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A SIMULATION STUDY ON PLACEMENT OPTIMIZATION FOR USED CLOTHING RECYCLING BINS

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Abstract
This study addresses the inefficiencies in the placement and utilization of used clothing recycling bins in Connecticut. By incorporating user donation preferences, social network dynamics, and available recycling bin locations, a site selection optimization model is proposed. This model uses a network-based approach, linking users' current locations and their social activity nodes to various recycling bin options. By analysing user preferences and alternative bin locations, the study seeks to maximize user satisfaction through optimal bin placement. A decision-making framework is developed to identify the best recycling bin locations for clothing donations. To validate the model, simulation experiments were conducted using geographic data from Connecticut. The findings offer actionable solutions for improving the efficiency and user-centricity of recycling bin siting strategies.
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Key Words: Used Clothing Recycling, Placement Optimisation, User Characteristics, Optimisation, Simulation

1. INTRODUCTION

Existing clothing recycling bin placement strategies prioritize operational objectives such as maximum coverage and cost efficiency, often neglecting the real-time preferences of donors. Current recommendation systems typically determine a user's donation point based on generalized data or platform-centric goals, rather than addressing the actual preferences of individual users. This approach limits user satisfaction, as it fails to accommodate specific preferences or social context, such as proximity to frequently visited locations (e.g., home, work, or shopping areas). Furthermore, existing systems often rely on algorithms to mine and analyse user data, recommending recycling bins based on availability without ensuring these options are optimal for individual needs [1-4].To address these shortcomings, this study proposes an operations optimization model that incorporates user preferences and social dynamics, using data mining techniques to provide tailored recommendations for optimal recycling bin locations. The model, validated with real-world data from Connecticut, bridges the gap between theory and practice, offering actionable insights for enhancing recycling system efficiency and user-centricity.

2. LITERATURE REVIEW

2.1 Green technology based recommendation

As an advanced extension of user profiling, green recommendation also has the function of collecting data, discovering user preferences, and revealing deep underlying information about user needs. The recommendation algorithms it employs can support the operation of an information delivery system that predicts relevant information and resources for the user now and potentially in the future. Li explored supply chain optimization techniques using the Fuzzy

MCDM method [5], while Wang et al. examined the application of green recycling technology in supply chains [6], similarly Zhang et al. examined optimization of supply chain efficiency by fuzzy CRITIC-EDAS method [7]. Mircea et al. constructed a recycling model, and Arbabi focused on reverse supply chain processes [8]. Related methods also include system dynamics, game theory and optimization. Multi-objective user modelling, user path selection, efficiency optimization and consumer preferences are key factors highlighted in this research area [9-11].

2.2 Recommendations based on user characteristics

Previous similarities between users and needs were studied by common recommendation algorithms based on users and needs initially relying on cosine similarity, correlation coefficients, Jaccard's similarity function, and correlation at Spearman's hierarchy for measurement. However, the limitations of these functions in solving real-world problems have prompted scholars to extend and improve them [12, 13]. In order to be able to predict user preferences and subsequently recommend services or items, filtering algorithm models that use rating matrices generated based on user needs have been favoured by scholars' research. Commonly used models include linear regression models, Bayesian models, probabilistic correlation models, entropy models, Gibbs sampling algorithms for clustering, Markov decision processes, graph neural networks and deep learning frameworks [14-16].

Lee et al. formalized the collaborative filtering problem as a Markov decision process and proposed a collaborative filtering algorithm that incorporates the dynamic nature of user ratings, leveraging reinforcement learning applied to rating sequences [17]. Shi et al. introduced a neural network-based collaborative filtering model that utilized latent factor models to extract different similarity matrices for users and requirements through various meta-paths. These matrices were then processed by a deep neural network designed to learn aspect-level latent factors [18]. Kang et al. integrated a deep neural network to model non-linear and complex feature interactions and employed an attention mechanism to emphasize the varying importance of these interactions. They proposed a hybrid causal model featuring a novel neural network architecture for Web API recommendations [19].

Chou et al. took a sequential approach, linking customers with similar purchase and redemption patterns by constructing a graph-structured network. They introduced a graphical deep collaborative filtering algorithm for personalized demand recommendations [20]. Kuo and Li applied a particle swarm optimization algorithm to collaborative filtering systems to mitigate data sparsity issues, using a transformer-based bidirectional encoder to extract features from consumer feedback [21]. Alharbe et al. proposed UI2vec, a collaborative filtering algorithm based on embedding representation and word embedding techniques [22]. This method utilized a joint feature extraction network to embed users and demands in latent space, predicting user interest based on item similarity. Furthermore, they introduced VUI2vec, a generative model that enhances stability by mapping users and items into independent Gaussian distributions and applying variational inference to estimate their posterior distributions.

2.3 Content-based demand recommendation

Content-based recommender systems generate relevant recommendations by extracting user and demand characteristics, training user interest models, and evaluating the degree of match between user profiles and candidate recommendation points. The basis of their recommendations lies in the effective identification and analysis of user and demand features. However, processing feature data of various types and dimensions is crucial for generating accurate recommendations. Hence, feature extraction and analytical modelling become the key focus of content-based recommendation algorithms. Scholars have investigated recommendation algorithms in the context of the needs of technologies in various industries.

Paradarami et al. proposed a deep learning neural network framework that not only covers content-based features, but also incorporates user reviews [23]. Ai et al. proposed a PS-D3QN algorithm based on a duelling double-deep Q-network with prioritized experience replay and a soft-max policy [24]. These methods enhance the predictive power of the model while also being able to generate recommendations that are more accurate and improve scheduling efficiency by analysing combinations of user requirements.

3. PROBLEM DESCRIPTION

The optimal location recommendation for clothing recycling bins can be considered a variation of the traditional bin siting problem. The bin siting problem involves determining the placement of a set of service bins to meet the needs of predefined demand points, as illustrated in Fig. 1. In contrast, the optimal location recommendation for clothing recycling bins focuses on selecting one or more ideal bins from a set of available alternatives, as shown in Fig. 2, based on the actual demand of a specific user or demand point.

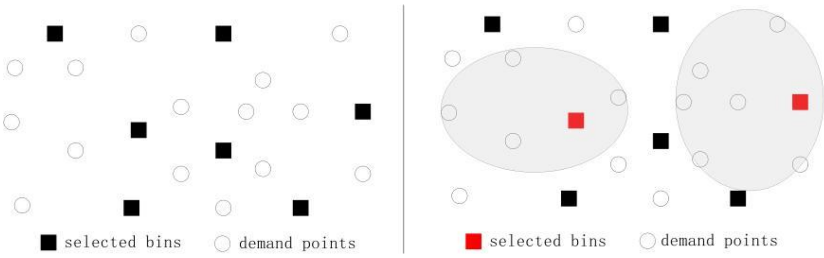

Figure 1: Bins siting problem map description.

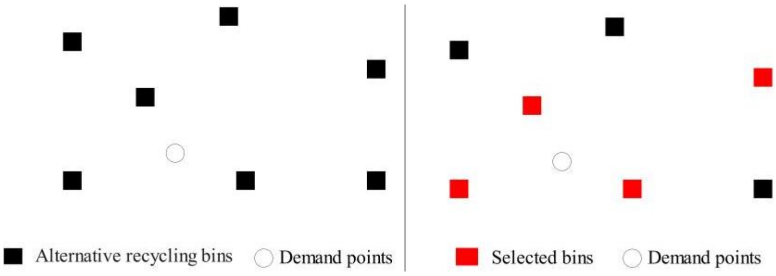

Figure 2: Optimal location of clothing recycling bin.

From the two figures, the bin siting problem addresses the needs of a group of customers, whereas the clothing recycling bin recommendation targets the preferences and requirements of a single user. Additionally, the recommendation system for clothing recycling bins considers the influence of the user's social relationships on their selection process. This includes taking into account the user's next destination within their social network, such as home, a friend's house, or shopping locations.

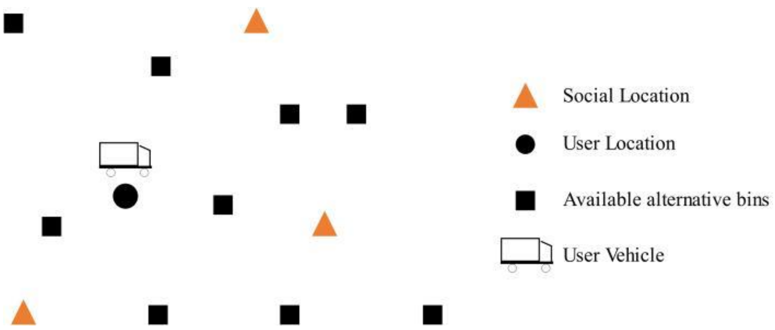

Figure 3: Location-based social network for clothing recycling bin location selection.

The actual demand preferences and social background of the user are derived from the results of the data mining and analysis provided by the recommender system. An operational optimization model constructed using this information identifies and recommends one or more optimal recycling bin locations to the user. As shown in Fig. 3, the network consists of the user's current location, his/her social activity nodes, and multiple alternative clothing recycling bins. These recycling bins are evaluated by the model as potential destinations for the user's clothing donations.

4. MODEL DEVELOPMENT

Based on the new research perspective and the characteristics of the clothing recycling bin recommendation system, the following hypotheses are proposed in this study:

- **Assumption 1:** The locations and capacities of alternative clothing recycling bins are derived from user demand mining. Since the exact capacity of the alternative recycling bins is not clear, it is assumed that the capacity of each bin is sufficient to accommodate the donations made by the users upon arrival.
- **Assumption 2:** The dynamic state of the road network was not considered in this study. The travel time from the user's current location to each clothing recycling bin was assumed to be static and determined from historical travel time data.
- **Assumption 3:** After visiting the clothing recycling bins, users can choose whether or not to visit social locations. In this study, we assume that they only visit one social location, such as a friend's house, a shopping centre or another destination.

4.1 Parameter and variable definition

Gathering:

F – a collection of available alternative clothing recycling bin locations.

K – the set of user social locations.

o – user location starting point.

V – the set of all nodes, $V = F \cup K \cup o$.

A – the set of lines in the network consisting of user social-box locations, $A = \{(i,j) | i, j \epsilon V, i \neq j\}$.

$\wp$ – the set of user preferences mined through data mining, e.g., the set consisting of time preference, cost preference, distance travelled preference, etc.

Parameters:

i, j – indicates the node number in the network constituted by the user's social-box location.

(i, j) – denotes the line in the network constituted by the user's social-box location.

ρ – denotes the most dominant preference of the user clothing donation obtained by data mining out.

τ – denotes a preference number other than the user's foremost preference for clothing donation. For example, if the user's predominant preference for this clothing donation is time, then τ indicates monetary cost preference, walking distance preference, etc., in addition to the time requirement, $\tau \in \wp$.

$c_{\rho f}$ – the cost to be spent by the clothing donation vehicle to complete the clothing collection task at the box site under the user's preference.

$c_{\tau f}$ – denotes the cost to be spent by the clothing donation vehicle to complete the clothing recycling task at the box point under the preference.

$c_{\rho ij}$ – the cost spent by the clothing donation vehicle travelling on the route under the user's preference.

$\partial_{\rho fk}$ – the cost it takes to travel from the clothing collection box location to the socialisation location under the user preference.

M_τ – denotes the maximum tolerance value for preferences other than the user's preference, which can be obtained based on data mining.

Decision variables:

$$y_{of} = \begin{cases} 1 & \text{users in position } o \text{ select alternative clothing recycling bin } f \text{ as the recommended bin} \\ 0 & \text{otherwise} \end{cases}$$

$$x_{\rho ij} = \begin{cases} 1 & \text{route } (i,j) \text{ is the route travelled to reach the alternative clothing recycling bin } f \text{ with preference } \rho \\ 0 & \text{otherwise} \end{cases}$$

4.2 Mathematical model development

$$\text{Min} \sum_{f \in F} c_{\rho f} y_{of} + \sum_{(i,j) \in A} c_{\rho ij} x_{\rho ij} y_{of} \tag{1}$$

$$\sum_{f \in F} y_{of} = 1 \tag{2}$$

$$\sum_{j \in K} x_{ij} \geq 1 \quad \forall i \in F \tag{3}$$

$$\sum_{f \in F} x_{if} = 1 \quad \forall i = o \tag{4}$$

$$\sum_{j \in K} x_{ij} \geq y_{of} \quad \forall f = F \tag{5}$$

$$\sum_{f \in F} x_{\rho of} = \sum_{f \in F} x_{\rho fj} \quad \forall j \in K \tag{6}$$

$$\sum_{i \in V} \sum_{j \in V} c_{\tau ij} x_{\tau ij} y_{of} + c_{\tau f} y_{of} \leq M_{\tau} \quad \forall f \in F, \tau \in \wp, \tau \neq \rho \tag{7}$$

$$y_{of}, x_{\rho ij} \in \{0, 1\} \quad \forall f \in F, (i,j) \in A, \rho \in \wp \tag{8}$$

The objective function (1) represents minimizing the cost of clothing donation at the bin location under the primary preference, as well as the cost of traveling along the route. Constraint (2) ensures the selection of the optimal clothing recycling bin to recommend to the user. Constraint (3) specifies that the user must select at least one social location to visit after donating at the recycling bin. Constraint (4) requires the user to depart from their current location. Constraint (5) states that if a clothing recycling bin is chosen, the user must subsequently visit a social location upon leaving the bin.

Constraint (6) establishes the flow equilibrium at the bin, meaning the user must exit the bin location after arriving there. Constraint (7) ensures that the costs associated with preferences other than the primary preference do not exceed their respective maximum tolerance thresholds. Finally, constraint (8) defines the domains of the decision variables, providing the necessary boundaries for their interpretation.

4.3 The simulation model

The model of clothing recycling bin location selection developed in this study incorporates user preferences for clothing donation needs and expresses them as a 0-1 integer programming model. Since the model is designed for individual users, the solution domain is relatively small. In addition, the range of available recycling bins will be further reduced after user demand mining. Therefore, the model will be simulated to find an exact solution.

There are two approaches to obtaining an exact solution to the model: (1) Using an optimization solver such as CPLEX, GUROBI or LINGO; and (2) Designing a specific exact solution algorithm based on the structural features of the model. Given that the optimization model is embedded in the user's clothing recycling bin recommendation algorithm, the first approach allows the CPLEX solver to be called directly during the execution of the recommendation algorithm to determine the best recycling bin and recommend it to the user. To ensure the accuracy of the solution and the compatibility between the recommendation algorithm and the solver, this paper introduces a novel simulation-based solution algorithm designed to be consistent with the specific features of the problem.

The simulation algorithm designed in this paper calculates the objective function value based on the corresponding function values of each user's primary and other preferences. At the same time, a greedy strategy is applied to select the options that satisfy the tolerance of the secondary preferences and recommend to the user the clothing recycling bin that has the smallest value of the primary objective function.

The specific implementation steps of the simulation algorithm are as follows:

1. **Initialization**: Create a recommendation table to record each user's recommended bin location, the primary preference objective function value, and other preference function values $f(z_\tau)$.
2. **User Data Setup**: For each user, initialize their primary demand preference, current location, alternative available recycling bin locations, social location, and a matrix of values for time, cost, walking distance, and other preference tolerances.
3. **Objective Function Calculation**: For all available alternative bins, calculate the objective function values for the primary preference and the corresponding values for other preferences. Sort the bins in ascending order of the primary objective function values.
4. **Preference Check**: Starting from the first bin in the sorted list, determine whether the secondary preferences satisfy the tolerance values. If the tolerances are met, exit the loop and output the bin and its associated values. If not, continue to the next bin until a suitable option is found.
5. **Recommendation**: Record the best bin location for each user along with the time, cost, and walking distance associated with it. Recommend this bin to the user.

The code implementing the simulation algorithm is shown in the following.

Algorithm: Clothing recycling bin location selection process that takes into account customer preferences for clothing donation needs

```
function Recommendation ():
  Initialise the recommendation form for choosing the location of the user's clothes bin
  for each user do:
    Initialise the user's main requirement preferences, the user's current location, alternative available bin locations, the user's social location, a matrix of time, cost and distance travelled, and other preference tolerance values f(Z_τ)
    for each clothing bin do:
      Calculate the objective function values from the user's current location to the clothing recycling bin and social location for the main preference
      Calculate the value of the function from the current location to the clothing recycling bin and the social location for the other preferences
    end for
    Sort the bins according to the objective function value of the main preference to each clothing bin
    for first bin after sorting i do:
      if f(Z_iτ) ≤ M_iτ:
        Break
      else:
        Continue
    end for
  end for
end function
main
  Recommendation ()
  Record each user's preference objective function value, other preference values and recommended locations
  Recommends to the user the best location for the clothing recycling bin, along with cost, time and distance travelled
end procedure
```

5. DATA AND SIMULATION PROCESSES

5.1 Data collection

Data collection and processing of user clothing donation elements: The data for this study used non-public data on general user clothing recycling orders from Connecticut municipal recycling bins between August 2020 and February 2021, which included over 50,000 records of clothing donation behaviour. Fields include bin name, order status, start time, end time, and duration of clothing donation in seconds. We extracted ID information for 18,453 unique users and information on the 1,633 clothing bins used by these users.

Collecting and collating data on user preference characteristics and social characteristics: As the current data on matching the social information of a person with the user ID corresponding to the clothing donation order involves limitations in data security and sharing. For this reason, this study uses a random matching approach to assign each user a corresponding social location and calculate the relevant data fields. In addition, the study used Python code to select points of interest (POIs) within a 10 km radius of a user's clothing recycling bin location, taking into account the user's actual clothing donation behaviour. And these points of interest are randomly assigned to each order record to enrich the dataset.

5.2 Cluster simulation analysis of users' demand for clothing donation

Given the complexity of social network relationships, this study focuses on four dimensions of features – clothing donation duration, distance, cost, and time – for cluster analysis. The objective is to develop a specific recommendation strategy for clothing recycling bins based on the user's social network location.

To determine the optimal *K*-value, the study identifies the number of clusters with the highest mean silhouette coefficient by evaluating different cluster numbers ranging from 2 to 9. *K*-means clustering is performed for each cluster number, and the corresponding mean silhouette coefficient is calculated. Ultimately, the analysis classified users into three distinct groups, represented by codes 0, 1, and 2. A portion of the data resulting from the clustering process is presented in Table I.

Table I: Partial clustering results.

Order number	Recycling site	Ranges	User groups
4250107650000000000029843142	Site A	10	0
4250107650000000000029850007	Site B	10	0
4250107650000000000029852380	Site C	10	0
4250107650000000000029855446	Site D	10	0
4250107650000000000029856183	Site E	10	0

The user groups were categorized into time preference users, no preference users and distance preference users based on the corresponding statistical information. As shown in Table II, the average length of clothing donation for User group 1 is 0.938722, the distance travelled is 6.700949, and the cost is 30.239750.

Table II: Statistical information on User group 1.

	Clothing donate duration (hour)	**Distance** (km)	c_1
Mean	0.938722	6.700949	30.239750
St.d.	1.401467	2.301388	18.648169
Min	0.000278	0.019397	0.260740
25 %	0.444722	5.130398	19.445809
50 %	0.708333	7.099476	27.974042
75 %	0.968611	8.626991	37.313261
Max	70.846111	9.999986	386.864444

Comparing the characteristics of the user demand dimensions, the data of this User group shows that it is acceptable to travel to a farther distance for clothing recycling bins for clothing recycling. Therefore, User group 1 is more concerned about the time factor in the process of donating clothes.

Table III: Statistical information on User group 2.

	Clothing donate duration (hour)	**Distance** (m)	c_1
Count	666	666	666
Mean	0.539657	1293.67	12954.977037
St.d.	0.549313	5.94	13.019639
Min	0.004167	1291.86	12918.682646
25 %	0.256042	1293.71	12947.242609
50 %	0.451250	1293.71	12953.972609
75 %	0.729583	1293.71	12963.450379
Max	6.366111	1296.48	12995.727050

Table III shows the statistics of User Group 2, which represents the non-preferred users. The data shows that the average length of time spent by this group was 0.54 hours, the average distance travelled was 1,293.67 metres and the average time taken was 323.96 seconds. Analysis of the user needs dimension showed that 75 % of the users in this group spent less than 1 hour on clothing donation activities, but they travelled significantly longer distances. For this group, factors such as distance, time or cost had little or no impact on their choice of bins. At the same time, the donation behaviour of this group of users does not show a specific preference profile, emphasising accessibility over other factors.

Table IV presents information on the data for User Group 3 of the distance preference category. The data indicate that the average duration of clothing donation for this group is 1310 seconds, the average travel distance is 4.93 kilometres, the average cost is 33.48 units. Analysing the dimensions of user needs, this group demonstrates longer donation durations but shorter travel distances. This suggests that users in this category are familiar with the layout of clothing recycling bins in their vicinity and tend to plan their donation activities accordingly. They exhibit a clear preference for bins located closer to them, with a travel distance threshold of approximately 4.93 kilometres. Therefore, User group 3 represents a distance preference type, prioritizing proximity in their clothing donation activities. At the same time, the results of the *K*-means clustering visualization for the three user groups are shown in Fig. 4.

Table IV: Statistical information on User group 3.

	Clothing donate duration (s)	**Distance** (km)	c_1
Count	50000	1.000000	1.000000
Mean	1310	4.932381	33.482381
St.d.	NaN	NaN	NaN
Min	1583	4.95	33.482381
25 %	1610	3.94	33.482381
50 %	1433	4.92	33.482381
75 %	1510	5.94	33.482381
Max	1415	3.97	33.482381

6. RESULTS AND DISCUSSION

Simulation of Clothing Recycling Bin Recommendation for Cost-Preferring Users: Based on the proposed model, we have selected 10 cost-preferring users for clothing recycling bin recommendation. The relevant cost data are shown in Table V. After that, Fig. 5 shows the simulation of recycling bin locations for three users.

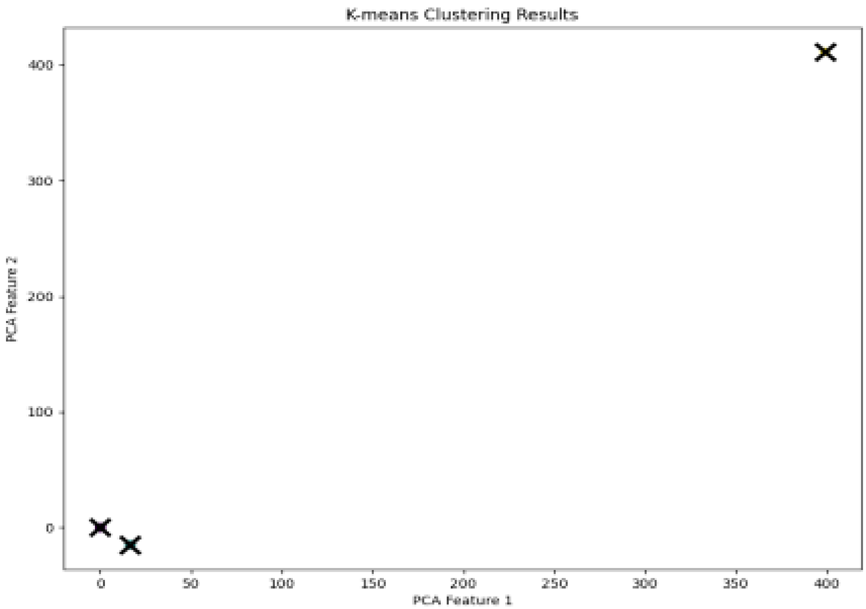

Figure 4: Clustered visualisation of clothing donation needs of regular users.

Table V: Presentation of model solving results for 10 cost preference users.

User no.	**Objective function value** ($)			**Recommended bin sites**	**Time** (hour)		**Walking distance** (m)
	Driving cost	**Clothing donate cost**	**Total cost**		**Travelling time**	**Clothing donate time**	
00256	20	26	46	Site F	0.5	2	960
00289	23	30	53	Site G	0.6	3	800
00264	41	50	91	Site H	1.2	1	569
00286	20	60	80	Site I	0.8	0.5	235
00569	30	84	114	Site A	0.5	3	1200
00358	50	15	65	Site J	0.6	6	596
01258	69	80	149	Site K	0.4	2	2000
15263	18	56	74	Site L	0.2	1	890
13924	23	26	49	Site M	1.0	3	1596
11963	55	43	98	Site N	1.1	4.0	1435

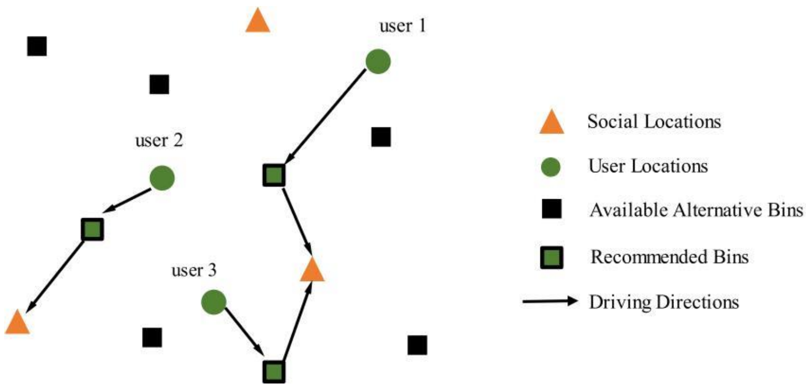

Figure 5: Three cost preference user's initial locations and clothing recycling bin simulation.

Simulation of clothing recycling bin recommendation for time preference users: We selected 10 users to analyse clothing recycling bin recommendations for time-preferred users. Table VI shows the associated costs and fees. Then, Fig. 6 shows the simulation of clothing bin recommendation locations for three of the users.

Table VI: Presentation of model solving results for 10 time preference users.

User no.	**Objective function value** (hour)			**Recommended bin sites**	**Cost** ($)		**Walking distance** (m)
	Driving time	**Clothing donate time**	**Total time**		**Travelling cost**	**Clothing donate cost**	
00236	0.2	1	1.2	Site A	20	26	890
00189	0.8	2	2.8	Site O	23	30	1210
01264	0.2	0.8	1.0	Site H	41	50	669
05386	1.2	0.5	1.7	Site I	20	60	245
12569	1.0	2	3.0	Site A	30	84	100
10358	0.6	2.5	3.1	Site M	50	15	996
09258	0.4	2	2.4	Site P	69	80	1500
11263	0.2	1	1.2	Site L	18	56	1090
10924	1.1	0.5	1.6	Site M	23	26	1296
00963	0.8	1.2	2.0	Site Q	55	43	985

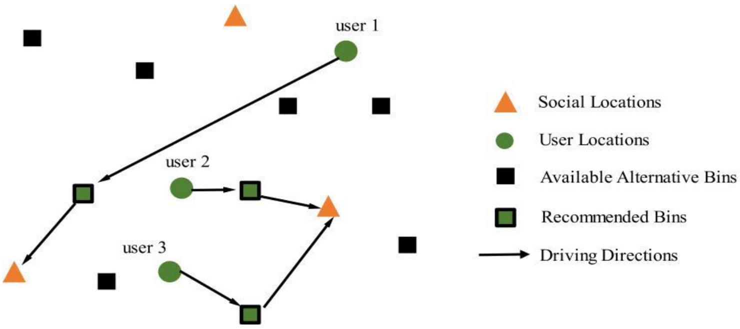

Figure 6: Initial location and clothing recycling bin simulation for 3 time preference users.

Simulation of clothing recycling bin recommendation for users with walking distance preference: We analysed users with walking distance preference to achieve the best recommended clothing recycling bins. The costs and fees associated with the 10 users are shown in Table VII. Fig. 7 shows a simulation of bin locations for three users.

Table VII: Presentation of model simulation results for 10 walking distance preference users.

User no.	**Objective function value** (m)	**Recommended bin sites**	**Cost** ($)		**Time** (hour)	
			Travelling cost	**Clothing donate cost**	**Travelling time**	**Clothing donate time**
00569	352	Site A	52	35	0.3	1
10183	520	Site O	25	59	0.6	2
11223	463	Site R	36	89	1.3	3
05386	189	Site I	29	40	0.9	2.2
00069	230	Site A	50	34	2.1	2
12558	369	Site M	89	32	0.5	2.5
05695	600	Site S	20	56	0.2	3
08563	563	Site T	43	26	0.1	3
02023	236	Site M	23	16	1.1	0.5
14523	385	Site U	20	53	0.8	1.2

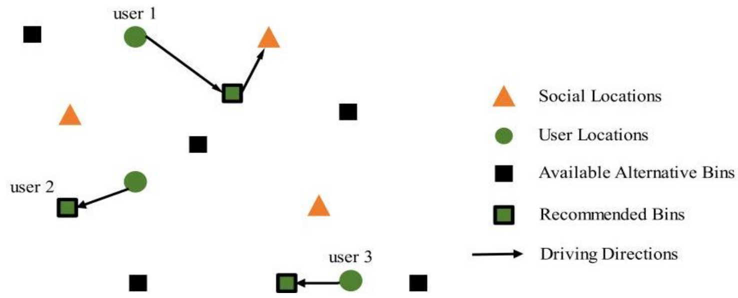

Figure 7: Initial position and clothing recycling bin simulation for 3 walking distance preference users.

We classify users into three categories: time preference, cost preference and walking distance preference for clothing recycling bins, and generalize the preference majority into preference tolerance values. Meanwhile, based on the users' clothing donation demand preferences combined with the social location information and the set of available recycling bin locations, an optimization model and a design solution algorithm are applied to determine the optimal clothing recycling bin locations and their associated costs for the users in the current situation. The study validates the effectiveness of the proposed model and algorithm and provides effective selection suggestions for users.

7. CONCLUSION

This study addresses the challenge of recommending the best clothing recycling bins in a location-based social network by combining users' clothing donation preferences and social information obtained from the Internet. The key to this problem lies in understanding users' preferences and considering their social activities after visiting the recycling bins in order to provide tailored recommendations. Therefore, we propose a novel research framework: 'Cluster Analysis of User Clothing Donation Needs under Multidimensional Features + Optimal Recommendation of the Best Recycling Bins'. First, we provide an in-depth analysis and definition of the research problem, highlighting its differences with existing approaches. Second, we combined statistical theory and data mining techniques to develop a multidimensional feature system for mining users' clothing donation needs. We used cluster analysis to group users based on their multidimensional features. Based on the clustering results, we constructed a recommendation model that considers users' preferences to select the best locations for clothing recycling bins. Finally, we validated the model with a case study using data from Connecticut. This approach provides a new perspective on solving the clothing donation recommendation problem, offering a practical and effective solution that combines advanced analytics with user-centred design.

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