445	.111	.341	.017
SN6	.409	.331	.306	−.007
SN7	.336	.139	.229	.126

4.3.2. Discriminant validity

Discriminant validity indicates the extent to which a given latent variable is different from another latent variable in the model (Hulland, 1999) [29]. According to Fornell and Larcker (1981) [30], we replace the square root of AVE with the diagonal of the implied correlation matrix. It is clear that the square root of AVE of each latent variable is larger than the correlation of two latent variables (see Table 7). The discriminant validity test does not reveal any serious problem, and all latent variables are different from each other.

Table 5
The fitting standard and outcome of structural equation models.

Evaluation Indicators	Parsimony Fit Index				Absolute Fit Index				Value-added Fit Index		
	χ^2/df	PCFI	PGFI	PNFI	RMSEA	GFI	AGFI	NFI	IFI	TLI	CFI
Standard	1–3	>0.5	>0.5	>0.5	<0.08	>0.9	>0.9	>0.9	>0.9	>0.9	>0.9
Modified Model	3.874	0.684	0.588	0.671	0.078	0.929	0.888	0.927	0.945	0.923	0.944
Fitting Outcome results	close	ideal	ideal	ideal	ideal	ideal	close	ideal	ideal	ideal	ideal

Table 6
Test of convergent validity.

Latent variables	Observation variables	Std. coefficients	S.E.	t value	P	SMC	CR	AVE
Behavior attitude	BA1	0.842				0.709	0.834	0.629
	BA2	0.842	0.050	18.832	***	0.709		
	BA3	0.684	0.056	14.990	***	0.468		
Perceived behavior costs	PBC1	0.906				0.821	0.841	0.523
	PBC2	0.764	0.046	19.760	***	0.584		
	PBC3	0.759	0.049	19.171	***	0.576		
	PBC4	0.608	0.053	13.997	***	0.370		
	PBC5	0.513	0.056	11.401	***	0.263		
Social norms	SN1	0.805				0.648	0.795	0.502
	SN2	0.859	0.066	16.232	***	0.738		
	SN3	0.532	0.062	11.248	***	0.283		
	SN4	0.583	0.061	12.142	***	0.340		
Willingness	BE1	0.815				0.664	0.908	0.769
	BE2	0.946	0.049	24.789	***	0.895		
	BE3	0.864	0.050	22.426	***	0.746		

Table 7
Implied correlations matrix.

	AVE	Perceived behavior costs	Social norms	Behavior attitude	Willingness
Perceived behavior costs	0.523	**0.723**			
Social norms	0.502	−0.017	**0.709**		
Behavior attitude	0.629	0.364	0.319	**0.793**	
Willingness	0.769	−0.212	0.49	0.239	**0.877**

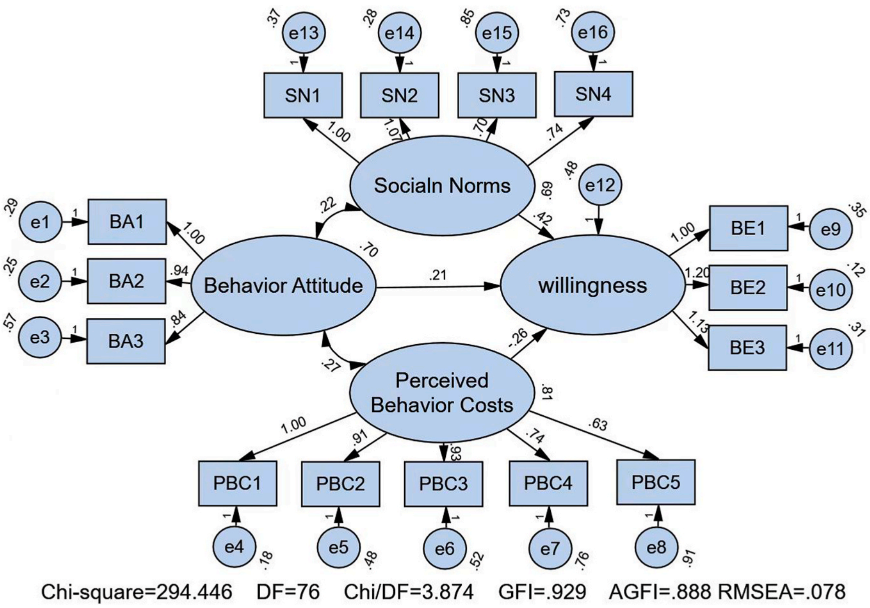

Fig. 2. The Structural Equation Models and Path coefficient.

4.4. Common method bias

Common method bias is very general in psychology and behavior science, especially when the data are generated by questionnaires; it is systematic error variance shared among variables measured with and introduced as a function of the same method and/or source.

The common method bias test is a routine step in empirical studies of psychology because the same measurement method probably produces common method variance in variables that might falsely inflate or deflate observed relationships (Podsakoff, 2012) [31]. We used Harman's single-factor test to check for common method bias. Harman's single-factor test is conducted by examining the results of an exploratory factor analysis, and it checks whether the first extracted factor could explain more than 50 percent of the variance (Aguirre-Urretaand Hu, 2019) [32]. It is shown in Table 3 that the variance interpretation percentage of the first common factor is 32%, which is less than 50%. Therefore, there is no serious common method bias.

4.5. Model path analysis and result analysis

Fig. 2 is the path and coefficient diagram of the structural equation model (for simplicity, the relevant paths between residuals and the correlation arrow between PBC and SN have been omitted), in which the path coefficients on each arrow are unstandardized. From Table 8 the estimation result, all paths are statistically significant ($p < 0.001$). By fitting the structural equation model, we further calculate the direct effect of the influencing factors of waste classification willingness.

Direct effect analysis: 1) Behavioral attitude, social norms and perceived behavior costs have a direct effect on waste classification willingness; the effect size is social norms (0.42) >perceived behavior costs (−0.28) >behavior attitude (0.21), and only the perceived behavior costs have a negative effect. Therefore, we do not reject Hypotheses H1, H2 and H3. It can be seen that social norms have the greatest impact on residents' willingness to classify waste, indicating that social norms, such as views from friends and family, and influence by the government and community, play an important role. The next is perceived behavior costs; residents may spend more time in waste classification when the perceived behavior costs increase, which will reduce residents' willingness to classify waste. Finally, the more concerned the behavior attitude is about environmental protection and the higher the recognition of waste classification, the higher the willingness to classify waste will be. In summary, social norms become the dominant influencing factor of waste classification willingness.

4.6. Multigroup analysis

A multigroup structural equation model is used to study whether some specific parameters and paths are equivalent in different sample groups and whether significant differences exist (it is usually used to study whether the model has cross-group invariance). Taking the epidemic situation at the end of January 2022 in Hangzhou as the breakpoint, we mark the sample survey data based on two periods: 1 = before the epidemic and 2 = after the epidemic. In multigroup analysis, various parameter constraints are required to determine the most suitable path model. By comparing the unconstrained model, the measurement weights model, the structural weights model, the structural covariances model, the structural residuals model, and the measurement residuals model, we choose the measurement weights model for multigroup analysis. Both the CFI value and GFI value are between 0.916 and 0.934, which are greater than the standard value of 0.9; the RMSEA value is between 0.056 and 0.062, which are all less than the critical value of 0.08. The above indicators suggest a good fitness of the multigroup structural equation model.

When testing for moderation using multiple groups, the difference test should be conducted (Sörbom, 1978) [33]. Comparing the measurement weights model with the unconstrained model, the difference in the P value is less than 0.05, indicating that there is a significant difference (see Table 9).

Table 10 shows the results of multigroup analysis of residents' waste classification willingness under the influence of the epidemic. All three paths are statistically significant since they pass the test. In the path of "behavior attitude → waste classification willingness", the impact after the epidemic ($b = 0.314$, $p < 0.01$) is more significant and stronger than that before the epidemic ($b = 0.138$, $p < 0.05$), suggesting that the positive effect of behavior attitude on residents' willingness to classify waste was strengthened by the epidemic. In the path of "social norms → waste classification willingness", the impact after the epidemic ($b = 0.369$, $p < 0.01$) is weaker than that before the epidemic ($b = 0.458$, $p < 0.01$), so the impact from social norms to classification willingness has been weakened, and people have reduced their social activities and care less about others' opinions. In the path of "perceived behavior costs → waste classification willingness", the impact after the epidemic ($b = -0.287$, $p < 0.001$) is stronger than that before the epidemic ($b = -0.266$, $p < 0.001$), and the perceived difficulty of waste classification has increased because of the suspension of community waste management.

5. Conclusions and recommendations

Based on the theory of planned behavior, this paper uses a structural equation model to empirically study the influencing factors of urban residents' waste classification willingness in Hangzhou during the epidemic. Perceived behavior costs have a negative impact on willingness, and other factors have a positive impact. First, social norms are the primary factor affecting waste classification by residents, suggesting that the promotion of and education on waste classification from friends and communities are important. During the epidemic, residents must stay at home, and social contact is limited, so the influence of social norms is weakened. Second, the perceived behavior costs. When residents notice that the difficulty of waste classification is increased, they are less willing to classify

Table 8
The estimation results of the path and load coefficients.

Path			Hypothesis	Unstandardized/Standardized Coefficients	S.E.	t value	P
Willingness	←	Behavior attitude	H1	0.208/0.208	0.054	3.837	***
Willingness	←	Perceived behavior costs	H2	−0.261/-0.281	0.048	−5.463	***
Willingness	←	Social norms	H3	0.423/0.419	0.054	7.842	***

Note: SE is the standard error; P *** means the significance level is less than 0.001.

Table 9
Difference test.

Model	delta-CMIN	delta-DF	delta-P	delta-RMR	delta-GFI	delta-PGFI
Measurement residuals model	73.188	43.000	0.002	0.015	−0.017	0.150

Table 10
The results of multigroup analysis.

Path			Influence	
			Before Epidemic	After Epidemic
Willingness	←	Behavior attitude	0.138*	0.314**
Willingness	←	Perceived behavior costs	−0.266***	−0.287***
Willingness	←	Social norms	0.458**	0.369**

Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

waste. During the epidemic, due to the requirements of epidemic prevention, community and publicity waste classification are suspended, and the negative influence path of perceived behavior costs on willingness has been strengthened. Finally, the behavior attitudes. When residents' awareness of environmental protection and their attitude towards waste classification are enhanced, they will be more willing to classify waste. During the epidemic, residents pay more attention to the sanitation of the living environment, so that the direct effect of behavior attitude on the willingness will be further strengthened and residents will spend more time on waste classification. Therefore, based on the findings of this paper, we suggest the following to effectively raise residents' willingness to classify waste:

First, the government should strengthen the promotion of and guidance on waste classification, implementing reasonable reward and penalty measures. During an epidemic, there are certain limitations in the promotion of waste classification, so a new mode of "Internet Plus Waste Classification" could be introduced. As a city at the forefront of digital construction in China, Hangzhou should actively explore this new mode, expanding the channels for waste classification promotion and focusing on the importance of waste classification, waste classification methods and related laws and regulations. However, there are still problems such as ambiguous rights and responsibilities of governance subjects, a lack of governance rules, insufficient governance information and insufficient feedback in the process of waste classification. Therefore, it is necessary to further improve the system of laws and regulations.

The second is to improve the construction of supporting facilities and make full use of intelligent technology. Local communities should further improve waste classification facilities and increase the number of distribution points. The specific circumstances of each community should also be fully considered when configuring waste classification facilities. The disposal facilities must be easy and convenient to use, so they can help to raise the participation of residents in waste classification.

Author contribution statement

Zhiqi Zhao: Analyzed and interpreted the data; Wrote the paper.

Ying Dong: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data.

Zhenyang Cao: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Haiping Lyu: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

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Data availability statement

The authors do not have permission to share data.

Declaration of interest's statement

The authors declare no conflict of interest.

Appendix B. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.heliyon.2023.e13065.

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