Exploring urban scenarios with an agent-based model to assess residential waste sorting

Jonathan Cohen[1*]; Jorge Gil[1]; Leonardo Rosado[1]

[1] Department of Architecture and Civil Engineering, Chalmers University of Technology, 412 96 Gothenburg, Sweden

[*]Corresponding author, Department of Architecture and Civil Engineering, Chalmers University of Technology, 412 96, Gothenburg, Sweden; E-mail: jonathan.cohen@chalmers.se

Abstract

Efficient waste management is vital for sustainable urban development, reducing emissions, and increasing recycling. Waste separation at the source relies on citizens' behaviour. The theory of planned behaviour (TPB) can explain waste sorting behaviour, but factors like bin distance, recycling facilities' characteristics, and information campaigns need more research. This study explores the relationship between the built environment and residential waste sorting using a spatially explicit agent-based model (ABM) with TPB. The article details how TPB was exploited to model the behaviour of waste sorting. The ABM was implemented in two urban areas with low and high population densities, showing that changing bin placement affects sorting and proximity to recycling bins influences adequately sorted residual waste. This article demonstrates how to model and study the link between urban planning and waste sorting performance, revealing the impact of individual residents' behaviour on sorting percentages.

Keywords:

Agent-based model; Theory of Planned Behaviour; Waste sorting; Waste Management; Urban planning

1. Introduction

Under the current linear economic system, waste materials are an unavoidable and undesirable by-product of daily activities that need adequate management. Globally, it is estimated that by 2050, waste generation will grow to 3.4 billion tons, and municipal waste management (MWM) related emissions will grow to 2.6 billion tons of CO_2e (i.e. 5% of global emissions) (Kaza et al., 2018). As environmental concern continues to increase, waste-related issues are gaining attention and ranking high in priority worldwide (Matiiuk & Liobikienė, 2021).

The activity of MWM involves collecting, transporting, disposing, and recycling waste materials generated by households, and municipalities dedicate between 4% to 20% (high-income and low-income countries) of their budgets to managing waste (Kaza et al., 2018. p102). Despite being often overlooked (Ewijk & Stegemann, 2020), improvements in MWM systems contribute to moving forward several Sustainable Development Goals (SDGs) (Elsheekh et al., 2021; Roy et al., 2023). Environmentally, efficient waste management provides a healthy and clean environment, reduces greenhouse gases (GHGs), and reduces resource depletion by recycling and reusing strategies.

Waste separation at source is perceived as an effective MWM strategy. This strategy depends on citizens' behaviour in separating their waste into different fractions, and it is adopted or implemented in many cities. However, the success of such a strategy relies on an adequate understanding of the drivers of waste-sorting behaviour (Kaplan Mintz et al., 2019; Matiiuk & Liobikienė, 2021) and how different aspects of the system interact.

The behaviour of waste sorting and recycling has been extensively studied in various contexts and analysed through different theoretical frameworks. The Theory of Planned Behaviour

(TPB) (Ajzen, 1991) stands out as the most widely used and validated theory for understanding the drivers behind individual waste sorting (Phulwani et al., 2020; Raghu & Rodrigues, 2020). Besides internal factors determining the behaviour of residents, such as environmental knowledge or attitudes, the urban environment also plays a role in determining the behaviour towards waste separation (Cohen et al., 2024; Rousta et al., 2020; Struk, 2017a). Moreover, few studies have focused on linking the behaviour of individual residents with the actual amounts disposed of (Perrin, D; Barton, 2000). Research on this gap is relevant to determine how much and how well waste is being sorted at neighbourhood and city levels.

To tackle these issues, waste sorting and waste management can be studied and understood as Complex Adaptive Systems (CAS) (Chen & Gao, 2021; G. Luo et al., 2016; H. Luo et al., 2020). This perspective allows research to include multiple agents with microscopic behaviours that interact with each other and their environment. Within CAS, Agent-Based Models (ABMs) are computational tools for developing simulations that incorporate these agents and their interactions. ABMs are an adequate methodological approach to addressing the complexity of waste sorting because they include rich decision-making and bottom-up processes that allow for the emergence of system properties (Ceschi et al., 2021; Tong et al., 2018). As a result, ABMs can contribute to answering questions that would otherwise be difficult to assess, such as "How would the recycling rate of a neighbourhood change if there were twice as many waste bins?".

Several studies advocate the integration of TPB and ABMs (Jager, 2017; Muelder & Filatova, 2018; Scalco et al., 2018) since TPB offers a behavioural model for the agents. However, more applications for residential waste sorting and recycling are needed. First, we need to understand how individual behaviours result at a household or city level. Moreover, simulations are often non-spatial(Chen & Gao, 2022; Meng et al., 2018; Tucker & Smith, 1999), or space and location of different urban elements related to waste sorting are abstracted (Tong et al., 2018), making the models unsuitable for urban planning.

This study aims to explore the relationship between the built environment and residential waste sorting through individual behaviour. To accomplish this, this paper describes an ABM that incorporates the TPB to model how residents sort their waste. The model is spatially explicit by incorporating relevant characteristics of the built environment and allows for the assessment of urban scenarios. By simulating the interactions between the built environment and the residents' behaviour in different hypothetical scenarios, the research offers a tool to quantify and visualise the quality of residential waste sorting.

The remainder of this paper is structured as follows. Section 2 introduces the state of the art on TPB and ABM for waste sorting. Section 3 describes the methodology and the proposed ABM. Section 4 describes the data and case study of Gothenburg. Section 5 presents the application of the ABM to different urban scenarios, which is discussed in Section 5. Section 6 concludes by highlighting the main findings.

2. Models for studying waste sorting: state-of-the-art

This study builds on two research streams: Theory of Planned Behaviour (TPB) and Agent-Based Models (ABM). Firstly, the TPB has been extensively applied to study waste-sorting behaviour (Phulwani et al., 2020), and it offers a valuable understanding of the various factors affecting waste sorting. Secondly, ABM provides an adequate (bottom-up) approach to analysing a system with many agents and their interactions. The TPB fits this approach by informing how the ABM agents behave, and the integration of ABM with TPB has been used as a framework for studying waste sorting outcomes.

2.1. Waste Sorting and Theory of Planned Behaviour

According to the TPB, people's behaviour (BEH) is determined by four primary constructs: intention (INT), social norm (SN), attitude (ATT), and perceived behavioural control (PBC) (Ajzen, 1991). ATT refers to an individual's evaluation of performing a particular behaviour. It encompasses beliefs, knowledge, and a subjective valuation of performance. SN refers to the perceived social pressure or influence by other individuals to perform a behaviour. Finally, PBC refers to the perceived ease or difficulty of performing the behaviour. It encompasses internal and external factors such as skills, resources, opportunities, and barriers. Combined, ATT, SN and PBC are used to determine the INT that (with PCB) leads to a specific BEH. Figure 1 presents the original conceptualisation proposed by Ajzen. It can be noted that the constructs are determined using observable variables (att1, att2, att3, sn1 …, beh3).

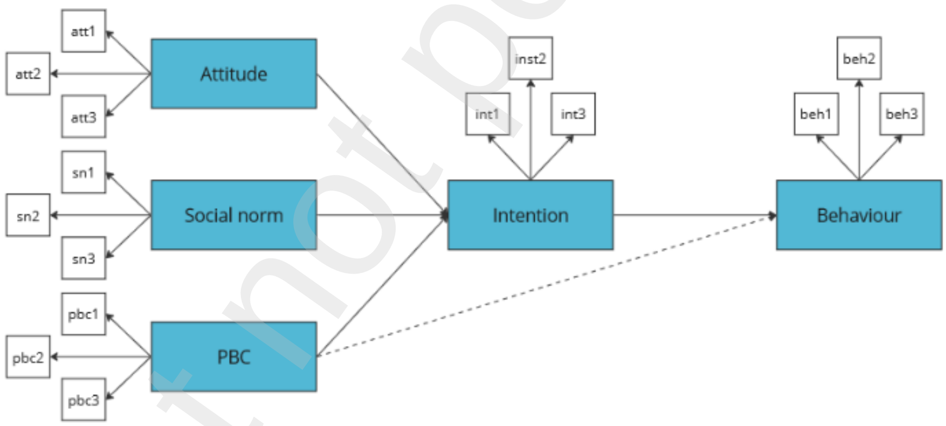


Figure 1 Conceptualisation of the Theory of Planned Behaviour (Ajzen, 1991).

TPB allows the inclusion of other constructs in addition to these primary constructs, and previous research has shown evidence that awareness of consequences (Hu et al., 2021; Tonglet et al., 2004; Wang et al., 2020), situational factors (Azlina et al., 2013; Govindan et al., 2022; Tonglet et al., 2004; Zhang et al., 2019), self-identification (Issock Issock et al., 2020; Knussen et al., 2004) or past behaviour (Knussen et al., 2004; Lakhan, 2018) are relevant constructs in specific contexts. Empirically, to evaluate the validity of a TPB model, researchers design a survey that captures various aspects of each construct.

Existing studies usually consider the behaviour of individual waste sorting or recycling as a single phenomenon. For instance, specific studies have focused on food waste (Abdelradi, 2018; Azlina et al., 2013) and the return of packaging (Struk, 2017b). Moreover, research shows that perceived increased distance towards waste bins can reduce how residents sort their waste. Li, et al. (2020) provide evidence that distance does not play a significant role in participation in recycling, while other studies found that shorter distances to bins are associated with more involvement in recycling and pro-environmental attitudes (Cohen et al., 2024; Ibrahim, 2020; Lange et al., 2014; Rousta et al., 2020; Struk, 2017a).

Despite these advancements, linking the individual behaviour of residents with the actual amounts disposed of needs to be further researched (Perrin, D; Barton, 2000). Research on this gap is relevant to determining how much and how well waste is sorted at neighbourhood and city levels. Moreover, studies have yet to address the temporal aspect of behaviour. For instance, Hu et al. (2021) follow a community for three months and show evidence that environmental knowledge and guidelines can induce behavioural changes over time.

2.2. Waste sorting and Agent-Based Models

Tucker et al. provided the first example of an ABM simulation for waste and resources (Tucker & Fletcher, 2000; Tucker & Smith, 1999) to study how waste sorting changes over time by introducing different disturbances to the system. Although their early conceptualisation does not explicitly incorporate TPB, the authors include Attitudes, Norms and Conditions in their model to determine the behavioural aspects of the simulation.

Other studies have used or proposed using TPB with ABM to explore waste sorting outcomes. TPB is beneficial in an ABM context because it enriches the behavioural mechanism that determines the agent's actions with an established model, bringing realism to the simulations. The integration of TPB within an ABM framework is represented in Figure 2.

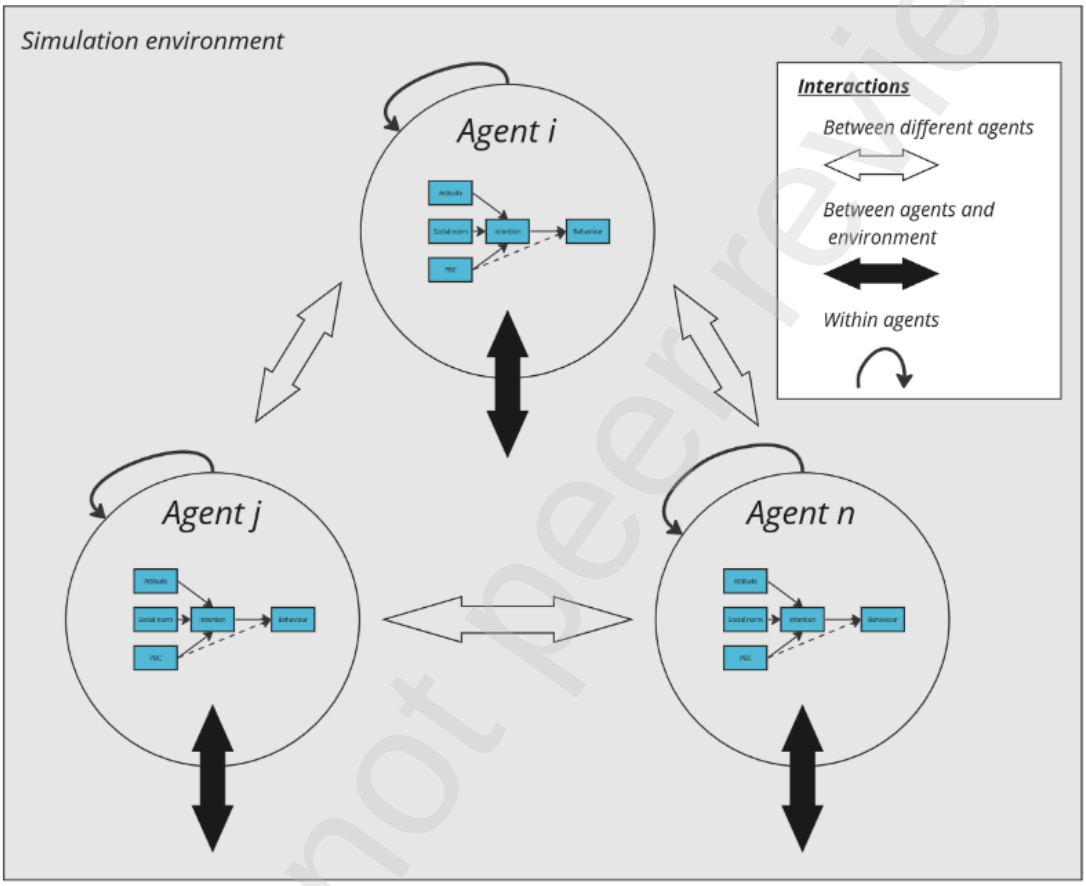


Figure 2 Integration of TPB and Agent-Based Models.

Researchers have approached the topic of waste recycling using ABM to explore the role of the informal waste system (Chen & Gao, 2021) and the introduction of taxes (Meng et al., 2018). In both ABMs, the agents include psychological variables and a utility function is used to determine their behaviour. Tong et al. (2018) ran a social experiment using technology to affect residents' incentives for waste recycling, and TPB was used as a baseline mechanism to represent their behaviour. Results showed that Social Norms played a crucial role in their context. An ABM was then developed to explore different waste disposal possibilities and study the level of recycling participation, using an abstract representation of the town divided into zones with other demographics. Finally, Ceschi et al. (2021) developed an ABM incorporating the TPB primary constructs for waste recycling to evaluate norm-nudging policies. Although the ABM was able to reproduce historical data and provide evidence of how TPB can be used in an ABM setting, the model takes advantage of two simplifications: first, it is spatially abstract by representing households as grid cells, and second, the TPB individual behaviour is applied at the household level.

To sum up, three gaps have been identified in the literature: (1) Empirical studies that estimate TPB mainly focus on intentions or self-reported behaviour, leaving a need to establish a link between internal perception of behaviour and the actual action; (2) Simulations are spatially abstract or do not take into consideration environmental determinants such as the location or status of waste bins; (3) The unit of analysis at which TPB has been integrated into ABM has been the household, despite empirical data being collected at the level of residents.

3. Methodology

This section describes the proposed ABM for simulating waste sorting in urban scenarios, including how waste sorting behaviour was calculated and integrated into the ABM framework “Residents planned behaviour of waste sorting to explore urban situations

(1.4.0).”[1]. First, following the TPB, a set of equations is described to estimate the behaviour of waste sorting. Second, the agents and the heuristics of the ABM are presented.

3.1. Determining the behaviour of waste sorting

The coefficients of the TPB model were specified based on empirical observations by extracting the mean values of the path coefficients from a Structural Equation Model (Cohen et al., 2024). The values in Figure 3 correspond to the estimated coefficients and offer a visual representation of how the waste sorting behaviour of an agent in the ABM is calculated. Following the estimation methods used to determine the behaviour, each of the TPB constructs were computed using linear equations (Eq 1 to Eq 6). All these equations include a constant, and the estimated coefficients are in italics with a sub-index representing the dependent variable, while upper-case refers to factors. For more details on the mean value and standard deviation of these coefficients, see the appendix **Error! Reference source not found.**.

[1] Update and extensions of the model are available at https://www.comses.net/codebases/592f0caf-8a02-48f5-bb73-b6fdc969982f/.

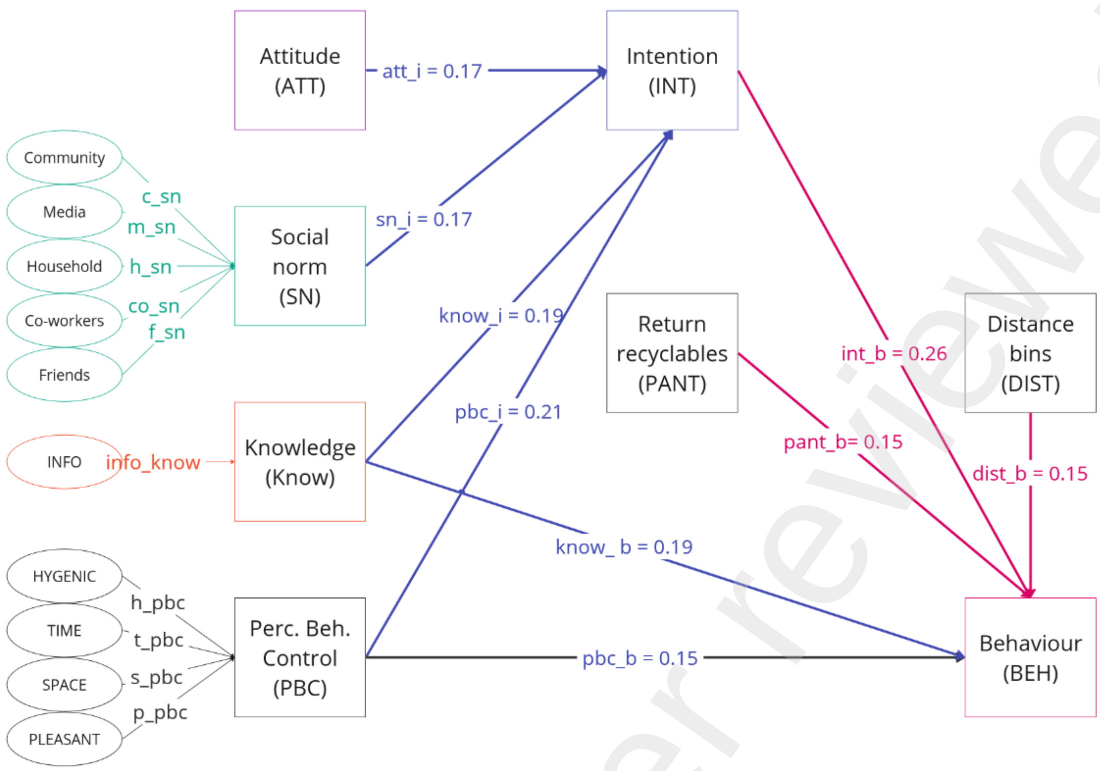


Figure 3 Path analysis of TPB coefficients. Source: adapted from (Cohen et al., 2024).

INT, PBC, KNOW, DIST and PANT determine the calculation of behaviour (BEH). Each of these factors have an associated estimated coefficient ($int_b, pbc_b, know_b dist_b, ret_b$) as presented in Eq 1.

$$BEH = constant_b + int_b \times INT + pbc_b \times PBC + know_b \times KNOW + dist_b \times I \times PANT \qquad Eq\ 1$$

In the equation above, DIST accounts for the average distance (meters) that a resident travels to dispose of organics, residuals, and recyclable waste. PANT is a dummy variable that identifies whether a resident exchanges packages for their economic value at supermarkets.

Also, following the path analysis, intention (INT) is estimated using Eq 4 and includes SN, ATT, PBC and KNOW, with their associated estimated coefficients ($att_i, sn_i, pcb_i, know_i$).

$$INT = constant_i + att_i \times ATT + sn_i \times SN + pbc_i \times PBC + know_i \times KNOW \qquad Eq\ 2$$

The value of Attitude (ATT) is assumed to be a normally distributed variable with a mean value of $\bar{x}$ and δ^2 as its standard deviation. Each resident is assigned a value because it represents internal valuations and preferences (Eq 3). There is no interaction with the environment, and it is an internal characteristic of the agents.

$$ATT \sim N(\bar{x},\ \delta^2) \qquad \text{Eq 3}$$

Social Norm (SN) represents the waste-sorting behaviour of the residents' social context. It is calculated using the average behaviour of each resident’s friends, co-workers, household, and community. Moreover, SN also includes the effect of social media (MEDIA). The estimated coefficients in Eq 4 are $friend_{sn}$, $media_{sn}$, $work_{sn}$, hh_{sn}, $bins_{sn}$.

$$SN = constant_{sn} + friend_{sn} \times FRIEND + media_{sn} \times MEDIA \cdot \times HOUSEHOLD + bins_{sn} \times COMMUNITY \qquad \text{Eq 4}$$

Perceived Behavioural Control (PBC) represents how much a resident believes that it can sort waste. It is calculated using a linear combination of a variable of the status of the waste bin and another of how much waste sorting space agents have at home. The estimated coefficients in Eq 5 h_{pbc}, t_{pbc}, p_{pbc}, s_{pbc}.

$$PBC = constant_{pbc} + h_{pbc} \times HYGENIC + t_{pbc} \times TIME + p_{pbc} \times PLEAS \times SPACE \qquad \text{Eq 5}$$

Knowledge (KNOW) represents the resident's knowledge level. It is assumed to be a function of the information displayed in the public waste bins. The estimated coefficient in Eq 6 is inf o_{know}.

$$KNOW = constant_{know} + info_{know} \times INFO \qquad \text{Eq 6}$$

The values of the TPB constructs range between 0 and 100, with 0 being the lowest possible score. More information in the Supplementary Materials describes the estimation process of PBC, SN, KNOW and ATT.

3.2. The ABM of residential waste sorting

The developed ABM is a micro-simulation of residential waste sorting at the individual level, where residents of a neighbourhood decide how to sort their waste according to TPB. This individual level is consistent with the TPB framework used to determine individual behaviour. It avoids assumptions on how a household (integrated by a set of individuals) solves its waste-sorting problems based on individual preferences.

The ABM simulates the behaviour and interactions between various agents, namely residents, buildings, households, workplaces, waste bins and bin collectors. The model was developed to represent an entire year, and every step in the simulation represents a third of a day. The agent classes and their attributes are based on the entities presented in Cohen & Gil (2021). Each of the agents represented in the model is described below.

3.2.1. Residential buildings

Residential buildings are spatially explicit agents represented by polygons, and their primary function is to create the households and the total population of residents. Each building has information about the number of households and the total population living in each building.

3.2.2. Households

The households are an abstract agent in the ABM to determine which residents share the same housing unit, and the average behaviour of these residents is used to determine SN.

Moreover, the households have attributes that represent the private waste bins for organic, residual, and recyclable waste at residents' homes. Because the model aims to trace how residents dispose of waste, a set of variables tracks how much waste of each type is placed in an organics, residuals, and recyclables bin.

Every time the sum of waste in a private waste bin is greater than zero, a counter for every time step starts. This mechanism reflects the effect of waste decomposition so that after a specific count, waste needs to be transported to the designated public waste bins (the closest) outside the building.

3.2.3. Public waste bins

The public waste bins hold waste outside the households of the residents. These bins can be used for organic, residual, or recyclable waste. As the waste bins of each household reach their limit (a random value between 1 and 2 kg), waste is transferred to public waste bins. The waste bins have specific attributes to trace how much waste of a particular type is being placed in each bin. Moreover, the public waste bins have an attribute to indicate the level of information displayed in each bin, which is used for the calculation of knowledge.

1.1.1. Workplaces

The workplaces are spatially explicit agents represented by polygons and have two functions. Firstly, they hold all the waste material that needs to be disposed of outside of the home. The model does not focus on how waste is disposed of outside the home because the waste sorting behaviour may be different (Greaves et al., 2013a). Specific literature has focused on waste sorting behaviour in working environments, and the determinants of such behaviour may vary (Greaves et al., 2013b). Secondly, this agent represents the various working groups.

Each resident is randomly assigned to a workplace, forming groups of residents that are co-workers. The average behaviour of a group is used to determine the SN (Eq 2) of a resident.

1.1.2. Residents

Each resident agent belongs to a household with designated public waste bins for organic, residual, and recyclable waste and a workplace. Resident agents also belong to different social groups that impact SN: friend groups are a random set of resident agents; co-worker groups are resident agents that share the same workplace; household groups are resident agents that share the same household; and community groups are resident agents that share the same public waste bin.

During each step of the model, the residents follow a daily routine that includes commuting to work, generating waste, assessing its behaviour, disposing of waste at home, and later transferring it to waste bins. Based on their behaviour, the residents make different decisions on how to sort their waste.

Figure 4 presents the sequence of actions followed by the residents during every step of the simulation. First, the residents' TPB constructs are updated, and their behaviour is calculated. Second, based on the probability of heading to work, the agents commute. The waste generated away from home is outside the scope of the model. The agents staying at home receive a sum of organic, residual, and recyclable waste that they dispose of in their private waste bins. The amount of waste assigned varies across residents.

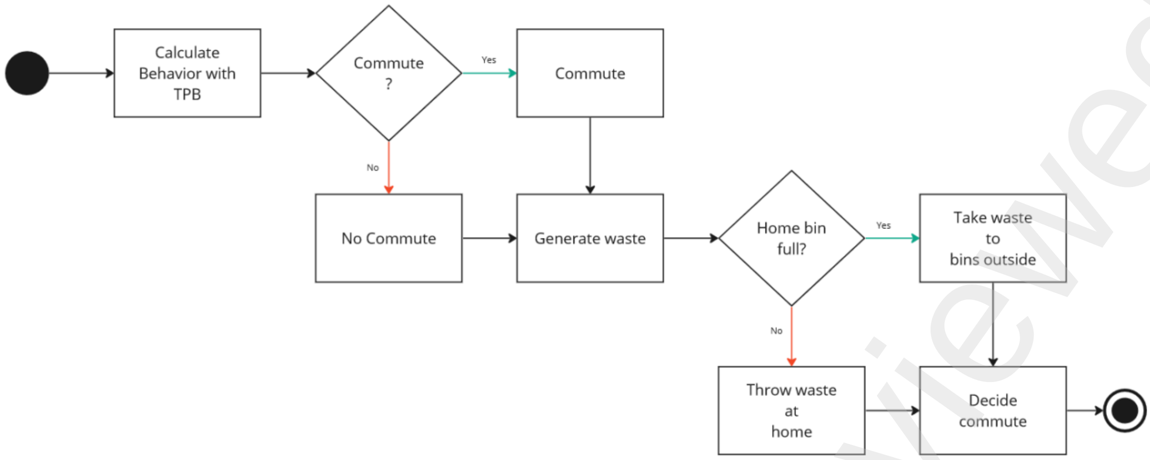


Figure 4 Routine of residents

At this stage, the residents' behaviour score determines how they dispose of their home waste based on a set of probabilities presented in

If the waste bins at home are found to be full, or the waste has been standing for a certain number of days, one resident of the household proceeds to empty the household waste bins and the waste amount is transferred to the public waste bins. For instance, when a resident has a positive amount of organic waste, it accesses the behaviour score. Let us imagine this is 65, which, according to the model, represents "Good" behaviour. The agent is assigned an 80% to 95% probability of throwing the organic waste into the organic waste bin and a 10% to 30% probability of throwing the organic waste into the residual waste bin. The cut-off values of what defines very bad, bad, or good behaviour are based on the results presented in the appendix **Error! Reference source not found.**.

Table 1 Probability distribution of disposal of various waste streams, depending on the averaged behaviour of residents.

	Behaviour			
	0-30 Very bad	30-55 Bad	55-75 Good	75-100 Very good
Disposal of organic				

Prob(… in organic)	0-50	50-80	80-95	95-100
Prob(… in residual)	60-100	30-60	10-30	0-10
Disposal of residual				
Prob(… in residual)	0-65	65-75	75-80	80-100
Prob(… in organic)	0-0	0-5	2-5	0-2
Disposal of recyclable				
Prob(… in recyclable)	0-75	75-80	80-85	85-100
Prob(… in residual)	80-100	50-80	25-50	0-25

If the waste bins at home are found to be full, or the waste has been standing for a certain number of days, one resident of the household proceeds to empty the household waste bins and the waste amount is transferred to the public waste bins.

2. Simulation of residential waste sorting in Gothenburg

The ABM developed for this research has been applied to two distinct neighbourhoods in the city of Gothenburg, Sweden. The model parameters, the location of buildings, households, and public waste bins, are specific to these selected locations. Here, we present the data inputs and the urban scenarios used in the simulations, which further elucidate the ABM simulation requirements.

2.1. Data inputs

The ABM requires three data sets as input to the simulation: (i) the amounts of waste generated per day for each waste stream, (ii) the value of the coefficients to specify the TPB for waste sorting, (iii) and a set of geodata files that determine the spatial context.

First, the amount of waste generated per individual resident is determined by a set of values taken from the Annual Swedish Waste Management Report (Avfall Sverige, 2022), which reports that residents generate approximately 42 kg/year of organic waste, 157 kg/year of residual waste, and 65 kg/year of recyclable waste (glass, paper, metal, and so forth).

The second input needed by the ABM, the parameters to specify the residential waste sorting behaviour, were derived from the data collected and the analysis developed in a study of waste sorting behaviour in Gothenburg (Cohen et al., 2024)Table A 1 in the appendix contains the values of the estimated coefficients used in the TPB model.

To determine the four types of behaviour (very bad to very good) and the probabilities of how to dispose of waste, empirical data from the survey was used. In this case, the respondents indicated a percentage of properly sorted waste for organic, residual, and recyclable waste. These three values were averaged, and the calculation of quartiles of the averaged behaviour gave the ranges of four distinguishable groups, which are presented in the appendix in **Error! Reference source not found.**.

Finally, a set of 3 geographic data files are required to define the spatial context of the simulation: (i) polygons representing residential buildings' footprints, (ii) polygons representing workplace locations and (iii) points representing public waste bins. The data files defining the building footprints were obtained from Lantmäteriet (Swedish cadastre agency). The point data set of waste bins has information about the designated type of waste of each bin: residual for mixed and burnable waste; organics for food scraps and other forms of degradable material; and recyclable bin stations.

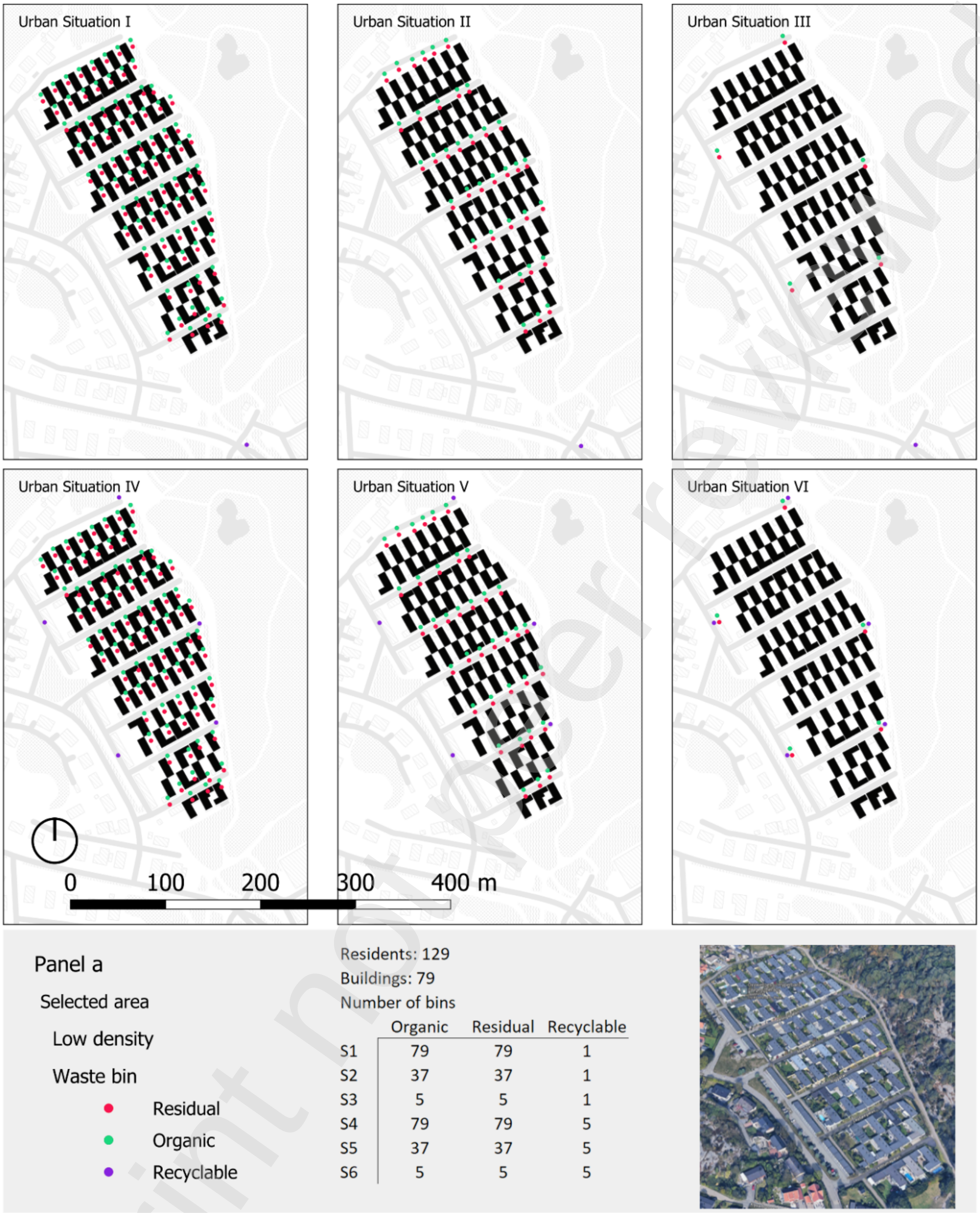
In Sweden, residents are expected to dispose of plastics, metals, glass, papers, and other recyclable materials in recycling stations. The location of these recycling stations was used to identify two distinct urban areas in terms of population density. Google Street View was used to determine the location of residual and organic bins. Usually, low-density areas have waste bins next to each house, while in higher-density areas, households share bins with others from the same building.

2.2. Urban scenarios

In this study, we simulate two urban areas: a low-population housing area and a high-density population area. Figure 5 presents the low-population density (Panel 5a) and high-population density (Panel 5b) urban areas. For each urban area, six urban scenarios were created using different numbers and locations of public waste bins.

Scenario 1 (S1) represents the current situation. In the low-density area, each household owns a pair of waste bins for residual and organic waste and uses one shared recycling station for recyclable materials located outside the neighbourhood. In the high-density area, each building has its bins for residual and organic waste, and all buildings use the same recycling station outside the neighbourhood. In scenarios 2 and 3 (S2 & S3), the recycling station is kept in the exact location as in S1. However, the number of residual and organic waste bins is reduced so that the distance to the bins increases, and the interaction between residential agents also increases. In scenarios 4, 5, and 6 (S4 – S6), the number of recycling stations increases, and they are located in the neighbourhood, close to the buildings, while the location and number of the residual and organic waste bins are the same as in scenarios S1, S2, and S3.

Combined, the geographic data files representing residential buildings, work areas, and waste bins are used to define a single urban scenario. In this study, the model was implemented in two urban areas by changing the location within the city and providing data files on different residential buildings and workplaces. This enables the simulation of how the behaviour of waste sorting is affected by these changes.



	Organic	Residual	Recyclable
S1	79	79	1
S2	37	37	1
S3	5	5	1
S4	79	79	5
S5	37	37	5
S6	5	5	5

Panel 5a

	Organic	Residual	Recyclable
S1	9	9	1
S2	4	4	1
S3	1	1	1
S4	9	9	9
S5	4	4	9
S6	1	1	9

Panel 5b

Figure 5 Urban scenarios created for the ABM simulations: panel 5a) low population density scenarios; panel 5b) high population density scenarios.

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2.3. Simulation and analysis

To explore the relationship between behaviour and waste sorting, each urban scenario was simulated 200 times. The ABM was programmed to retrieve the percentages of properly sorted waste of each waste stream and the behaviour of the residents. More specifically, the results will be assessed by looking at the average value of behaviour and the percentages of properly sorted waste (i.e. organic, residual, and packaging) across the population at the end of one year.

3. Results

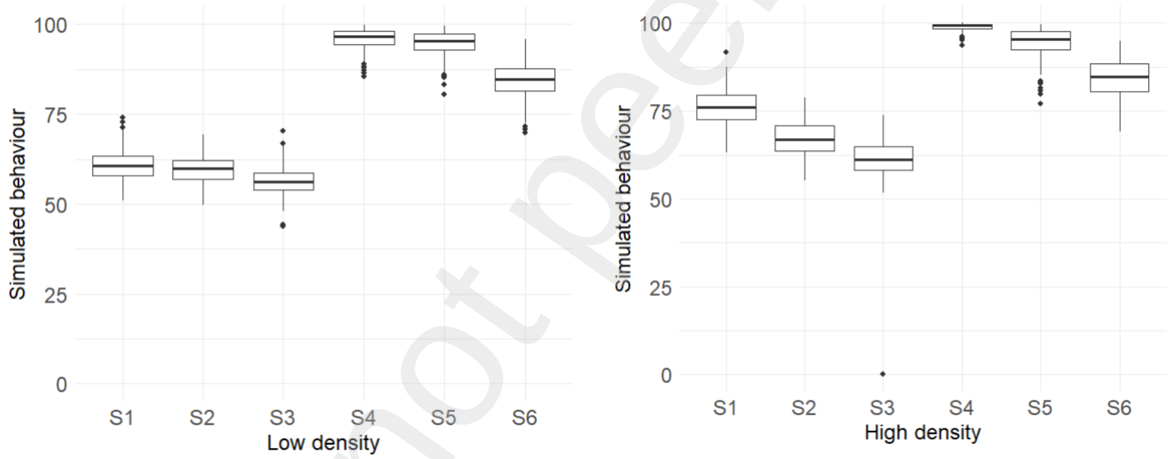
In this section, we present a summary of the results obtained from the simulation runs of the ABM on the different urban scenarios. For each urban area (i.e. low and high density), six urban scenarios are evaluated (S1 to S6), where scenarios S1 – S3 explore the impact of reducing the number of organic and mixed waste bins, and scenarios S4 – S6 explore the effect of increasing the number of recycling stations. Specific details of the results of the simulations are provided in the Supplementary material.

3.1. Residents' waste sorting behaviour

The waste sorting behaviour of the residents is presented in Figure 6. Panel 6a presents the results for the low-density single-family housing urban area, and Panel 6b presents the results for the high-density multifamily housing urban area. Comparable results can be appreciated across both urban areas. In both cases, S1, S2, and S3 have lower average behaviour than S4, S5, and S6. Recall that more waste bins for recyclable materials were placed in the latter scenarios.

In the low-density area, the initial scenario (S1) produced an average behaviour of 60 with a standard deviation of 4. As expected, the simulated behaviour decreases when residual and organic bins decrease in S2 and S3 to an average of 59 and 56, respectively. S4, the scenario with the most waste bins, presents the best-behaved simulated agents with a score of 96. Again, moving to scenarios S5 and S6, where the number of residual and organic bins decreases, so does the average waste sorting behaviour, to 94 and 84, respectively.

In the high-density area, S1 has an average behaviour of 76 with a standard deviation of 5. As residual and organic bins decrease in S2 and S3, the average behaviour decreases to 67 and 59. Urban scenario S4 presents an average behaviour of 98 and a standard deviation of 1. As the number of residual and organic bins decreases, the average behaviour drops to 94 in S5 and 84 in S6.



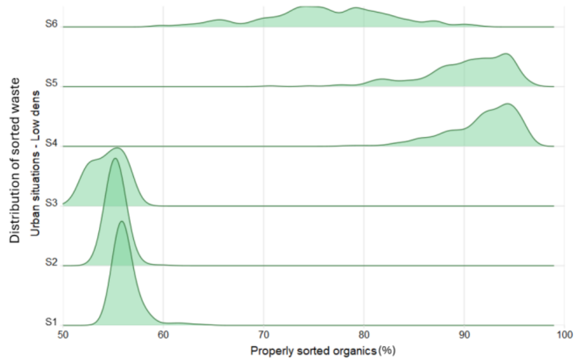
Panel 6a

Panel 6b

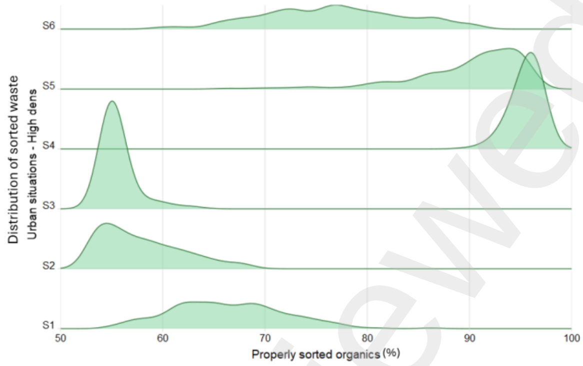
Figure 6 Average waste sorting behaviour under different urban scenarios: a) low population density scenarios; b) high population density scenarios.

3.2. Properly sorted waste percentages

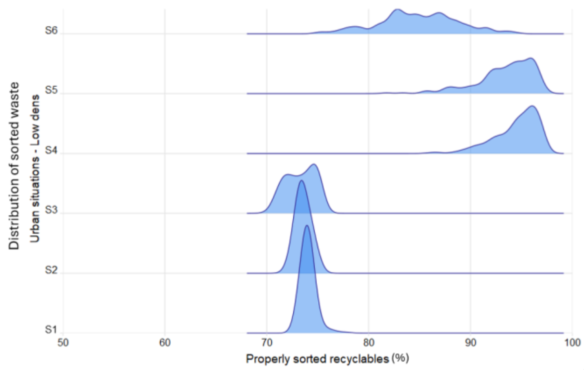
Besides tracking the residents' waste sorting behaviour, the model follows the amounts of adequately sorted waste. Figure 7 shows plots of the distribution of the percentage of adequately sorted waste for three waste streams (i.e., organic, residual, and recyclable) in each urban area (i.e., low-density and high-density) for the different simulated urban scenarios. In each plot, one can find six distributions, one for each scenario (S1 to S6).



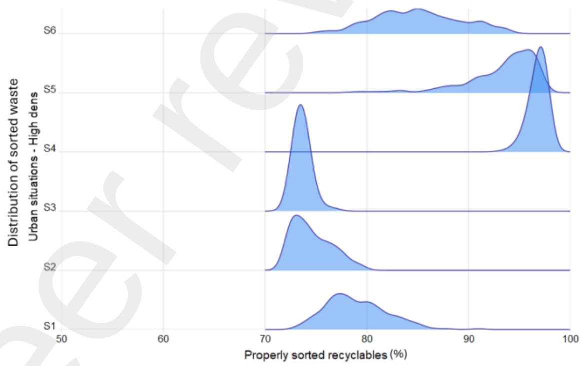
Panel 7a



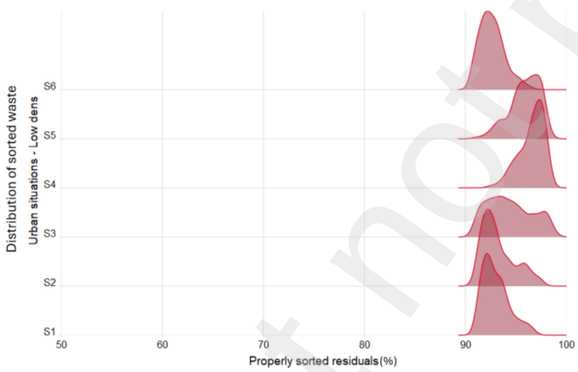
Panel 7b



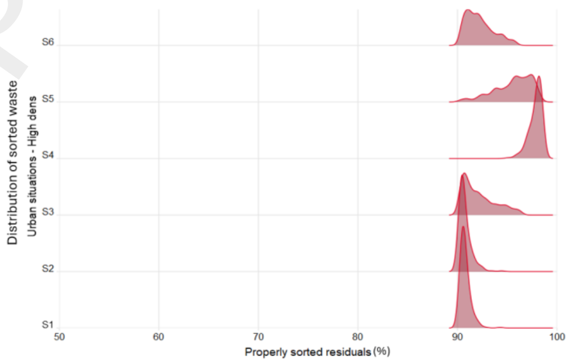
Panel 7c



Panel 7d



Panel 7e



Panel 7f

Figure 7 shows the Density distribution of the percentage of adequately sorted waste in low and high-population density scenarios. Panels 7a, 7c, and 7e present results of low-density scenarios for organic (green), recyclable (blue), and residual (red) waste streams, respectively. Panels 7b, 7d, and 7f present results of high-density scenarios for the same waste streams.

The results presented in Panel 7a and Panel 7b show that in all urban scenarios, at least 50% of organic waste is correctly sorted. However, scenarios S4 to S6 (top) perform better than scenarios S1 to S3 (bottom). In high-density scenarios (Panel 7b), there is more variability than in low-density scenarios (Panel 7a).

S1 has an average of 56% properly sorted organic waste in the low-density area. As the number of waste bins decreases in S2 and S3, the average of properly sorted waste increases, but the standard deviation slightly worsens. In the high-density area, the current situation S1 exhibits higher variability and a higher average than S2 and S3.

S4 has the highest number of bins, and as a result, the percentage of adequately sorted organics increases to 92% on average. In S5, the tail of the distribution shifts to the left, indicating less properly sorted waste. Finally, S6 demonstrates the highest volatility across the population, and by increasing the number of recyclable bins, the average of organic sorting increases along with the variability.

When it comes to recyclable waste (as shown in Panel 7c and Panel 7d), every scenario (S1 to S6) has an average of over 70% of adequately sorted waste. Even in low-density scenarios (Panel 7c), sorting accuracy ranges from 70% to 78% in S1 to S3. However, when the bins for organic and residual waste are reduced (S2 and S3), the percentage of correctly sorted recyclables decreases slightly. Equivalent results were observed in high-density areas (Panel 7d), where S1 had an average of 79%. However, reducing the number of bins (S2 and S3) led to a decrease in the percentage to 71%. In both urban areas, placing more accessible bins for recyclable materials increased the percentage of waste that was sorted correctly, specifically in S4, to 94% in low-density areas and 97% in high-population-density areas. In the low-density area, as waste bins were located further away from residential units, the average percentage of properly sorted waste decreased. S5 has, on average, 93% of correctly sorted recyclable waste, while S6 has only 84%. The high-density scenario produced comparable results.

Proper waste sorting is highest with residual waste (Panel 7e and Panel 7f), with more than 90% properly sorted in all urban scenarios. The distributions follow a similar trend to the previous waste types, with scenario S4 performing the best. However, the changes observed between scenarios are small, and introducing more recyclable bins may not necessarily increase the proper waste sorting of residual waste.

In summary, the results indicate that waste is being appropriately sorted by more than 50% in all scenarios and that there are significant differences across waste streams and scenarios. The percentage of properly sorted residual waste has minor variability, ranging from 90% to 100% in all scenarios; recyclable waste varies from 70% to 100% depending on the urban scenario, and organic waste displays the most variability across all scenarios. Lastly, the baseline scenario (S1) presents more significant variability in the high-density urban area when it comes to organic and recyclables.

4. Discussion

The behaviour of waste sorting is usually considered dichotomous: individuals recycle or do not sort (or recycle) their waste. The ABM simulations in this work, incorporating a TPB model of waste sorting, have shown that residents behave differently for different waste streams. Improvements in how the waste sorting behaviour is measured are critical to understanding how municipalities can increase the amount of waste purity or material circularity. The relationship between individual behaviour and waste streams is not independent of the built environment or each other. After 200 simulations in each urban scenario, it was possible to extract the effect of different waste bin scenarios. The results seem to indicate that improvements in the spatial distribution and number of recyclable material collection points can also yield improvements in properly sorted residuals and organics.

4.1. Contributions

Firstly, the present study has developed an ABM that researchers and city planners can use to analyse how different urban scenarios might affect residential waste sorting. Users can change the parameters in the model, such as the level of information available in the bins or how often they are cleaned. Additionally, they can provide alternative initialisation files, such as geodata on the location of waste bins or the buildings and population distribution. This will allow users to explore different what-if scenarios. The ABM of waste sorting behaviour is available online as an open-source resource with an ODD protocol that can help users adapt the model to fit other contexts or TPB formalisations. Future research will be able to look at the programmed functions in detail, allowing for discussion, improvement, and expansion of the model.

Secondly, the ABM advances agent-based modelling for waste sorting by explicitly modelling space and by introducing a direct connection between the built environment, individual behaviour, and waste sorting quantities. By being spatially explicit, the ABM enables city planners to evaluate how different what-if scenarios perform in relation to waste sorting. Moreover, agents in the model are individual residents instead of households, harmonising the unit of analysis between TPB and its implementation in an ABM setting. In addition, the model formalises the relationship between behaviour and percentages of properly sorted waste, demonstrating a direct relationship between TPB and waste sorting.

Finally, the simulations reveal the effect of various waste bin quantities and locations on waste sorting quality. Since the model was calibrated using results from a survey study, the simulation results follow the main trends from the statistical model. The results show that although placing more bins leads to better waste sorting, there is room for planners to make decisions regarding how many waste bins, of what kind, and where they should be placed. A critical outcome of the study is showing the relationship between organic, residual, and recycling waste bins. More recyclable bins increase the proportion of adequately sorted waste for recyclables and for residual waste. The results show that high-density urban areas perform better than low-density ones, reflecting the fact that bins are positioned closer to the residents. However, these results require further research as socio-demographics and population density are not independent.

4.2. Limitations and future research

In the ABM, the relationships between the items used to calculate the TPB constructs and the objects in the model are not validated. For instance, from the empirical model, it is possible to know that the distance to waste bins is a factor that hinders the probability of adequately sorting waste. However, since the distance to bins is a variable outside the scope of the TPB, the coefficient linking both was assumed. This is also the case for other items and constructs of TPB. How a resident's perceived peer pressure relates to the peers' actual behaviour still needs to be researched. To summarise this point, previous research has found TPB to be a practical framework to map individual behaviours. However, for TPB and other psychological theories to become relevant for models supporting public policy, future research must address the connection between perceptions and quantifiable variables of the objective realm.

Another aspect of the study that needs to be further developed is the dynamic aspects of TPB. While the behaviour of individual agents can change during the simulation, given the interactions with the environment, the coefficients of TPB used in the ABM stay constant over time, and this assumption can be challenged. Future research involving longitudinal surveys would make it possible to assess changes in behaviour and TPB constructs, addressing this knowledge gap.

Although the residents in the ABM are heterogeneous, these differences are driven by stochastic processes rather than socio-demographics or lifestyles. The earlier survey did not collect information about the respondents' personal characteristics or living environments. Therefore, the outputs in this study used the same distribution of perceived home space in all the simulations, regardless of housing typology. Future models could use synthetic populations to explore this heterogeneity.

This study evaluated specific urban scenarios; however, other relevant variables not considered here can positively affect waste sorting. The information available at waste bins, how clean the waste bins are, and the amount of household space are variables encoded in the proposed ABM and can be set as parameters for different scenarios. Further exploration of such determinants of waste sorting can be used to guide urban policy (Bernstad, 2014).

In this study, the ABM operationalised TPB to model waste sorting behaviour. While this theory is widely used in waste sorting research, future studies should explore how to incorporate other relevant behavioural models, such as social contagion theory. (Griliches, 1957; Mansfield, 1961).

A stochastic process in the global section of the ABM defines the amount of waste generated by residents. As a result, waste reduction strategies relevant to the Circular Economy and environmental sustainability in general are beyond the scope of this model. This aspect of waste management is essential, and future studies should also focus on researching how effective waste reduction strategies are.

5. Conclusion

This study implements an Agent-Based Model (ABM) to investigate how changing the spatial distribution and quantity of waste bins of diverse types affects recycling rates. The research is based on previous studies that support the use of TPB as a framework for modelling waste sorting behaviour. The ABM was applied to two urban areas with different building typologies and population densities, and various scenarios were simulated to assess how changes in waste bin location affect waste sorting rates. The results of the study show that reducing the distance to recycling bins has a significant and positive impact on waste sorting rates. Additionally, the simulation results indicate that the number of bins for residual and organic waste could be reduced without significantly affecting how people sort waste.

This model allows other researchers and urban planners to explore waste management scenarios. The model is based on empirical data derived from surveys, and the residential agents' behaviour is based on a behavioural theory that allows for complex decision-making by residents. The ABM developed for this study advances previous efforts by creating a spatially explicit model, modelling individuals as agents instead of households, and establishing a direct link between behaviour and the percentage of adequately sorted waste for different waste streams. Finally, the study's model is open source, which enables future research to investigate how waste sorting might change under various conditions and to improve the details of the model.

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