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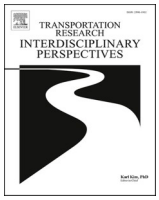

A behavioral analysis of food recovery logistics volunteering using an integrated choice and latent variable (ICLV) modeling framework

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ABSTRACT

Food waste in the United States constitutes a significant portion of the food supply. Different organizations are contributing to reducing waste by managing food recovery logistics, which are heavily dependent on volunteers to transport recovered food. Given the value of volunteers in food recovery logistics, we developed an integrated choice and latent-variable modeling framework that jointly examines how different demographics, latent attitudes, and perceptions influence volunteer status (active vs. inactive) and the duration of volunteer participation. We surveyed both long-time active volunteers and individuals who had become inactive from 25 locations operated by two food recovery organizations. Our results show that among active volunteers, older individuals tend to volunteer for longer durations, whereas women and full-time employees are less likely to volunteer frequently. Significant life events, such as marriage, may shift active volunteers to inactive volunteers. Beyond observable demographic factors, latent attitudes and perceptual factors have a strong influence on food recovery volunteering. We found that *environmental concern*, *car affinity,* and *unchained mobility preference* latent attitudes influence an individual to remain an active volunteer. Meanwhile, *altruistic values*, *perceived volunteering experiences*, and *car affinity* latent factors are associated with the duration of volunteering. Our results challenge the assumption that car usage inherently reflects environmental disengagement and highlight how 'unsustainable' *car affinity* can coexist with, and even support, pro-environmental food recovery actions. The findings from this study can assist organizations in devising behaviorally informed strategies to retain volunteers and manage food recovery logistics.

Introduction

Food waste in the United States represents approximately 30–40 % of the food supply, amounting to 74 million tons and costing $382 billion annually (Buzby et al., 2014; ReFED, 2025, 2023). Wasted food represents a large loss of nutritional content (Chen et al., 2020) and a missed opportunity to address food insecurity (Thyberg and Tonjes, 2016). It also impacts the environment negatively through the use of cropland, water, and fertilizer that are used to produce food that is never consumed (Chen et al., 2020), as well as emissions attributed to the storage, transportation, and disposal of uneaten food (Thyberg and Tonjes, 2016).

According to the United States Environmental Protection Agency (EPA) Wasted Food Scale, recovery of excess food is the second most preferred method of reducing the environmental impacts of wasted food, following the prevention of food waste (U.S. Environmental Protection Agency, 2024). Federal strategies and increased investments also signal a broader commitment to halving food waste by 2030 (U.S. Environmental Protection Agency, 2024). Food rescue is the process of recovering edible food from food growers, suppliers, or retailers that would have otherwise been wasted and redistributing it for human consumption (Hecht and Neff, 2019). This practice is also known as food recovery (Zheng and Ai, 2022) or food redistribution (Damiani et al., 2021; Phillips et al., 2011). Food rescue represents an opportunity to both

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reduce food waste and its associated impacts, and reduce food insecurity (Hecht and Neff, 2019). While few studies exist that quantify the amount of food that is rescued, one report estimates that 1.7 million tons of food are rescued annually in the US (ReFED, 2016).

Organizations that participate in food rescue take a variety of forms with the goal of providing food to individuals at no cost. Food banks are a traditional form of food rescue organization that have historically managed shelf-stable goods (Hecht and Neff, 2019). Nonprofit, religiously-affiliated, private, and community-based organizations often participate in food recovery alongside other functions for their community (Mousa and Freeland-Graves, 2017a). Some organizations are focused on food rescue as their primary function, and may work on the local, regional, or national level to rescue and redistribute food. These organizations will either collect or receive surplus food from donors, and then store, package, and/or reprocess food for distribution (Bergström et al., 2020). These organizations, often made up of both staff and volunteers, conduct food recovery operations to move food to food donation locations to be distributed or directly to people. Several food recovery organization working in the US have recovered millions of pounds of surplus food, redistributed it to food-insecure communities, thereby offsetting substantial food waste-derived greenhouse gas (GHG) emissions and other environmental impacts (Scientific American, 2024).

The majority of the food recovery organizations in the US are nonprofit (86 %) which means they are heavily dependent on participation from volunteers (ReFED, 2019). For example, Feeding America, receives more than two million volunteers each month for its food recovery initiatives (Feeding America, 2016). While some food rescue organizations are fully volunteer-run (Mousa and Freeland-Graves, 2017a), others utilize a combination of volunteers and paid staff. Many food rescue organizations rely heavily on volunteers, largely due to their limited available funds to pay staff (Hecht and Neff, 2019), and maintaining sufficient volunteer numbers is essential for the success of many food rescue organizations (Mousa and Freeland-Graves, 2017a). With nearly 46 million Americans facing food insecurity (Rabbitt et al., 2024), food recovery organizations have an enormous need to deliver more food at scale.

Volunteerism is a significant form of civic engagement in which individuals dedicate their time, energy, and financial resources to activities that support the public good. The United States Department of Labor estimates that approximately 24.9 % of Americans aged 16 and older participate in volunteering (Bureau of Labor Statistics, 2016). However, there is a substantial difference in volunteer participation among different demographic groups, likely due to underlying latent behavioral factors. For instance, of individuals who identify as White, 26.4 % participate in volunteer activities. This rate is 19.3 % for Blacks, 17.9 % for Asians, and 15.5 % for Hispanics or Latinos. Moreover, more women (27.8 %) than men (21.8 %) participate in volunteering activities (Bureau of Labor Statistics, 2016). Many organizations are involved in food recovery and volunteering activities: approximately 372 food banks and more than 60,000 food pantries operate across the US (Waite, 2019). Given that many nonprofit service organizations rely on volunteers to provide valued services to their communities, understanding the motivations that drive individuals to volunteer for food recovery is important for advancing the literature on volunteer behavior and for informing the practical management of volunteer-dependent food recovery logistics.

Several studies have explored the motivation behind volunteer participation. Early theoretical models of volunteerism suggest that the primary motivations were intrinsic, including the welfare of others (altruistic) and self-interest (egoistic), such as the desire to feel good (Shye, 2010). Recent studies have confirmed this and identified additional factors. Mousa and Freeland-Graves (2017b) show that the primary reason for volunteer participation is altruism. Using data from Ontario, Canada, Rondeau et al. (2020) demonstrate that the primary motivations for volunteer participation are altruism, self-development, and enhancing social life. Some alternative models of volunteer motivation explain how both intrinsic and extrinsic factors influence volunteering (Gidron, 1978). Sheldon et al. (2022) surveyed food bank volunteers and found that participants reported feeling less self-determined, less motivated, and experiencing lower subjective well-being, possibly due to the costs associated with participating in volunteering (Sheldon et al., 2023).

A key concern in food recovery volunteering is the attrition rate – whether individuals who initially participate continue their involvement over the long term. Volunteer retention is important for food rescue organizations due to their heavy reliance on volunteer labor. An individual's initial motivation for volunteering, as well as their satisfaction with the volunteer role, have both been found to be related to volunteer retention rates (Bidee et al., 2017). Given the value of volunteers within food recovery organizations, having a clear understanding of volunteer retention and engagement is important for maintaining operations. This raises important research questions: *Do the factors that initially motivate individuals to volunteer persist across all participants? If not, what distinct factors influence sustained participation? Does initial motivation diminish as new challenges emerge during the volunteering process?*

The travel behavior and mobility-related factors that affect volunteer participation in food recovery are not well studied. In the context of food recovery volunteering, participation often demands significant time, logistical coordination, and reliable access to transportation. Previous research, such as Latham-Mintus et al. (2022), has demonstrated that mobility, particularly the use of alternative transportation other than a personal car, is positively correlated with older adults' participation in social activities. However, food rescue efforts often require access to a personal vehicle, as the task necessitates the efficient transportation of large quantities of food within strict time constraints. At the same time, volunteers may also hold strong environmentally supportive values, which could manifest as a preference for sustainable travel modes and reduced reliance on private automobiles (Steg and Vlek, 2009). This raises an important question: *Do volunteers' environmental attitudes conflict with the practical demands of vehicle use in food recovery?* Despite its relevance, the intersection between travel-related attitudes and volunteer participation, particularly in roles that require transportation, has received limited scholarly attention. Investigating this relationship could offer valuable insights into how mobility preferences and environmental values shape engagement in volunteer-based service delivery.

The decision to continue volunteering and the duration of participation can be conceptualized as a multi-stage decision-making process influenced by both psychological and behavioral factors. Food recovery volunteering involves motivation and altruistic intent as well as significant time commitment and physical effort, including transporting goods from donors to recipients. To understand these complex dynamics involved in decision-making processes, an integrated modeling framework is necessary. Data from both active volunteers (who have volunteered for a long period) and inactive volunteers (those who volunteered for a short period and then discontinued) are required. A challenge that arises is quantifying motivational constructs and incorporating them into the modeling framework. Keeping these factors in mind, in this study, we developed a modeling framework that jointly analyzes the underlying decision-making process of food recovery volunteers.

Methods

Study area

The survey was conducted among the active locations of two food rescue programs, Food Rescue US (FRUS) and Manna Food Center. An Institutional Review Board (IRB) approval was obtained before conducting the survey. Food Rescue US is one of the largest volunteer-based organizations working in the food recovery space. At the beginning of the research phase, we shortlisted 25 locations from the 48 total FRUS

sites and the single Manna Food Center site based on local demographics, built environment, and data on Supplemental Nutrition Assistance Program (SNAP) benefits recipients. Large cities, mid-sized cities, and small cities were all represented in this sample. In addition, we explored the organizations' volunteer information databases to select locations based on volunteering characteristics: such as the number of volunteers, average trip length for food recovery, the number of volunteer trips per volunteer, and monthly volunteer participation duration, among other factors. Based on the desired number of survey responses and anticipating varying response rates, we distributed the survey to the 25 selected locations over five phases; see Fig. 1.

Survey distribution

The survey was distributed using the Qualtrics platform from March 2025 to April 2025. Using the email list collected from the volunteer databases of FRUS and Manna Food Center, we invited each email address associated with the selected locations to participate in the survey. We categorized volunteers into one of two categories: active or inactive. Participants who volunteered for at least one trip during the previous six months of the survey period were considered active volunteers. Participants who volunteered for at least one trip during their lifetime but had not participated in a volunteering trip for at least six (6) months at the time of survey distribution were considered inactive volunteers. The survey burden differed for active and inactive volunteers, as we collected more information from the active category. We collected detailed trip-level data from active volunteers, including the origins and destinations of their food recovery volunteer trips. We collected socio-demographics information, attitudes towards volunteering, environmental concerns, food waste, and barriers to volunteer participation from both active and inactive volunteer groups. We offered $20 gift cards to active volunteers and $10 gift cards to inactive volunteers in appreciation for their participation in the survey. To maximize the survey response rate, we sent two follow-up reminders after our initial survey invitation email. The number of emails sent and the responses received in each phase are listed in Table 1. To maximize the survey response rate, we sent two follow-up reminders after our initial survey invitation email. Table 2 shows the demographics and other important information for active and inactive volunteer survey participants.

ICLV modeling

Basic framework

Whether to be an active volunteer and, if so, the extent of involvement, are interrelated and can be jointly determined. We adopt an integrated economic framework that simultaneously captures both the discrete and continuous nature of the two choices. The decision to become an active volunteer is treated as a discrete binary choice (1 = yes, 0 = no), while the duration of volunteering is measured by the specific time spent on volunteering during a month.

Binary choice models typically assume an unobservable latent utility index for individual n of the form:

$$u_n = \alpha + x_n'\beta + \epsilon_n \quad (1)$$

where u_n measures the individual's utility of being an active volunteer, x_n is a vector of observable explanatory variables for individual n, α, and β are parameters, and ϵ_n is a random disturbance term representing unobservable factors. For this study, the binary dependent variable , $y_n = 1$ if the individual is an active volunteer, and 0 if not an active volunteer. The choice of becoming an active volunteer occurs if the utility index exceeds the threshold value of 0.

This framework can be extended to a parsimonious discrete/continuous model by assuming the utility index is instead a measure of an individual's propensity to become an active volunteer. Under the strong assumption that the volunteer participation duration $y_n = u_n$ when $y_n > 0$, a positive participation duration could then be interpreted as a direct indicator that the individual is an "active volunteer." If u_n is a continuous variable, this approach yields a model commonly known as the Tobit model, which is discussed in Cameron and Trivedi (2005, section 16.3). However, in our case, these assumptions are too strong, and the Tobit model is not appropriate. The two decision processes, while sharing overlapping features, might have components that differ. A utility index for the decision process of choosing whether to remain an active volunteer is unlikely to coincide identically with that used to represent the decision to participate in volunteering for a given duration. For such cases, a two-part hurdle model has been suggested, and we adopted the approach here as discussed in Cameron and Trivedi (2005, section 16.4). This approach requires that the beta parameters for each variable be estimated separately for the binary volunteer active status

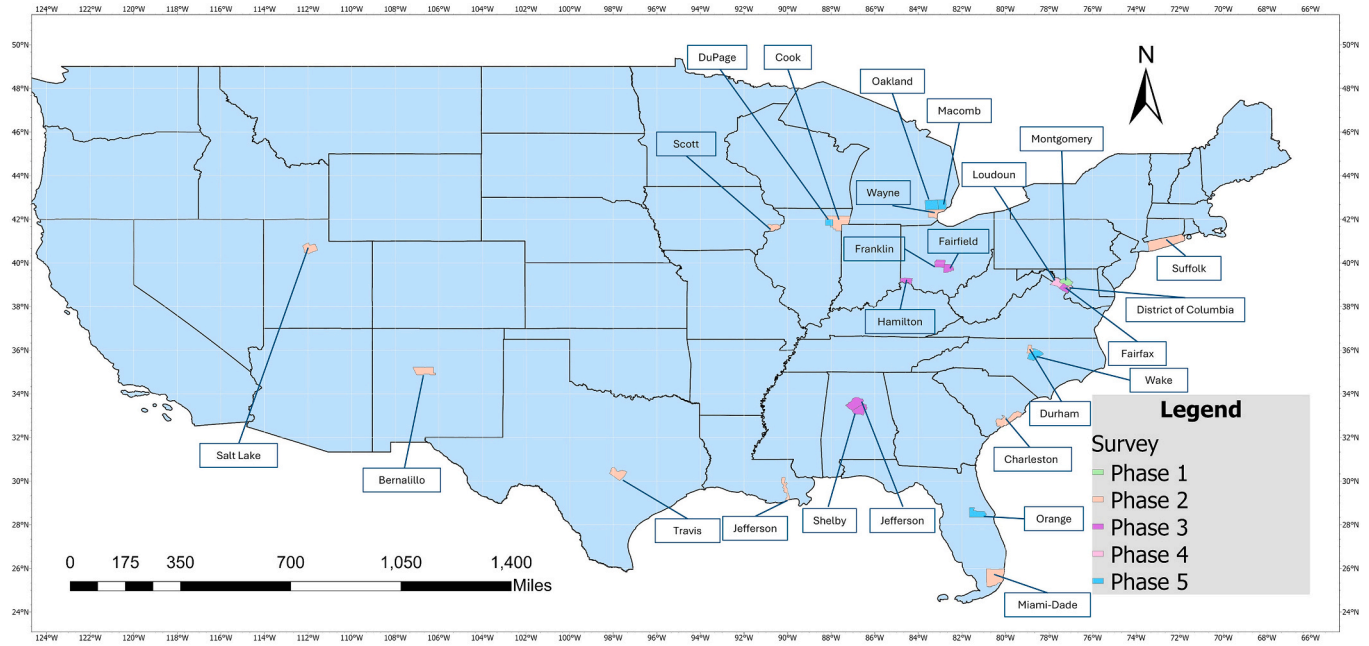

Fig. 1. Study area map.

Table 1
Survey distribution phases and response rates.

Survey Phases	*Active volunteer survey*			*Inactive volunteer survey*		
	Sent (1572)	**Received (373)**	**Response Rate (24 %)**	**Sent (692)**	**Received (84)**	**Response Rate (12 %)**
Phase 1	257	61	23 %	84	9	11 %
Phase 2	439	126	28 %	186	33	18 %
Phase 3	625	125	20 %	310	25	8 %
Phase 4	192	43	22 %	78	10	12 %
Phase 5	59	18	29 %	34	7	21 %

Table 2
Descriptive statistics of the survey participants.

Variable	Category	Active Volunteer Survey N = 373	Inactive Volunteer Survey N = 84
Age	18 to 24	4 %	4 %
	25 to 34	9 %	22 %
	35 to 44	15 %	12 %
	45 to 54	17 %	12 %
	55 to 64	25 %	20 %
	65+	30 %	30 %
Gender	Female	72 %	74 %
Race	White	69 %	73 %
Employment Status	Full-time employed	29 %	42 %
Marital Status	Married	51 %	56 %
Number of Vehicles	0	1 %	0 %
	1	36 %	29 %
	2	27 %	55 %
	3+	15 %	17 %
Household Size	1	22 %	21 %
	2	50 %	58 %
	3+	28 %	21 %
Monthly Volunteering Duration	Less than 1 h	60 %	–
	1–5 h	13 %	–
	6–10 h	17 %	–
	More than 10 h	10 %	–

model and the ordered volunteering duration model within the ICLV framework. In addition, in our case, we have data that allows us to separate the two processes (as we collected participation duration data from active volunteers).

Volunteer participation duration data were collected from active volunteers and are limited to volunteering activities over a one-month period. We adopt a framework relying on the utility index(es) of the form in **Equation (1),** which allows for a range of specifications and testing for both active volunteer and volunteer duration, including the case where the decision processes are coupled. We adopt the ordered logit model for modeling the outcome variable. We specify u_n^o as an index of an individual's volunteer participation tendency, but code the use outcome variable y_n^o using the four volunteer monthly participation categories (i.e., typical monthly volunteer participation durations collected from the survey) defined below

$$y_n^o = \begin{cases} 1 \text{if} u_n^o < \tau_1 (lessthan1hour) \\ 2 \text{if} \tau_1 \le u_n^o < \tau_2 (1 - 5hours) \\ 3 \text{if} \tau_2 \le u_n^o < \tau_3 (6 - 10hours) \\ 4 if u_n^o \ge \tau_3 (> 10hours) \end{cases} \quad (2)$$

where $u_n^o = x_n^{o\prime}\beta + \epsilon_n^0$, the $\tau_i's$ are threshold parameters and the disturbance term ϵ_n^0 is IID Gumbel.

While the initial framework uses observable explanatory variables (e.g., socio-demographics such as gender, age, race, employment status, household size, vehicle ownership, and geographic location), we can extend the framework to include unobservable latent variables and attitudinal measures collected in our surveys. We use built environmental covariates such as block-level auto-oriented intersection density and auto-oriented centrality index collected from the Smart Location Data provided by the United States Environmental Protection Agency (U.S. Environmental Protection Agency, 2021). The auto-oriented intersection density measures are based on the number of intersections per square mile that are primarily designed for automobile movement (wide roads, limited pedestrian elements). The higher value indicates a more car-dominated street network with more intersections optimized for vehicle flow rather than walkability. The auto-oriented centrality index measures how centrally a block group is positioned within a regional road network based on automobile travel patterns and accessibility. A higher value of this variable means an area is more auto central, such as closer to major road corridors and regional activity hubs when traveling by car. The final modeling framework, depicted in Fig. 2, yields Integrated Choice and Latent Variable (ICLV) models (Vij and Walker, 2016), which incorporate both observed and latent variables.

Incorporation of attitude and perception indicators

One of the key features of this analysis is the incorporation of attitudes. Unlike socio-demographics, attitudes are latent factors and are not directly observable from surveys. However, an individual's attitudes towards different environmental aspects, cars, experiences from volunteering that develop their perception of volunteering, etc., can be inferred from responses to well-designed attitudinal and perception measurement scales, typically the level of agreement/disagreement with statements (e.g., Likert-type scales) in surveys (Choo and Mokhtarian, 2004; Daly et al., 2012). ICLV modeling framework using survey-based attitudes and perception statements are widely used in the academic transportation literature (Iogansen et al., 2023; Mohiuddin et al., 2022a, b, 2025; Rao et al., 2025; Shah et al., 2023; Subedi and Singleton, 2025). Twenty statements in our survey were designed to measure attitudes toward the environment, volunteering, trip combining behaviors, and perceptions of the challenges of volunteer participation. The level of agreement and disagreement with these statements was measured using a 5-level Likert-type scale (from "strongly disagree" (1) to "strongly agree" (5)). The statements and associated latent variables are listed in Fig. 2. The mean values of the responses to these statements from the survey are provided in Fig. 3. The design of these statements suggests a likely pattern of association with five factors (i.e., latent variables) that could be implemented in the ICLV model.

Model specifications

We considered multiple model specifications for the joint determination of being an active volunteer and the duration of volunteer participation, based on the framework discussed earlier. We estimated and tested versions that included observable explanatory variables only

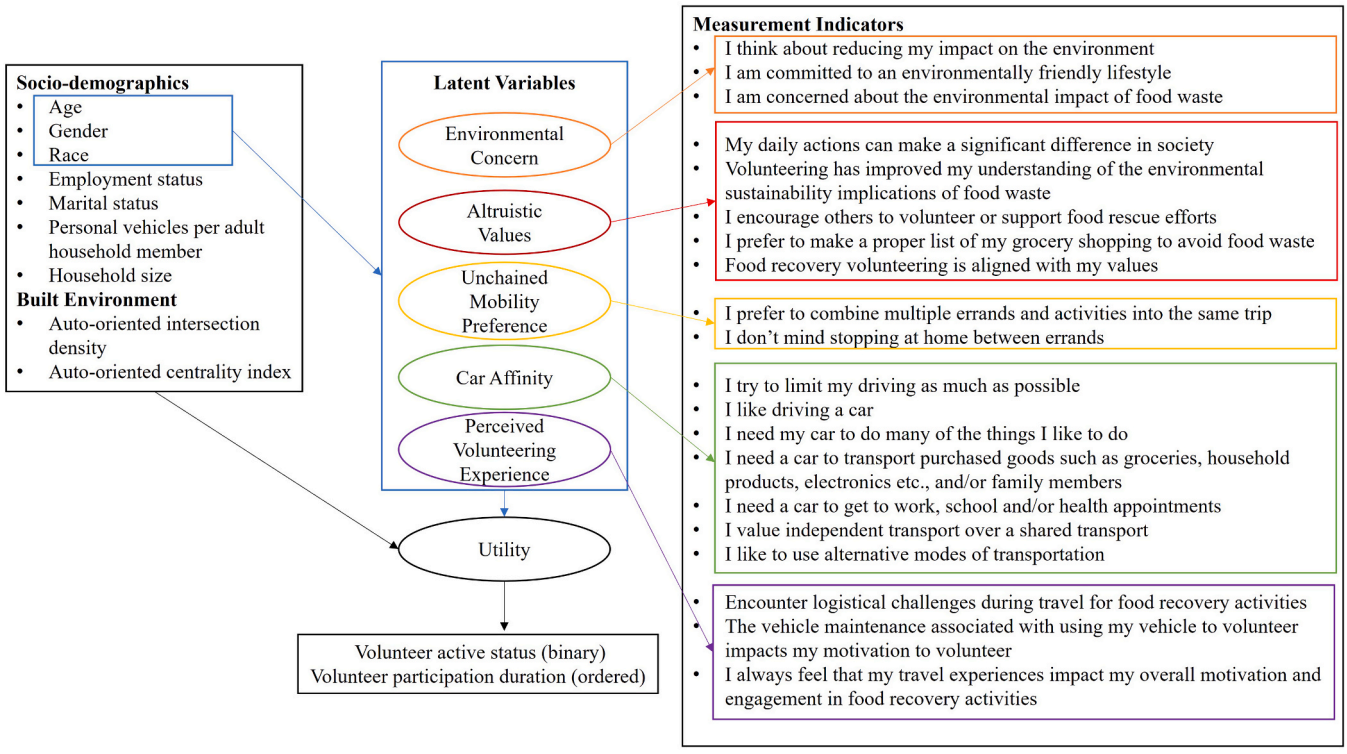

Fig. 2. Conceptual integrated choice and latent variable modeling framework for volunteer participation decision. (The variables age, gender, and race are also used in the structural equation model of the latent variables described from Equations (6.1) to (6.5)).

and other versions that included observable explanatory variables, attitudes, and perceptions. Descriptive statistics for these variables across different sample groups are provided in Table 2.

We consider a utility index function (logit-linked) that includes both observable and unobservable explanatory variables (latent attitude variables), consistent with Fig. 2:

$$u_n = ASC + \beta_1 Age_n + \beta_2 Gender_n + \beta_3 RaceWhite_n + \beta_4 Employed_n + \beta_5 Householdsize_n + \beta_6 Carperperson_n + \beta_7 IntersectionDensity_n + \beta_8 AutoOrientedCertralityIndex_n + \Gamma_1 EnvironmentalConcern_n + \Gamma_2 VolunteeringMotivation_n + \Gamma_3 Tripcombiningaffinity_n + \Gamma_4 Carnecessity_n + \Gamma_5 Volunteerexperience_n + \epsilon_n \quad (3)$$

Here, we extend our earlier notation to model binary choices using an ICLV model by including an alternative specific constant (ASC) (denoted α earlier), coefficients for observable explanatory variables (β_i's), and coefficients for latent variables (Γ_i's). In this specification, all observable variables (except Age, Car per person, and built environmental factors) are categorical with two or more levels, implemented using 0/1 dummy coding, with the usual implication that one of the levels serves as the "base level" (with a coefficient of zero). The variables age, car per person, household size, the built environment factors (auto-oriented intersection density and auto-oriented regional centrality index), and the five latent variables are continuous (metric). We collected the block-level built environment data from the Smart location dataset provided by the Environmental Protection Agency (EPA) (U.S. Environmental Protection Agency, 2021). We transformed the auto-oriented intersection density variable on a 0 to 1 scale. The other auto-oriented regional centrality index variable was already on a 0 to 1 scale. Our model simultaneously explains both the binary choice and the ordered level-of-duration measure using the same utility index above, without the ASC, and including three threshold parameters (τ_i's).

In the ICLV model, the twenty observed attitudinal measurements outlined earlier provide the information to help identify the values of five latent variables for each respondent. In our models, we assume a factor analytic structure captured by the following measurement equation:

$$i_n = Dx_n^* + \eta_n \quad (4)$$

where i_n is a vector of measurement indicators (the twenty attitudinal scales, standardized to have a mean of zero and variance of one), D is a 20x5 matrix of parameters representing the sensitivities of the measurement indicators to the vector of five latent variables x_n^*, and η_n is a vector of stochastic disturbances that are independent and normally distributed with mean 0 and standard deviation (sigma) σ_k, where k denotes the k^{th} attitude statement (Vij and Walker, 2016).

The latent variables may also be influenced by observable variables as modeled by the following structural equation:

$$x_n^* = Ax_n + \nu_n \quad (5)$$

where A is a matrix of parameters and ν_n is a vector of disturbance terms (typically IID standard normal). For our purposes, we hypothesized the following structural equations:

Fig. 3. Mean comparison between active and inactive volunteers on selected attitudes and perception statements.

$$EnvironmentalConcern_n = A_{EC,Female}Gender_n + A_{EC,RaceWhite}RaceWhite_n + A_{EC,Age}Age_n + v_n \quad (6.1)$$

$$AltruisticValues_n = A_{AV,Female}Gender_n + A_{AV,RaceWhite}RaceWhite_n + A_{AV,Age}Age_n + v_n \quad (6.2)$$

$$UnchainedMobilityPreference_n = A_{UMP,Female}Gender_n + A_{UMP,RaceWhite}RaceWhite_n + A_{UMP,Age}Age_n + v_n \quad (6.3)$$

$$CarAffinity_n = A_{CA,Female}Gender_n + A_{CA,RaceWhite}RaceWhite_n + A_{CA,Age}Age_n + v_n \quad (6.4)$$

$$PerceivedVolunteerExperience_n = A_{PVE,Female}Gender_n + A_{PVE,RaceWhite}RaceWhite_n + A_{PVE,Age}Age_n + v_n \quad (6.5)$$

This framework supports models with and without latent variables. We report results for models where we use the same specifications with and without latent variables. All models were estimated using the Maximum simulated likelihood estimation in R Studio using the *Apollo* choice modeling package (Hess and Palma, 2019) with the BGW estimation algorithm (Bunch et al., 1993). These ICLV models require maximum simulated likelihood because the distributional assumptions of **Equations (4) and (5)** yield log-likelihood expressions that require evaluation of integrals. We implemented this approach using 500 Sobol draws as documented in the *Apollo* manual (Hess and Palma, 2023, 2019).

Limitations

The sampling method for active and inactive volunteers in the food recovery sector may not have produced a representative sample across the United States. Without census or summary statistics of food recovery from governmental bodies or food recovery organizations, it is difficult to discuss the degree to which our sample represents the overall food recovery volunteer population. The purpose of this study is not to represent all volunteers in the food recovery sector across the United States, but to understand the factors influencing volunteer retention and volunteer participation duration. The modeling is focused on these relationships in this study, and according to Babbie (2015), sampling bias is less critical in explanatory research (like this one) than in descriptive research. One thing to note is that, as the sample used in this study may not be representative, the findings may not be generalizable. However, the results provide valuable insights and offer a strong foundation for future, more generalizable research.

Results

The results of the ICLV models are shown in Table 3. As the ICLV model comprises two choice models, measurement models, and structural equation models, we report the log-likelihoods of the two choice models (one binary model and one ordered model, as discussed in the Methods section) separately.

Effects of socio-demographics and built environment

The factors that significantly influence the decision to be an active volunteer are marital status, employment status, and household size.

Table 3
Results of the integrated choice and latent variable model.

Model Parameters	Models with Latent Variables		Models without Latent Variables	
	Estimate[a]	**Robust standard error**	**Estimates**[a]	**Robust standard error**
Parameters of the binary active volunteer model				
ASC	1.0854	1.20	0.0895	0.95
Car per person	−0.4357	0.53	−0.1660	0.40
Age	0.0876	0.16	0.2852**	0.12
Gender (Dummy: Woman = 1)	0.6176	0.63	0.0071	0.31
Marital status (Dummy: Married = 1)	−0.9694**	0.46	−0.8681**	0.38
Employment (Dummy: Full-time employed = 1)	−0.6275*	0.36	−0.3468	0.29
Race (Dummy: White = 1)	−0.2509	0.45	−0.1473	0.41
Household size	0.2325	0.20	0.2575	0.17
Auto-oriented intersection density	−2.9443*	1.71	−2.7128**	1.38
Regional centrality index based on automobile travel time	1.4236*	0.75	0.9318	0.59
Environmental concern (Latent Variable)	0.3951*	0.24		
Altruistic values (Latent Variable)	0.01723	0.23		
Unchained mobility preference (Latent Variable)	0.9768**	0.45		
Car affinity (Latent Variable)	0.4940**	0.22		
Perceived volunteer experience (Latent Variable)	−0.2231	0.23		
Parameters of the ordered volunteer participation duration model				
Tau (volunteering duration) 1[b]	−2.8177***	0.92	−2.8347***	0.89
Tau (volunteering duration) 2[b]	0.9615	0.92	0.5702	0.86
Tau (volunteering duration) 3[b]	2.1921**	0.94	1.7093**	0.86
Car per person	0.5010	0.32	0.5536**	0.28
Age	0.2547**	0.11	0.2290**	0.10
Gender (Dummy: Woman = 1)	−0.8572**	0.35	−0.5911**	0.27
Marital status (Dummy: Married = 1)	−0.2855	0.34	−0.2015	0.32
Employment (Dummy: Full-time employed = 1)	−0.6134**	0.28	−0.6961**	0.28
Race (Dummy: White = 1)	−0.5649	0.40	−0.9520**	0.39
Household size	0.0069	0.15	0.0293	0.14
Auto-oriented intersection density	1.0014	2.39	1.1049	2.37
Regional centrality index based on automobile travel time	−0.5117	0.58	−0.6627	0.52
Environmental concern (Latent Variable)	−0.0879	0.20		
Altruistic values (Latent Variable)	0.5664***	0.19		
Unchained mobility preference (Latent Variable)	0.1274	0.23		
Car affinity (Latent Variable)	0.3391**	0.17		
Perceived volunteer experience (Latent Variable)	0.4209**	0.20		
Measurement models associated with the latent variables based on Equation (4)				
Reduce impact	0.6248***	0.07		
Environmental lifestyles	0.7024***	0.05		
Environmental impact of food	0.5458***	0.06		
Like car	0.3543***	0.07		
Need car	0.6860***	0.07		
Need car shopping	0.7242***	0.08		
Need car work	0.6779***	0.08		
Limit driving	−0.2413***	0.06		
Combine trip	−0.2273***	0.05		
Do not combine trips	0.5801***	0.17		
Daily action	0.2841***	0.05		
Vehicle maintenance	0.5420***	0.09		
Volunteering improves sustainability	0.4533***	0.06		
Encourage volunteer	0.3934***	0.06		
Avoid food waste	0.2747***	0.06		
Volunteer values	0.2723***	0.03		
Logistical challenge	0.5278***	0.07		
Travel experience	0.4282***	0.08		
Independent transport preference	0.5262***	0.07		
Alternative mode preference	−0.5643***	0.08		
*Standard errors of measurement models (*standard deviation (sigma) σ_k)				
Reduce impact	0.6669***	0.06		
Environmental lifestyles	0.5101***	0.05		
Environmental impact of food	0.5383***	0.04		
Like car	0.8961***	0.04		
Need car	0.5242***	0.04		
Need car shopping	0.5071***	0.04		
Need car work	0.6046***	0.04		
Limit driving	0.9372***	0.03		
Combine trip	0.6132***	0.03		
Do not combine trips	0.8376***	0.13		
Daily action	0.6988***	0.04		
Vehicle maintenance	0.8686***	0.07		
Volunteering improves sustainability	0.7078***	0.05		

(*continued on next page*)

Table 3 (*continued*)

Model Parameters	Models with Latent Variables		Models without Latent Variables	
	Estimate[a]	**Robust standard error**	**Estimates**[a]	**Robust standard error**
Encourage volunteer	0.5742***	0.06		
Avoid food waste	0.7919***	0.04		
Volunteer values	0.4561***	0.02		
Logistical challenge	0.6859***	0.05		
Travel experience	0.8163***	0.04		
Independent transport preference	0.8975***	0.05		
Alternative mode preference	1.0365***	0.04		
Structural equation models for the five latent variables based on Equations (6.1) to (6.5)				
Gender (Dummy: Woman = 1) (EC)	0.1991	0.16		
Race (Dummy: White = 1) (EC)	0.0977	0.16		
Age (EC)	−0.0485	0.03		
Gender (Dummy: Woman = 1) (AV)	0.3467**	0.16		
Race (Dummy: White = 1) (AV)	−0.4417**	0.20		
Age (AV)	0.0292	0.04		
Gender (Dummy: Woman = 1) (UMP)	−0.8945***	0.26		
Race (Dummy: White = 1) (UMP)	−0.0172	0.23		
Age (UMP)	0.1618***	0.05		
Gender (Dummy: Woman = 1) (CA)	0.2156	0.18		
Race (Dummy: White = 1) (CA)	−0.3353	0.22		
Age (CA)	0.0180	0.04		
Gender (Dummy: Woman = 1) (PVE)	0.2052	0.15		
Race (Dummy: White = 1) (PVE)	−0.1160	0.19		
Age (PVE)	−0.0178	0.04		
Number of parameters (full modeling framework)[c]	87			22
Number of parameters (binary active volunteer model)	15			10
Number of parameters (ordered volunteer participation duration model)	17			12
Number of observations				
Active volunteer binary model (consists of both active and inactive volunteers)[d]	350		350	
Volunteering duration model (consists only of active volunteers)[e]	282		282	
Log Likelihood	−8697.68		−454.44	
Log-likelihood (binary active volunteer model)	−165.48		–	
Log-likelihood (ordered volunteer participation duration model)	−290.12		–	
AIC	17569.35		952.89	
BIC	17904.99		1033.01	

[a] *We labeled the significance of a parameter based on a 1% (***), 5% (**), and 10% (*) significance level.*

[b] *These are developed based on* ***Equation (2)****.*

[c] *This number of parameters is the sum of all the parameters estimated in the full ICLV modeling framework which consists of choice models, structural equation models, and measurement models as described in the method section Equations.*

[d] *Number of observations that consists of active and inactive volunteers dropped to 350 due to missing value on some observations.*

[e] *On the volunteer participation duration model, only active volunteer observations are included.*

Individuals who are married or full-time employed are less likely to continue volunteering and become active volunteers. However, a volunteer living in a larger household is more likely to become an active volunteer. Age appears to positively affect the likelihood of continuing as an active volunteer, but only in models that do not include latent variables. When latent variables are incorporated into the model, the age variable becomes non-significant.

Several socio-demographic variables also significantly influence the duration of volunteer participation. Age positively influences volunteer participation, which is expected, as retired individuals over the age of 60 are more likely to dedicate their time to food recovery activities. Unlike its impact on the decision to remain an active volunteer, marital status does not significantly impact the duration of volunteer participation. Full-time employment, however, has a strong negative impact on the time for volunteer participation. Although gender did not significantly affect active volunteer status, being female is associated with a shorter duration of volunteer participation.

Compared to the model without latent variables, the number of cars per household member has a significantly positive influence on volunteer participation. However, the effect becomes non-significant when latent variables are included. Being white significantly negatively influences the duration of volunteer participation. However, the variable becomes non-significant when latent variables are included in the model, suggesting that race may have an indirect effect on volunteer participation duration.

Our ICLV model shows that the built environment significantly influences volunteer status, as individuals living in areas that are not conducive to walking and biking, and are more auto centric, are less likely to remain active volunteers. A higher regional centrality index value indicates a more central location within the region for auto travel (i.e., near the regional center or a major hub). Our model shows that individuals living in locations that are more accessible are more likely to remain active volunteers. However, we did not find any significant association between the built environment and the duration of regular

volunteering. This indicates accessible locations of food recovery sites and distribution sites influence individuals to remain active volunteers.

Influence of latent variables

It is expected that individuals who are more environmentally concerned are more likely to continue participating in volunteer activities that support environmental goals, such as lowering carbon emissions and reducing waste. Our model results reveal a significant difference in *environmental concern* attitudes between active and inactive volunteers. Surprisingly, altruistic values are not significant predictors of continuous participation in food recovery activities (i.e., being an active volunteer). However, more research is needed to better understand this result.

Travel-related preferences appear to significantly shape individuals' sustained engagement in volunteering activities. Specifically, individuals who prefer to make separate, home-based trips for individual activities rather than chaining multiple activities within a single tour are more likely to continue volunteering over time. We name this latent behavior *unchained mobility preference*. In travel behavior theory, a trip chain (or tour) is defined as a sequence of trips that begin and end at home, during which multiple activities may be undertaken. Traditional models posit that individuals plan these tours in advance to maximize efficiency and minimize travel (Bhat, 1997; Ye et al., 2007). However, our findings suggest that individuals who avoid trip chaining, opting instead for distinct trips, are more likely to remain active volunteers. This may seem counterintuitive from an environmental efficiency standpoint, as environmentally conscious individuals are typically assumed to consolidate trips. Yet, our results indicate that environmentally supportive values among volunteers may be more strongly expressed through participation in food waste reduction efforts than through minimizing vehicle use. This highlights a divergence between environmental intent and transport behavior, suggesting that sustainability-related actions may be domain-specific and shaped by personal routines and mobility preferences.

Our findings indicate that individuals who express a strong preference for using personal vehicles in daily life, enjoy driving, and show low receptivity to alternative modes of transportation are more likely to remain active volunteers. We conceptualize this orientation as a latent construct termed *car affinity,* which captures both the affective and functional dependence on private vehicle use. The *car affinity* latent construct significantly predicts not only the likelihood of continued volunteering but also the duration of volunteer participation.

Contrary to common assumptions in sustainability discourse, general environmental concern does not significantly influence long-term volunteer engagement. Instead, intrinsic motivation and *altruistic values* emerge as more salient psychological drivers. Interestingly, while general travel preferences (i.e., *unchained mobility preference*) do not significantly affect volunteering duration, the specific attitudinal dimension of *car affinity* does. This suggests that the perceived indispensability and enjoyment of car use may serve as a key enabler of ongoing volunteering behavior by facilitating reliable access to volunteering sites. These findings, particularly those linked to private vehicle use, underscore the importance of recognizing the enabling role of mobility attitudes, in sustaining civic and environmentally beneficial behaviors, even when such mobility practices themselves are not environmentally optimal.

The perceived experience with food recovery activities significantly influences the duration of volunteer participation. While this *perceived volunteering experience* latent factor does not predict whether individuals remain active volunteers, it is positively associated with the duration of their engagement. This suggests that while a positive volunteering experience may not be the primary driver of initial retention, it may play a role in sustaining long-term involvement. A possible explanation is that frequent volunteers may become more adept at managing logistical and vehicle-related challenges, such as maintenance or scheduling, that might otherwise deter their ongoing participation. Thus, positive experiences may help sustain engagement despite practical barriers, highlighting the role of both experiential and mobility-related factors.

Interaction between latent variables and demographics

One of the benefits of the ICLV model is that it can distinguish the direct and indirect effects of demographic variables on decision-making. When a demographic variable is included in the utility equation (see **Equation (3))**, we can observe the variable's direct effect on volunteer decision making. In contrast, when we use a demographic variable in the structural equation model (see **Equation (6.1) to Equation (6.5)),** we can see the variable's indirect effect on volunteer decision making. The demographic variable influences the latent variable, which in turn influences choice behavior.

From Table 3, we can observe that age has a negative influence on an individual's *environmental concerns,* with older individuals expressing less *environmental concern* than younger ones. As previously noted, age does not significantly influence active volunteer status. This indicates that age has an indirect negative effect on active volunteer status, as the effect of age works through the *environmental concern* latent variable. We previously discussed that adding latent variables makes the age variable not significant in the model. Without the inclusion of latent environmental attitudes, we would overestimate the effect of age on an individual's decision to become an active volunteer.

Our model also shows that women tend to have stronger volunteer motivation and *altruistic values*. In addition, people of color report stronger *altruistic values* than white individuals. As previously stated, race significantly predicts the duration of active volunteer participation, indicating an indirect effect through the *altruistic values* latent variable.

In terms of travel behavior, women are more likely than men to link multiple activities in a home-to-home chain, which is also found in the transportation literature (McGuckin and Murakami, 1999). Our results also show that older individuals are less likely to chain their activities and prefer separate trips for each activity. This finding reinforces our previous argument that excluding *unchained mobility preference* latent variables can lead to an overestimation of the impact of age on volunteer participation. Age has both direct and indirect influences on volunteering through multiple latent variables.

Latent variables and attitude statements

The association between the different statements and the latent variables is shown in Fig. 2. As shown in Table 3, all latent variables in the model are significantly associated with their corresponding survey statements. Statements representing reducing environmental impact, committing towards environmentally friendly lifestyles, and concerns about the environmental impacts of food waste are positively associated with *environmental concern* latent attitudes. Statements reflecting a liking for cars and dependency on cars are positively associated, and statements reflecting the intention to limit driving and preference for alternative modes are negatively associated with the *car affinity* statements. Statements reflecting altruistic values and encouraging volunteering participation are positively associated with the *altruistic values* latent attitudes. These results confirm both the validity of the latent variables and the appropriateness of the associated statements.

Conclusion and policy implications

To understand the factors motivating participation in food recovery volunteering, we surveyed both long-time active volunteers and individuals who had become inactive. Using a joint modeling approach, we examined how latent factors influenced volunteer status (active vs. inactive) and the duration of volunteer participation. An ICLV framework enabled us to incorporate attitudinal and perceptual data to better understand the two-stage decision-making process of first choosing to

remain an active volunteer and second deciding on the amount of time spent volunteering.

We found that several socio-demographic groups are more likely to remain active volunteers over time. Individuals in auto-oriented environments are more likely to remain active volunteers. Among active volunteers, older individuals tend to volunteer for longer durations, whereas women and full-time employees are less likely to volunteer for longer periods. Significant life events, such as marriage, may shift active volunteers to inactive status.

Beyond observable factors, like demographics and the built environment, latent factors have a strong influence on food recovery volunteering. Some latent factors influence whether a volunteer remains active, while other latent factors influence the duration of regular volunteer participation. *Environmental concern*, *car affinity,* and *unchained mobility preference* latent attitudes influence an individual to remain an active volunteer. Meanwhile, *altruistic values*, *perceived volunteering experiences*, and *car affinity* latent factors are associated with the duration of volunteering.

One important finding is the nuanced relationship between car-oriented lifestyles and environmental engagement. Individuals who report that they enjoy driving and exhibit dependency on cars are more likely to engage in food waste-reducing volunteering activities. While car dependency is typically viewed as environmentally detrimental, our results suggest that car usage facilitates access to environmentally beneficial volunteering opportunities. This challenges the assumption that car usage inherently reflects environmental disengagement and highlights how 'unsustainable' behavior can coexist, with, and even support, pro-environmental actions.

The results of this study provide guidelines for food recovery organizations that seek to retain their existing volunteers and attract new volunteers. Because volunteer active status and participation duration vary across demographic groups and attitudinal orientations, strategies should be tailored for different groups.

First, several socio-demographic groups would benefit from targeted interventions. Women and full-time employees—groups that volunteer for shorter durations—may require more flexible engagement options, including shorter shifts, precise scheduling, evening and weekend pick-ups, or job-sharing routes. Providing childcare support through partner agencies may further reduce barriers to their participation. Older adults, who exhibit longer volunteering duration, can be supported through predictable route assignments, assignments with another volunteer rather than alone, safety communication, personalized communication approaches, and opportunities to serve as peer mentors. For individuals experiencing major life transitions, such as marriage or loss, "pause-and-return" programs can reduce attrition by allowing temporary disengagement without fully exiting.

Second, latent attitudinal and perception factors identified in the model point to additional avenues for intervention. Volunteers with strong environmental concern may respond well to feedback tools highlighting the environmental benefits of their service, such as carbon-reduction dashboards or waste-diversion statistics. Although food recovery logistics are primarily conducted by cars, food recovery organizations can also encourage volunteers to use cargo bikes, which are used for urban logistics (Fitch-Polse et al., 2023), to reduce emissions. Those with altruistic orientations may be more motivated by community impact messaging and volunteer storytelling. Perceived volunteer experience— strongly associated with duration —can be strengthened through improved communication, well-organized routing, and recognition programs. Individuals with high car affinity, who are both more likely to remain active and participate frequently, can be engaged through mileage reimbursement, fuel support, and opportunities to take on longer-distance routes that align with their mobility preferences.

Finally, partnerships with local governments, educational institutions, and industry partners can enhance the overall food recovery ecosystem. Municipalities and rescued food providers can offer transportation vouchers, fuel stipends, small grants, or tax incentives for regular volunteers. Regional coordination among food recovery organizations can also improve routing efficiency and reduce logistical burdens on volunteers.

Together, these strategies highlight the value of behaviorally informed program design and demonstrate how interventions grounded in demographic and attitudinal insights can substantially improve volunteer engagement in food recovery logistics.

This study highlights the importance of considering both observable and latent factors in designing policies and programs to support food recovery volunteering. The findings from this study will be helpful for food recovery organizations looking to better understand volunteer motivations and devise behaviorally informed strategies for different demographic segments of volunteers to encourage their continued participation. Developing interventions that are based on the latent attitudes and perceptions of volunteers can help organizations improve their volunteer experience and improve the logistics of food recovery in a sector that is mostly volunteer driven. These approaches will address both food security and environmental sustainability in the food sector. Future studies can examine how psychological and behavioral intervention-based approaches can boost volunteer participation in the food recovery sector using before-and-after data collected from multiple cities located in different geographies. Although environmental impact is a large focus of this article, one aspect we did not consider is whether individuals with greater environmental concerns drive electric vehicles for food recovery. Using electric vehicles for food recovery will likely make the process more environmentally sustainable and could be a topic for future research.

CRediT authorship contribution statement

Hossain Mohiuddin: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Celeste Chavis:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization. **Corey Welcher:** Writing – review & editing, Writing – original draft, Data curation. **Alexa Kaminski:** Writing – review & editing, Writing – original draft, Data curation. **Michael Chukwurah:** Writing – review & editing, Writing – original draft, Data curation. **Margaret Burke:** Writing – review & editing, Data curation.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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