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E-waste Collection and Recycling Behaviours: An Agent-Based Model for Intervention Assessment in Singapore

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Abstract

Electronic waste (E-waste) is one of the fastest growing waste streams in the world. Despite the significant environmental and economic value of recycling e-wastes, its recovery rate is still below expectation. Singapore is facing the same challenge, while little efforts have been devoted to the systematic analysis of e-waste collection and recycling. To address the problem, this paper develops an Agent-Based Model (ABM) to simulate the e-waste recycling behaviour in a municipal level, considering various types of e-waste collection channels available in the country. Two primary objectives are reducing the retention time of e-wastes at home and increasing the overall e-waste recycling rate. We conduct extensive experiments to analyse the impact of two interventional strategies, namely, Nearest Recycling Sites Assignment and Recycling Information Campaign. The experiment results reveal the importance of convenience associated with proximity and the dissemination of knowledge in shaping e-waste recycling behaviours. The model enables a quantitative analysis of potential interventions, providing actionable insights for policymakers and various stakeholders to promote sustainability practices.

Keywords: E-waste recycling; Recycling behaviour; Simulation; Agent-Based Modelling

1. Introduction

With technological advancement and economic growth over the years, electronic products have become increasingly embedded into daily life. New products of Information and Communication Technology (ICT) and other e-devices are consistently being launched in the market, while older models are rapidly becoming outdated. As a result, the generation of electronic wastes (e-wastes) is increasing sharply, with a total amount of 62 Mt in 2022 globally, which is twice the quantity recorded in 2015 [1]. However, it is estimated that around 78% of the total e-waste generation was not documented and likely to be burnt openly or disposed of illegally [2].

Recycling, as a crucial component of the “Reduce, Reuse, Recycle” framework, offers a viable solution to mitigate the problem. In fact, recycling e-wastes fulfills two practical purposes. On the one hand, e-wastes comprise a wide range of materials such as gold, silver and copper, making them a valuable source of secondary raw materials [3]. On the other hand, improper treatment of e-wastes may cause substantial environmental threat due to the presence of hazardous components such as halogens metals [4]. Proper collection and recycling of e-wastes not only facilitates resource conservation but also reduces environmental and health risks.

Singapore, a highly urbanized country, faces the same challenge. It is reported that more than 60,000 tonnes of e-wastes are generated each year, while only 6% of them are recycled [5]. There has been some academic interest in waste in Singapore, yet little attention has been focused on the type of e-wastes specifically. For example, Xue et al. [6] designed

Table 1: Summary of Collection Channels for Various Types of E-waste.

	ICT Equipment (laptop, smartphone)	Household Battery	Bulb/Lamp	Large Household Appliance (Refrigerator)
3-in-1 Bin	✓	✓	✓	
Manned In-Store Counter	✓	✓		
Battery & Bulb (BB) Bin		✓	✓	
Battery-Only Bin		✓		
ALBA's Depot Drop-off	✓	✓	✓	✓
E-waste Collection Drive	✓	✓	✓	✓

an optimization model to allocate waste-to-energy plants for companies located in various regions. Ng et al. [7] reviewed the practices and challenges in the food waste management system. Kerdlap et al. [8] explored various drivers and barriers for a zero-waste transition in the manufacturing sector. Despite these contributions, systematic analyses of e-waste collection and recycling in Singapore remain limited. Studies found that people tend to retain e-wastes at home, leading to low participation rates in recycling activities [9]. Inconvenience and lack of knowledge also contribute to the unsatisfying recycling rates [10], [11]. However, studies on these mechanisms in the context of Singapore are lacking. To fill this gap, this study models the current e-waste collection system in Singapore, simulates the recycling behaviours of residents, and quantitatively assesses potential interventions with the aim to enhance e-waste recycling practices among residents.

Agent-based modeling (ABM) is a computational approach that simulates the actions of autonomous agents (e.g., individuals, organizations, infrastructures) to assess the impact of their interactions to the system as a whole. E-waste collection system can be regarded as a complex system that involves multiple types of agents (e.g., residents, recycling sites) and interactions among them. Therefore, we utilize the ABM technique to model the e-waste collection system and simulate the recycling behaviours of residents. We aim to use the developed model to assess several interventional strategies to: 1) reduce the retention time of e-wastes at home, and 2) increase the overall e-waste recycling rate. Specifically, the model considers common household e-wastes, including ICT equipment (smartphones and laptops), batteries, lamps/bulbs, and large appliance (refrigerators). Several factors are taken into consideration to simulate the decision-making processes regarding recycling behaviours, such as distance to the infrastructure, knowledge about recycling, and social impact. Finally, we assess two interventional strategies, namely, Nearest Recycling Site Assignment and Recycling Information Campaign implementation, which reveals practical insights for policymakers to promote e-waste recycling practices in Singapore.

In the remaining of the paper, Section 2 provides a background of the study region and the ABM technique. Section 3 illustrates the methodology, including the conceptual model and experiment setup. Section 4 presents the results for intervention assessment and sensitivity analysis. Finally, Section 5 discusses experiment implications and Section 6 concludes the paper.

2. Background

2.1. Overview of Study Region

Singapore, a city-state in Southeast Asia, covers a compact area of around 734.3 km2 with a dense population of 8058 inhabitants per km2 [12]. As a highly urbanized country with the challenge of land scarcity, Singapore is aiming for a zero-waste goal to reduce waste generation and mitigate adverse impact on the natural environment. E-waste is one of the targeted waste streams to be addressed, as highlighted in the Singapore's Zero Waste Masterplan [13]. In 2021, National Environmental Agency (NEA) introduced a regulated e-waste management system based on the Extended Producer Responsibility (EPR) approach. Under the system, producers are responsible for managing the collection and treatment of their products at the end of their life cycle. ALBA E-waste Smart Recycling Pte Ltd (ALBA) was assigned on behalf of all producers to collect regulated consumer e-wastes across Singapore for appropriate treatment and recycling from July 2021 to Jun 2026 [14].

Under the services of ALBA, there are 6 types of collection channels: 3-in-1 Bin, Manned In-Store Counter, Battery & Bulb Bin, Battery-Only Bin, ALBA's Depot Drop-Off, and E-waste Collection Drive [15]. Each of these channels accept specific types of e-wastes. Table 1 presents the summary of these channels, aligned with the types of e-wastes considered in our modelling system. For the sake of consistency, we will use "recycling sites" to refer to these 6 channels collectively in the remaining of the paper.

2.2. Agent-Based Modelling

E-waste collection system can be considered as a complex adaptive system (CAS), where multiple autonomous agents interact with each other, leading to the emergence of complex patterns that are often unpredictable from individual components [16]. Such systems are complex, dynamic, and are able to adapt to changes within its own environment. Simulation methods, such as Agent-Based Modelling (ABM), are recognized as effective strategies to address the complexity of such systems [17]. ABM simulates actions of agents individually, where each agent has unique characteristics and behaviours. The interactions among agents in a microscopic level lead to macroscopic phenomena of the system, which is often unpredictable initially [18]. This approach allows for accurate predictions and comparisons of various micro-level mechanisms with respect to the performance of the overall system. Frequently, ABM is coupled with the Theory of Planned Behaviour (TPB) [19] to simulate the decision-making processes of agents. TPB

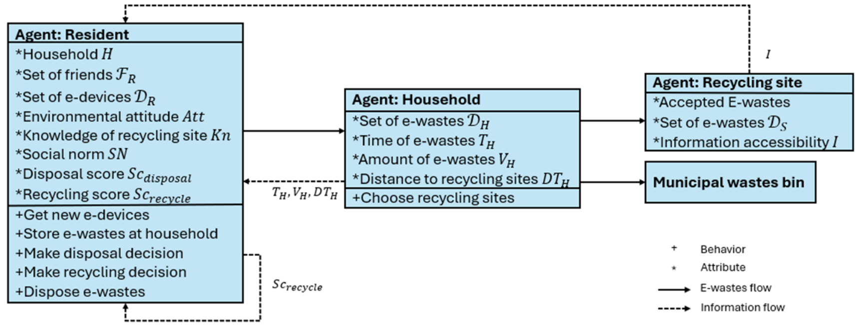

Fig. 1. Conceptual model of the proposed agent-based model for e-wastes collection and recycling behaviours.

assumes that individual behaviours are directly influenced by their intentions, which are shaped by their knowledge, attitudes and social impacts. Integrated with TPB, ABM can effectively model the decision-making processes of individual agents, enabling the study of various interventional strategies that influence the behaviours of agents and consequently, the overall performance of the system.

3. Methodology

This section presents the proposed conceptual model for the simulation of e-waste recycling using ABM, and the experimental setup for potential intervention assessment. To facilitate a clear explanation of the modelling process, a set of notations is introduced. Let $\mathcal{H} = \{H_1, H_2, \dots\}$, $\mathcal{R} = \{R_1, R_2, \dots\}$ and $\mathcal{S} = \{S_1, S_2, \dots\}$ represent the sets of all households, residents and recycling sites. $\mathcal{D} = \{D_1, D_2, \dots\}$ denotes the set of all e-wastes, characterized by their type, volume v, lifespan l, and storage time t.

3.1. Conceptual Model

The model comprises three main agents: Resident, Household and Recycling site. Figure 1 details the attributes and behaviors of each type of agents and the overall interactions among them. The environment of the model is designed to represent the actual geographical landscape, with locations of agents also corresponding to real-world geographical positions.

Household refers to a group of residents living in one apartment, responsible for storing e-wastes before disposal. A set of e-wastes $\mathcal{D}_H$ are maintained in the household and a record of them are updated during each cycle, including the accumulated amount of e-wastes V_H and total duration of storage T_H, both calculated as the sum of all devices in the household. Additionally, the traveling distance required to dispose of all types of maintained e-wastes, DT_{H_i}, is recorded, calculated as the sum of distance from the household to each required recycling site.

Recycling site is a collection point where residents can properly dispose of e-wastes. Each site is situated at a specific location, managing a set of e-wastes $\mathcal{D}_S$ and characterized by its information accessibility I_S . Information accessibility refers to how easily residents can access and comprehend information about a recycling site, including its location, accepted e-waste types, and operating hours. Besides recycling sites, residents may dispose of e-wastes into general municipal waste bins. However, e-wastes disposed of to these bins, denoted by a set $\mathcal{D}_M$, are considered as misplaced and uncollected.

Resident is the primary agent responsible for the generation and disposal of e-wastes. Each resident R is associated with a specific household H_i, possesses a network of randomly assigned friends $\mathcal{F}_R$, maintains a set of e-devices $\mathcal{D}_R$, and is characterized by the attitude toward circular practices Att . Main activities of the Resident agent are illustrated in Fig. 2. Initially, residents acquire new e-devices. An e-device is kept until it reaches the end of its lifespan, at which point it becomes an e-waste and is accumulated in the household. Subsequently, residents evaluate the current e-waste situation in the household and decide whether to proceed with disposal. If disposal is chosen, residents need to choose channels: either recycling sites (e-wastes recycled) or municipal wastes bins (e-wastes misplaced). Then the accumulated e-wastes in the household are transferred to the corresponding channel.

Throughout the whole process, residents make two critical decisions: disposal decision - whether to dispose of e-wastes or retain them at home, and recycling decision - whether to dispose of e-wastes into recycling sites or municipal waste bins. The decision-making processes are elaborated as below.

Disposal Decision. A disposal score $S_{disposal}$ is first derived as the linear combination of e-waste amount V_{H_i}, retention time T_{H_i} and traveling distance DT_{H_i} in the household, as in Eq. 1. Notably, α_{DT} is set negative due to the adverse impact of traveling distance on the disposal behaviours.

$$S_{disposal} = \alpha_T \cdot T_{H_i} + \alpha_V \cdot V_{H_i} + \alpha_{DT} \cdot DT_{H_i} \tag{1}$$

Probability of e-wastes disposal $P_{disposal}$ is then derived by applying a min-max scaling as shown in Eq. 2, where $S_{disposal_{min}}$ and $S_{disposal_{max}}$ are the minimum and maximum scores observed throughout the entire set of experiments.

$$P_{disposal} = \frac{S_{disposal} - S_{disposal_{min}}}{S_{disposal_{max}} - S_{disposal_{min}}} \tag{2}$$

Recycling Decision. Similarly, a recycling score $S_{recycle}$ is calculated as the weighted sum of attitude Att, social norm SN, recycling knowledge Kn and traveling distance DT_{H_i}, as shown in Eq. 3.

$$S_{recycle} = \beta_{SN} \cdot SN + \beta_{Att} \cdot Att + \beta_{Kn} \cdot Kn + \beta_{DT} \cdot DT_{H_i} \quad (3)$$

Specifically, social norm SN reflects the influence of friends and is calculated as the average recycling scores of friends. Attitude Att refers to the awareness towards the adoption of circular practices. Recycling knowledge Kn represents the level of understanding about recycling practices, measured as the average information accessibility, I_S, of recycling sites chosen by their household. Similar to the disposal score, the weight of traveling distance β_{DT} is set negative. Recycling behaviors are then classified into four categories based on recycling scores. Three parameters are introduced for the classification: θ_1, θ_2 and θ_3, with values in an ascending order. Those scores below θ_1 are categorized as *Very Bad*, between θ_1 and θ_2 are *Bad*, between θ_2 and θ_3 are *Good*, and above θ_3 are *Very Good*. Correspondingly, the probabilities of selecting recycling sites, $P_{recycling}$, are 0.2, 0.4, 0.6 and 0.8, respectively.

3.2. Experimental setup

This section describes the experimental setup for the assessment of potential interventions. We first introduce the indicators: averaged retention time of e-wastes T_{avg} and recycling rate $PCT_{recycled}$, which are calculated as Eqs. 4-5.

$$T_{avg} = \frac{\sum_{S\in\mathcal{S}} \sum_{D\in\mathcal{D}_S} t_D}{\sum_{S\in\mathcal{S}} |\mathcal{D}_S|} \quad (4)$$

$$PCT_{recycled} = \frac{V_{recycled}}{V_{recycled} + V_{misplaced}} \quad (5)$$

where $V_{recycled}$ is the amount of e-wastes properly disposed of into recycling sites and $V_{misplaced}$ is the amount of e-wastes improperly disposed of into municipal waste bins. We propose and assess two interventional strategies: Nearest Recycling Sites Assignment and Recycling Information Campaign, to enhance e-waste recycling practices. The former reveals insight on the importance of convenience associated with proximity, while the latter investigates the impact of knowledge, i.e., information accessibility, on recycling participation.

Nearest Recycling Sites Assignment. As each recycling site accepts specific types of e-wastes, one might need to travel to multiple sites to dispose of maintained e-wastes, leading to a set of alternative choices of site combinations. Let $\mathcal{O}_H$ be the set of all feasible options, and $\mathcal{S}_H \in \mathcal{O}_H$ be one of them. To demonstrate the effect of Nearest Recycling Site Assignment, two scenarios are evaluated: 1) $\mathcal{S}_H$ is a random choice from $\mathcal{O}_H$; and 2) $\mathcal{S}_H$ equals $\mathcal{S}_H^{nearest}$ that minimizes the travelling distance among all feasible options, as defined in Eq. 6.

$$\mathcal{S}_H^{nearest} = \arg\min_{\mathcal{S}_H\in\mathcal{O}_H} \sum_{S\in\mathcal{S}_H} dist(S, H) \quad (6)$$

Recycling Information Campaign. Information accessibility plays a significant role in affecting recycling behaviors. Without adequate information, residents may misplace e-wastes when they are motivated to recycle. To this end, Recycling Information Campaign is designed to organize recycling events to enhance information accessibility, thereby enriching the knowledge of residents on proper recycling practices. We design four scenarios to evaluate the impact of this intervention: organizing events annually, bi-annually, quarterly and not at all. Information accessibility I of recycling sites is increased by Δ_I after each event.

Moreover, while the two interventions can be implemented concurrently, their combined effect remains unclear. We design another set of experiments to evaluate the effect of implementing both interventions compared with the baseline, i.e., under the scenario of random site assignment and no information campaign. Finally, a sensitivity analysis is performed to ensure the robustness of experiments results.

4. Experiment results

Our model was implemented in GAMA Platform version 1.9.3 [20]. Aiming to accurately reflect the actual e-waste management and population in Singapore, data from NEA for recycling sites [15] was utilized to initialize the Recycling site agents. Housing & Development Board (HDB) geometric data [21] and HDB property information [22] were employed to establish household locations and population distribution of residents. These data were processed by GeoPandas and saved as ESRI shapefiles. GIS Data Hub Collection was utilized to convert street codes to street names to facilitate the mapping between the two HDB data. Numbers of residents and households of each building were set according to the number of dwelling units in the building. Due to the limitation of available memory, which would be exceeded by processing the entire population, we scaled down the whole population by a factor of 60, which leads to more than 11,000 residents and 946 recycling sites modeled in the system. Simulation was run for 20 years, equivalent to 2080 cycles, where one cycle represents half of a week. To minimize impact of randomness, each experiment was repeated four times and the averaged value was taken.

Parameters used in this study were determined through statistical analysis to facilitate the comparison across various scenarios. Specifically, coefficients for the disposal score associated with retention time (α_T), accumulated amount (α_V) and travelling distance (α_{DT}) were set to $1.5^{-1} \cdot 10^{-2}$, $1.5^{-1} \cdot 10^{-4}$, and $-1.5^{-1} \cdot 10^{-3}$, respectively. The values were chosen to balance the contributions of factors which possess varying units and scales. For the recycling score, coefficients associated with social norm (β_{SN}), attitude (β_{Att}) and knowledge (β_{Kn}) were set to 1 for simplicity, assuming these factors operate on a similar scale. However, the coefficient for traveling distance (β_{DT}) was set to -10^{-2} to offset its contribution. Thresholds for determining recycling behaviors (θ_1, θ_2, θ_3) were set to -120, 0, and 100, respectively, dividing recycling scores into four reasonable ranges. Finally, the increment of information accessibility (Δ_I) was set to 20.

4.1. Intervention assessment results

Figures 3a and 3b present the results for Nearest Recycling Sites Assignment. The recycling rate $PCT_{recycled}$ is enhanced

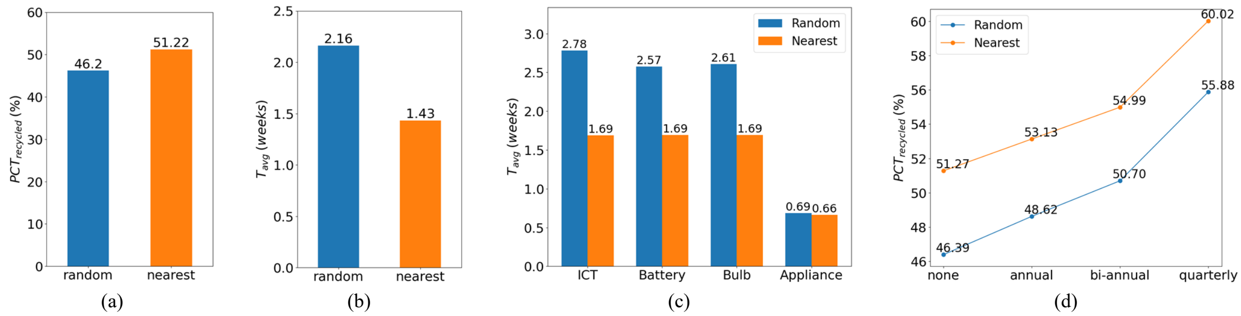

Fig. 3. Results of experiment for Nearest Recycling Sites Assignment: (a) recycling rate $PCT_{recycled}$; (b) average retention time T_{avg}; (c) average retention time by types of e-wastes; and for Recycling Information Campaign: (d) recycling rate $PCT_{recycled}$ by campaign frequency.

by 5%, increasing from 46.2% to 51.22%. Furthermore, average retention time T_{avg} also reduces by a half, decreasing from 2.16 to 1.43 weeks. This reduction is particularly notable in three categories: ICT equipment, battery, and bulb/lamp, while household appliances have the smallest decrease, as shown in Fig. 3c. This may result from the limited options for recycling household appliances. Only two types of recycling sites accept this type of e-wastes: ALBA's Depot Drop-Off and E-waste Collection Drive. The former only has one location far outside of the city center, and the latter are only organized quarterly. These limitations reduce the benefits of implementing Nearest Recycling Sites Assignment compared with random assignment.

Recycling Information Campaign is also effective in enhancing recycling practices. As depicted in Fig. 3d (blue line), recycling rate is positively correlated with the frequency of events. Notably, when recycling events are organized quarterly, the recycling rate increases from 46.39% to 55.88%. Implementing campaigns does not influence the e-waste retention time but affects residents' behaviours in selecting the appropriate channel for e-waste disposal, i.e., choosing recycling sites over municipal wastes bins, hence contributing to an increased recycling rate.

When implementing both interventions, the recycling rates are further improved, as shown by the orange line in Fig. 3d. Compared to the baseline scenario, combining Nearest Recycling Site Assignment and Recycling Information Campaign at a quarterly frequency increases the recycling rate by 14%. Notably, the combined effect is not a simple summation of the individual contributions, and the marginal gains of Nearest Recycling Site Assignment gradually shrink as the campaign frequency increases, decreasing from 4.88% at a zero frequency to 4.14% at a quarterly frequency.

4.2. Sensitivity analysis

We employed the one-factor-at-a-time (OFAT) sensitivity analysis [23] for parameters in the disposal and recycling scores, including α_T, α_V, α_{DT}, and β_{DT}, which directly influence residents' decision-making processes. We evaluated performances under the baseline scenario (no intervention) and the enhanced scenario (both interventions) with varying parameter values. As shown in Fig. 5, implementing interventions *consistently* outperforms the baseline in increasing recycling rate and reducing retention time. While it is often challenging to obtain parameter values that perfectly reflect the real-world, the results from sensitivity analysis confirm the general trends and insights in the effectiveness of the proposed interventions, highlighting the robustness and applicability of our findings.

5. Discussion

E-waste recycling remains a crucial component in municipal waste management systems. Studies have identified factors such as inconvenience, lack of awareness, limited knowledge, and insufficient incentives affecting recycling behaviours [10], [11]. Our experiment results reveal that reducing the distance to recycling sites could effectively decrease e-waste retention time at home. Furthermore, conducting information campaigns enriches residents' knowledge on proper recycling practices, hence improving the overall recycling rate. These results align with existing studies that convenience and knowledge are critical factors influencing e-waste recycling behaviours.

Our model is tailored to the context of Singapore, providing practical insights for policymakers to design strategies to enhance e-waste recycling practices. Specifically, integrating the shortest recycling site assignment feature into a smart application for e-waste recycling and tracking could enhance participation. Fostering public education through information campaigns is also effective to encourage proper recycling behaviours. In short, policies targeting at enhancing the convenience of recycling and the dissemination of knowledge would be effective in reducing e-waste retention time and increasing the overall recycling rate.

6. Conclusion

In this study, we successfully developed an agent-based model to simulate the current e-waste collection system in Singapore and the recycling behaviours of residents under various conditions. We assessed two potential interventions: Nearest Recycling Sites Assignment and Recycling Information Campaign. Simulation results demonstrate the effectiveness of both strategies. E-waste recycling is a crucial component in waste management in Singapore, and we contribute to this problem by developing a tailored agent-

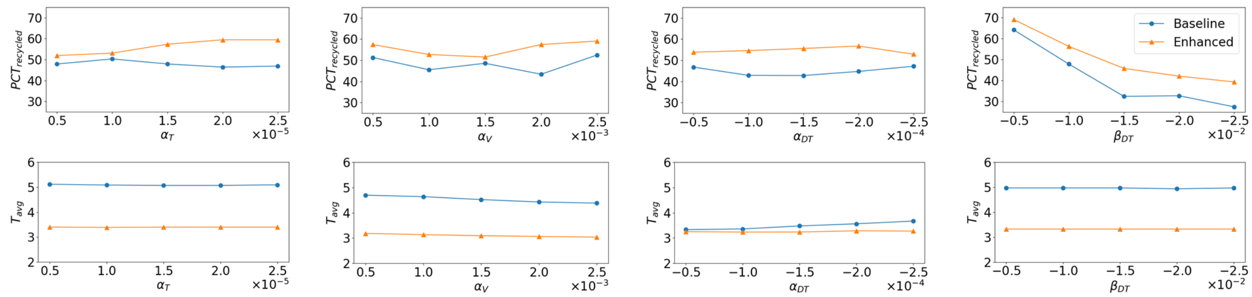

Fig. 5. Results for sensitivity analysis. Baseline: no intervention is implemented. Enhanced: implementing both Nearest Recycling Sites Assignment and Recycling Information Campaign (bi-annual frequency).

based model to facilitate the simulation of such complex system. Moreover, the model enables quantitative assessment of potential interventions, providing policymakers with reliable insights to support informed decision-making. The experiment results reveal the importance of knowledge dissemination and the convenience associated with proximity. Policies targeting at these two factors could effectively enhance e-waste recycling practices.

While the model offers valuable insights, some limitations exist. First, the simulation is based on a scaled population. While it does not affect the general insights obtained, it may result in small discrepancies in the magnitude of retention time and recycling rate compared with using the full population. Second, while simulation results exhibit clear trends, the quantitative performance gains depend on specific parameter values which are challenging to obtain in the real-world. Nevertheless, the model represents a simplified virtual society allowing for future extension. Future work may also incorporate the exploration of strategies including deposit-refund schemes and incentive programs. Though the model is developed based on the context of Singapore, it can be adapted to other regions by adopting region-specific data on recycling sites and residential information. The proposed model thereby provides a systematic method for studying e-waste collection and recycling for different locations at different scales.

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