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Research Paper

Exploring urban scenarios of individual residential waste sorting using a spatially explicit agent-based model

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ABSTRACT

Managing the diverse waste fractions generated by households presents a significant environmental and logistical challenge. One widely adopted solution is waste sorting at the source, where residents are required to separate their waste into designated containers. The success of this strategy depends on the extent of adoption and the behaviour of residents. Waste separation is a complex activity influenced by various interrelated factors. While the Theory of Planned Behaviour (TPB) has been effectively applied to characterise waste-sorting behaviour, it primarily focuses on internal psychological mechanisms, often overlooking environmental factors such as the placement of waste bins or the condition of sorting stations—critical elements for spatial planning. To bridge this gap, this study presents an agent-based model (ABM) that simulates residential waste sorting in urban scenarios, incorporating TPB for the agents' behavioural architecture (residents). Three features distinguish this ABM from previous efforts: (i) Agents in the model are residents and not aggregated households, allowing for a one-to-one integration with TPB; (ii) the ABM bridges the gap between individual waste sorting behaviour extracted by TPB and outcomes quantifiable through waste sorting metrics; and (iii) the ABM is spatially explicit, enabling the exploration of various urban scenarios.

The ABM was applied to two urban areas with differing population densities, demonstrating that changes in bin placement impacts sorting behaviour, and proximity to recyclable waste bins influences the correct sorting of residual waste. This study illustrates how modelling the interaction between the urban environment and waste sorting behaviour can reveal the impact of individual residents' actions on overall waste sorting performance.

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 CO2e (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 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.

To tackle these issues, waste sorting and waste management can be studied and understood as Complex Adaptive Systems (CAS) (Chen & Gao, 2021; H. Luo et al., 2020). This perspective allows research to consider multiple agents with microscopic behaviours interacting with each other and their environment and study the outcomes of such complex interactions. Within CAS, Agent-Based Models (ABMs) are computational tools for developing simulations incorporating these agents and their interactions. ABMs are an adequate methodological

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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 waste sorting rate of a neighbourhood change if there were twice as many waste bins?”.

The behaviour of waste sorting 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 (Rousta et al., 2020). 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 (Longhi, 2013).

Several studies advocate the integration of ABMs and TPB (Jager, 2017; Muelder & Filatova, 2018;) since TPB offers a behavioural model for the agents. However, more applications for residential waste sorting are needed. For instance, modelling at the household level requires assumptions about how TPB (a psychological model of an individual’s behaviour) is aggregated and instrumented at the household or neighbourhood levels. Moreover, past simulations for residential waste sorting 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 develop and showcase an ABM for exploring urban scenarios of individual residential waste building on previous research. First, the ABM offers a one-to-one integration between TPB and the agents in the model by defining agents as residents instead of households. Second, the model shows how behaviour according to TPB determines the percentage of waste sorting at the urban scale. Third, the ABM is spatially explicit, allowing the model to be used as a geo-design tool to explore various urban scenarios. Finally, the study offers concrete guidelines and discusses limitations on how such a model can be used in practice. This study focuses on residential waste sorting at the source, which is defined as separating waste before its disposal. It is vital to notice that this activity is not equivalent to waste recycling, which means engaging in transforming waste into materials or products.

The remainder of this paper is structured as follows. Section 2 introduces the state of the art on ABM and TPB 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 6. Section 7 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 the 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 social pressure an individual perceives when performing 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. ATT, SN and PBC determine the INT that (with PBC) leads to a specific BEH. Fig. 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).

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; Wang et al., 2020), situational factors (Govindan et al., 2022B. Zhang et al., 2019), self-identification (Issock Issock et al., 2020; Knussen et al., 2004) or past behaviour (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 interchangeably or an as a single phenomenon. For instance, specific studies have focused on food waste (Abdelradi, 2018) and the return of packaging (Struk, 2017). Similarly,(Gellynck et al., 2011) demonstrate that the quality of organic waste separation increases with the availability of waste bins for other waste steams such as packaging.

Moreover, in their review, (Knickmeyer, 2020) present a set of studies that show that a perceived reduction in distance –or reduction in time- towards waste bins can affect how residents sort their waste. Specific studies found that shorter distances to bins are associated with more involvement in waste sorting and pro-environmental attitudes (Ibrahim, 2020; Lange et al., 2014). Because the behaviour of waste sorting is ultimately a phenomenon that occurs and has tangible consequences in the physical realm, the relationship between behaviour and the built environment requires further exploration.

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. Finally, more data and data standards are needed to validate TPB with actual metrics and compare across the various TPB studies (Afshari et al., 2024).

2.2. Waste sorting and Agent-Based models

Delivered in a two parts, 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.

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 (Groeneveld et al., 2017; Hansen et al., 2019; Jager, 2017). More specifically, several studies have contributed to integrating TPB into ABMs in the context of waste sorting. 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

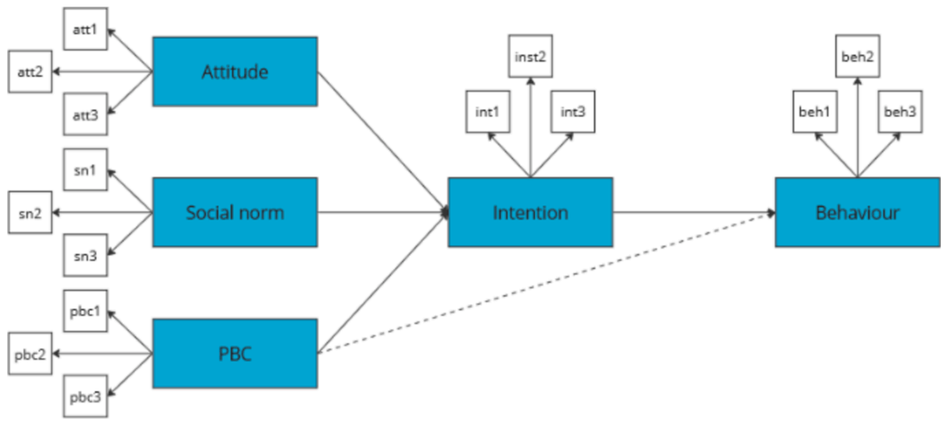


Fig. 1. Conceptualisation of the Theory of Planned Behaviour (Ajzen, 1991).

using technology to affect residents' incentives for waste sorting, 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. Specific research on how individual pro-environmental views differ from the household suggests that this assumption is complex and depends on various factors such as household size or socioeconomic status (Longhi, 2013).

Overall, such models and simulations should be made available to increase the transparency and reproducibility of the processes and algorithms. Collaboration and open source increases the productivity and quality of environmental research, thus desired (Pauliuk et al., 2015).

To sum up, three gaps have been identified in the literature: (1) 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; (2) 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. Efforts to overcome this gap are important to understand how TPB can be related to waste management metrics at the neighbourhood or city level. (3) Simulations are spatially abstract or do not take into consideration environmental determinants such as the location or status of waste bins.

3. Methodology

In this section, we outline the ABM proposed for simulating residential waste sorting in urban settings, detailing the methodology used to calculate waste sorting behaviour and its integration into the ABM framework "Residents' Planned Behaviour of Waste Sorting to Explore Urban Situations (1.4.0)".[1] The ABM was developed utilizing GAMA, primarily for its GIS capabilities. The complete model has been appended as Supplementary Material. Adhering to best practices in ABM development and documentation (Grimm et al., 2010, 2020), the model's Overview, Design Concepts, and Details (ODD) have also been provided in the Supplementary Material.

First, the equation used to estimate waste sorting behaviour, following a TPB model, is described. Second, the agents and 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 findings made in (Cohen et al., 2024). This work surveyed the Gothenburg population regarding waste sorting and used a Structural Equation Model (SEM) to estimate the behaviour of waste sorting. Fig. 2 presents the path coefficients of the SEM that are relevant for the ABM and offers a visual representation of the parameters used to estimate the waste sorting behaviour of residents. The coefficients shown in the arrows and their standard deviations are used to determine each equation that describes the TPB constructs. The present study only used coefficients relevant to the ABM's development. For instance, attitude is a "mental and neutral state of readiness" (X. Zhang, 2023), therefore its value was stochastically defined using the mean and standard deviation as in (Cohen et al., 2024).

Intention (INT), Perceived Behavioural Control (PBC), Knowledge (KNOW), Average distance to waste bins (DIST) and returning refundable deposit packages (PANT)[2] are the constructs that determine the behaviour (BEH) calculation. Each of these factors has an associated estimated coefficient (int_b,pbc_b,$know_b dist_b$,$pantt_b$) as presented in Eq (1). It is important to note that each coefficient has an associated standard error, which results from the SEM. As a result, the value of BEH is stochastic.

$$BEH = constant_b + int_b \times INT + pbc_b \times PBC + know_b \times KNOW + dist_b \times DIST + ret_b \times PANT \tag{1}$$

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

The value of BEH was constrained between 0 and 100, 0 being the worst possible behaviour towards waste sorting. The method to calculate the rest of the constructs such as INT, PBC, KNOW and PANT follows a similar logic, and their estimations are described in the Supplementary Material and the source code of the ABM.

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

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

[2] In the Swedish context it refers to the money paid as a security "pawn").

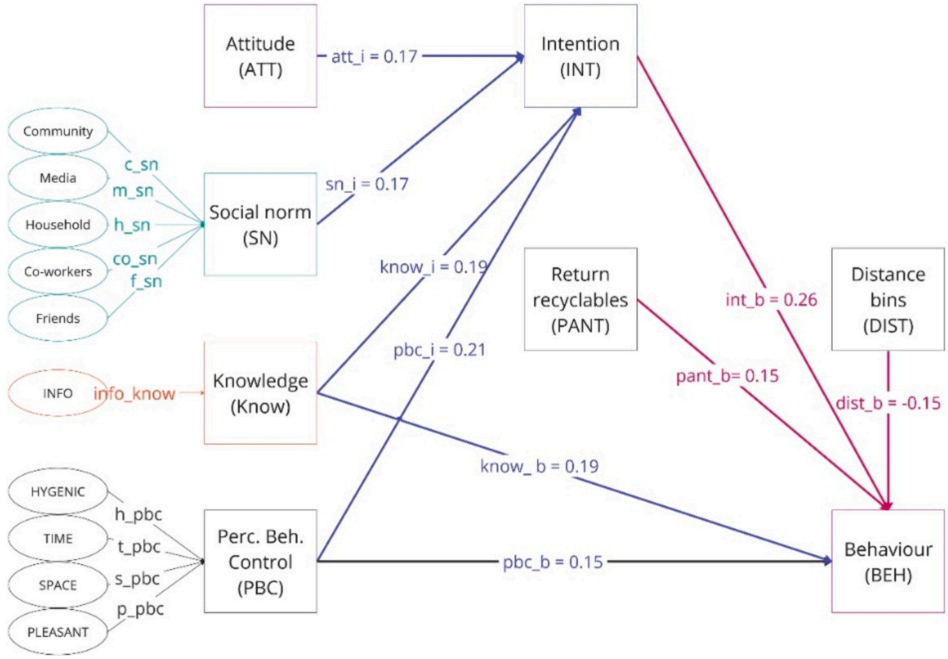


Fig. 2. Path analysis of extended TPB coefficients. Source: adapted from (Cohen et al., 2024).

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 (integrating a set of individuals) solves its waste-sorting problems based on individual preferences. The integration of TPB within the ABM framework is represented in Fig. 3.

The ABM simulates the behaviour and interactions between different agents: residents, buildings, households, workplaces, waste bins, and bin collectors. The agent classes and their attributes are based on the entities presented in Cohen & Gil (2021). The model was developed to represent an entire year, and every step in the simulation represents a third of a day. The model translates the behaviour of waste sorting (value between 0 and 100) into probabilities of sorting organic waste (such as food), residual waste (such as to incinerate) and recyclable waste (mainly packaging such as glass, plastics, metal or paper). These probabilities determine the percentages of properly sorted waste at the moment of

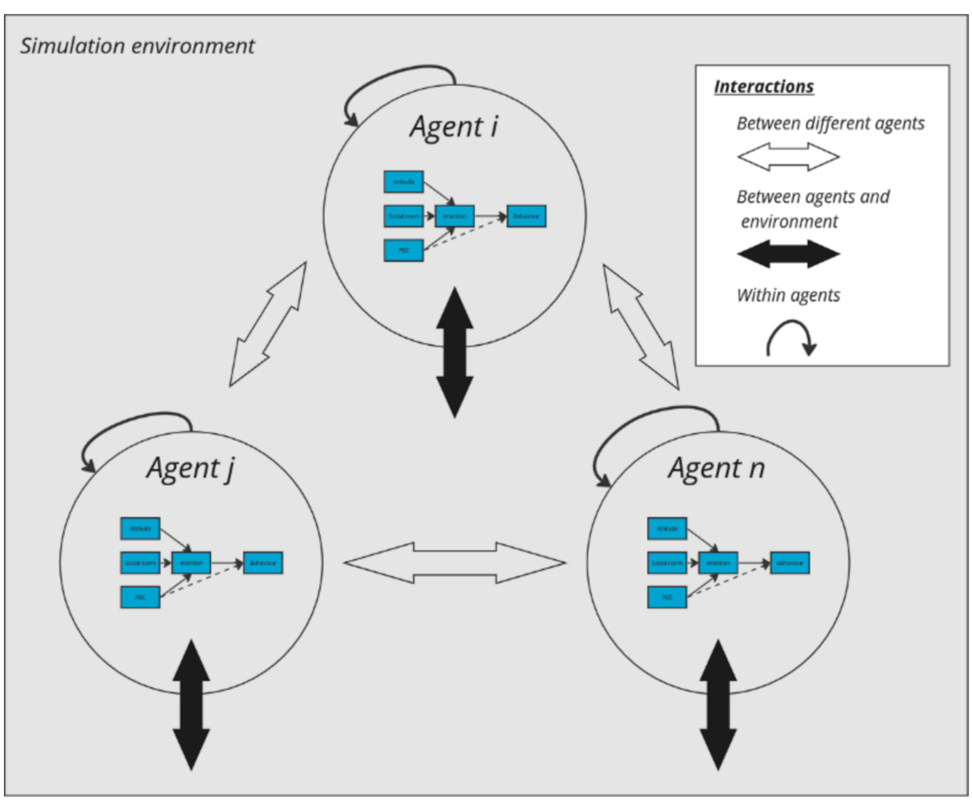


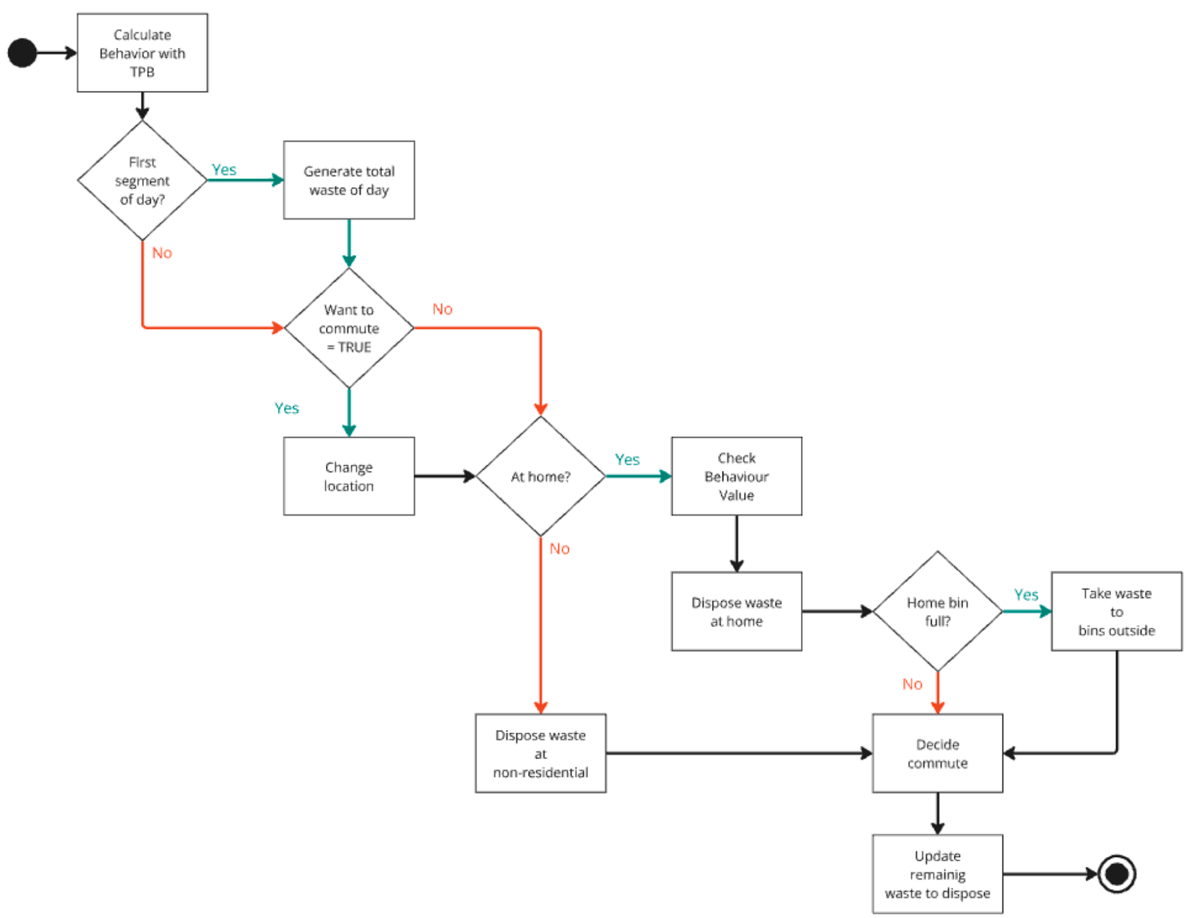
Fig. 3. Integration of TPB in Agent-Based Models.

disposal, and later, by aggregating the amount of waste found in the bins, it is possible to calculate the percentages of properly sorted organic, residual and recyclable waste in an urban area.

Each of the agents represented in the model is described below.

3.2.1. Residents

Each resident agent belongs to a household with a designated public waste bin for organic, residual, and recyclable waste and a workplace. Resident agents also belong to different social groups that impact SN:



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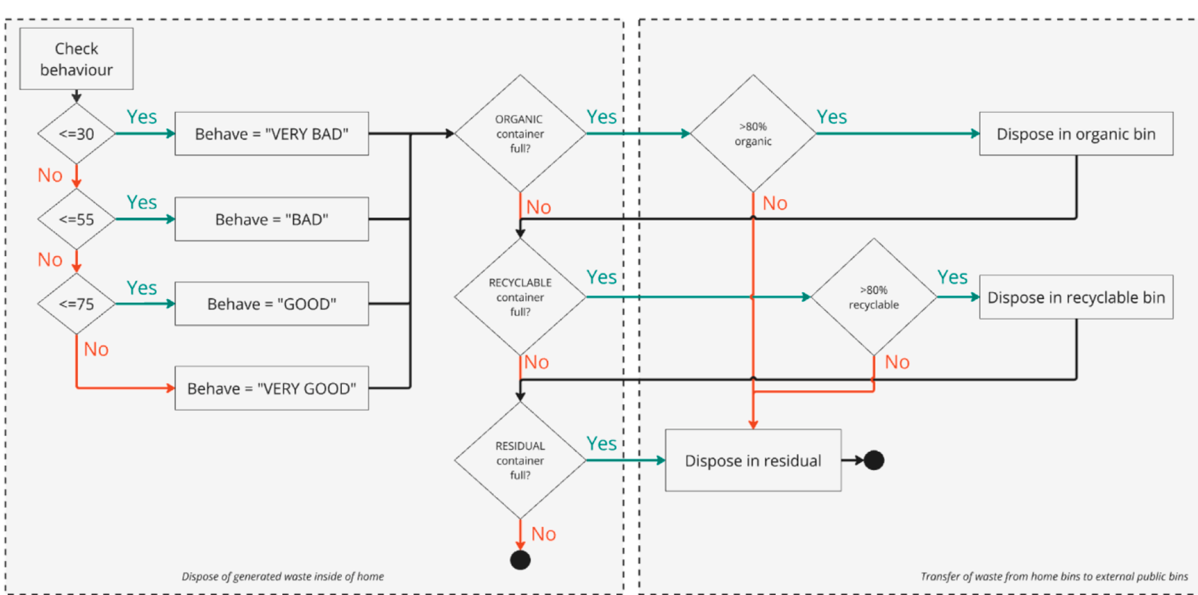

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Fig. 4. Resident's flow chart of processes in the ABM. Panel 4a) Routine of residents for every step. Panel 4b) Waste sorting and disposal process.

friend groups are a random set of resident agents; co-worker groups are resident agents who share the same workplace; household groups are resident agents who share the same household; and community groups are resident agents who 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, determine their internal TPB values, 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.

Fig. 4 illustrates the sequence of actions followed by the residents during every step of the simulation. Panel 4a, details the main processes followed by the residents. At the beginning of each step, the residents' TPB constructs are updated, and their behaviour is calculated. If the current step represents the first segment of the day, all agents are assigned a sum of daily organic, residual, and recyclable waste that they need dispose of. Next, a subset of residents changes their location based on their commuting probability. Residents who remain at home dispose of and sort their waste according to their behaviour values. The waste generated away from home is outside the scope of the model, but the disposed waste is accounted for. If the waste bins at home reach full capacity, the resident transfers the waste to public waste bins. Finally, the resident decides to change location, to work or back, and the amount of remaining waste to be disposed of is updated.

At this stage, the residents' behaviour score determines how they dispose of their home waste based on a set of probabilities presented in Table 1.

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.

If the waste bins at home are found to be full or the waste has been standing for a certain number of days, one household resident proceeds to empty the household waste bins, and the waste amount is transferred to the public waste bins, as presented in Panel 4b. The flow chart describes in greater detail the process of sorting and disposing of waste.

3.2.2. Residential buildings

Residential buildings are spatially explicit agents represented by polygons of the buildings' footprints, 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.

3.2.3. Households

The households are an abstract agent 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 representing the private waste bins for organic, residual, and recyclable

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

	Behaviour			
	Very bad	Bad	Good	Very good
	[0–30]	[30–55]	[55–75]	[75–100]
Disposal of organic				
Prob(… in organic): correct	0–50	50–80	80–95	95–100
Prob(… in residual): incorrect	60–100	30–60	10–30	0–10
Disposal of residual				
Prob(… in residual): correct	0–65	65–75	75–80	80–100
Prob(… in organic): incorrect	0–0	0–5	2–5	0–2
Disposal of recyclable				
Prob(… in recyclable): correct	0–75	75–80	80–85	85–100
Prob(… in residual): incorrect	80–100	50–80	25–50	0–25

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.

3.2.4. 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 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.

3.2.5. Workplaces

The workplaces are spatially explicit agents represented by polygons and have two functions. Firstly, they hold all the waste that must be disposed of outside 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 of a resident.

4. Simulation of residential waste sorting in Gothenburg

The ABM developed for this research has been applied to two neighbourhoods in 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, further clarifying the ABM simulation requirements.

4.1. 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 model for waste sorting; (iii) and a set of geodata files that define the spatial context.

First, the amount of waste generated per individual is determined by a set of values taken from the Annual Swedish Waste Management Report (Avfall Sverige, 2022), which reports the total values for all of Sweden regarding the waste management system. National statistics were used due to missing information at the municipal level. Therefore, it was assumed that residents of Gothenburg 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).

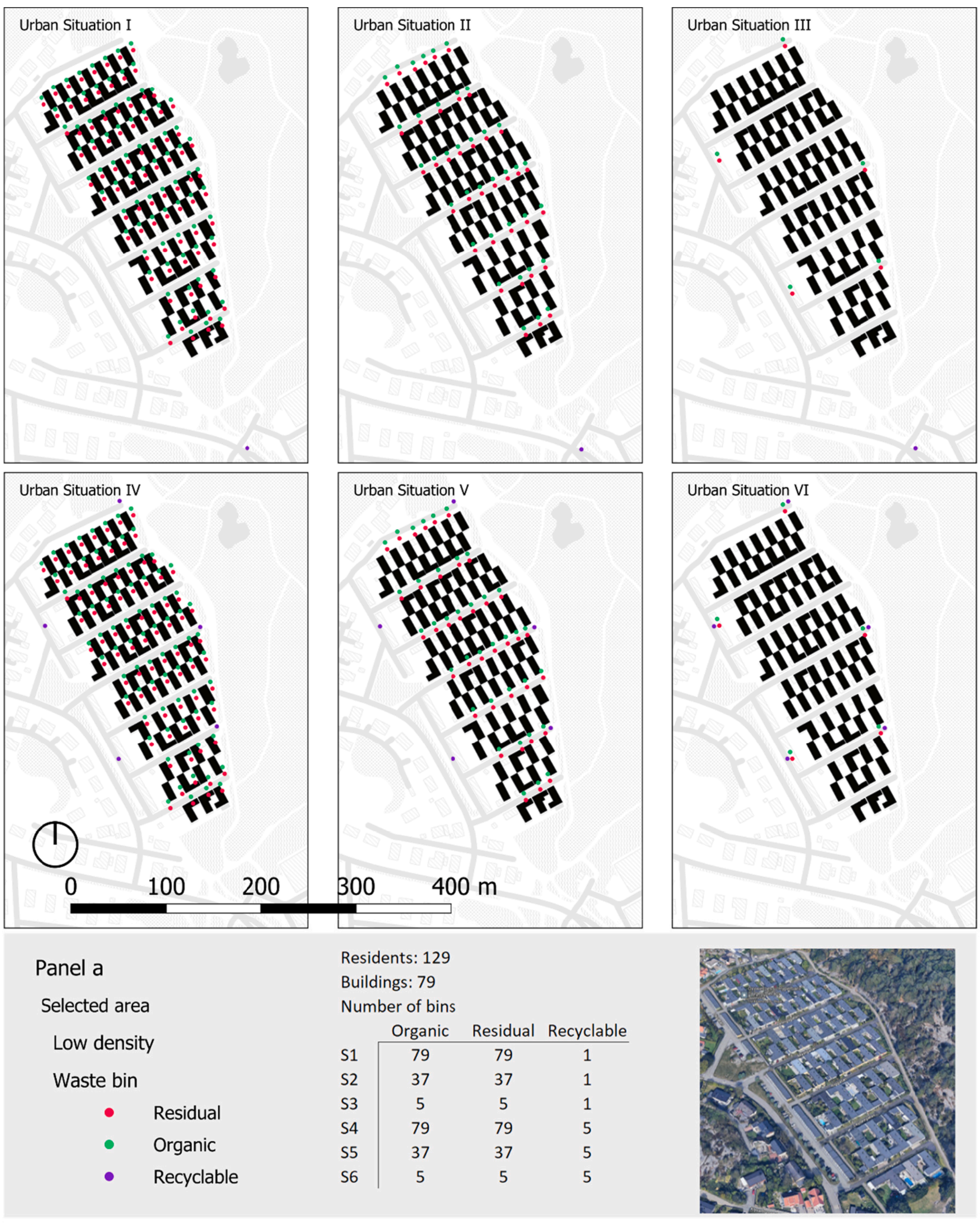
The second input needed by the ABM, the parameters to specify the residential waste sorting behaviour, were derived from the data collected and the analysis developed in a study of waste sorting behaviour in Gothenburg (Cohen et al., 2024). The values of these estimated coefficients are presented in the supplementary material.

Empirical data from a TPB survey and its analysis, previously developed by (Cohen et al., 2024) was used to determine the four types of behaviour (very bad to very good) and the probabilities of how to dispose of waste. More information about how to conduct a TPB study for waste sorting and how to extract the coefficient that describes the beaver can be found in the various articles cited in Section 2. 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 calculated quartiles of the averaged behaviour gave the ranges of four distinguishable groups, presented in the supplementary material.

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. This study obtained data files defining the building footprints from Lantmäteriet (Swedish cadastre agency). The point data 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 must dispose of plastics, metals, glass, papers, and other recyclable waste in recycling stations. The location of these waste sorting 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.

4.2. Urban scenarios

In this study, we simulate two urban areas (Fig. 5): a low-density (Panel 5a) and a high-density (Panel 5b) residential population area.



	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

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

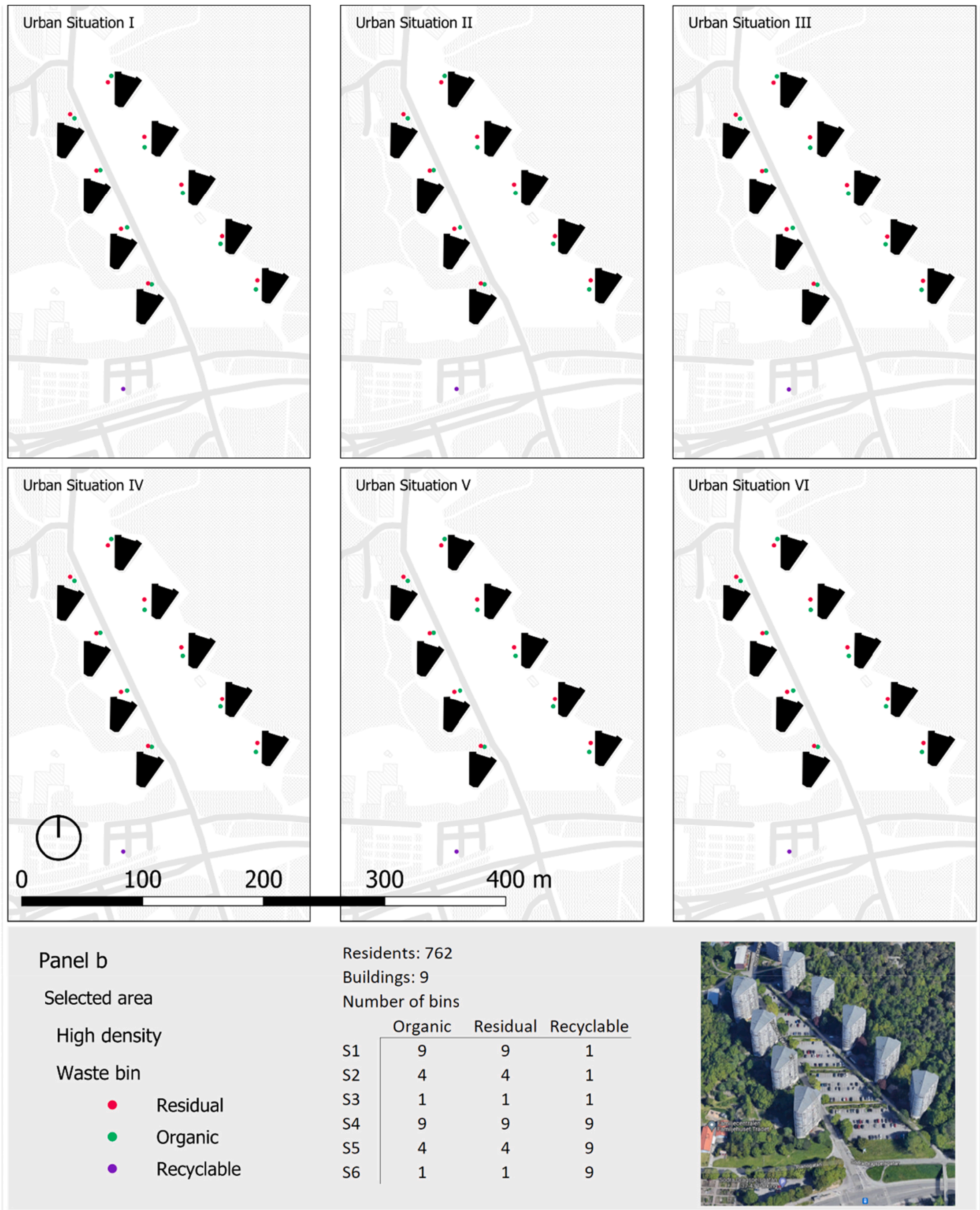


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Fig. 5. (*continued*).

The selection of these two neighbourhoods was based on catchment areas based on the resulting Voronoi polygons of the current locations of recycling waste stations. This preliminary analysis allowed us to identify which areas in the city are currently closer to recycling stations. Six urban scenarios were created for each urban area 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 residual and organic waste bins and uses one shared waste sorting station for recyclable waste outside the neighbourhood. In the high-density area, each building has its own residual and organic waste bins, and all buildings use the same waste sorting station outside the neighbourhood. In scenarios 2 and 3 (S2 & S3), the waste sorting 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 increases. In scenarios 4, 5, and 6 (S4 – S6), the number of waste sorting stations increases, and they are 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 – S3, respectively.

Combined, the geographic data files representing residential buildings, work areas, and waste bins define a single urban scenario. In this study, the model was implemented in two urban areas by providing data files on different residential buildings and workplaces in different locations within the city, enabling the exploration of how behaviour is affected by spatial changes.

4.3. Simulation and analysis

To explore the relationship between waste sorting behaviour and its outcomes under different urban scenarios, each scenario was simulated 200 times. The ABM was programmed to retrieve the behaviour of the residents and the percentages of properly sorted waste of each waste stream. 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.

5. 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 waste sorting stations. Specific details of the results of the simulations are provided in the Supplementary material.

5.1. Residents' waste sorting behaviour

The behaviour of the residents is presented in Fig. 6. Panel 6 a 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 observed 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 recyclables 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.

5.2. Properly sorted waste percentages

Besides tracking the residents' waste sorting behaviour, the model follows the amounts of adequately sorted waste. Fig. 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).

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). There is more variability in high-density scenarios (Panel 7b) than in low-density scenarios (Panel 7b).

In the low-density area, S1 has an average of 56 % properly sorted organic waste. 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 scenario 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.

Regarding 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) decreased the percentage to 71 %. In both urban areas, placing more accessible bins for recyclable waste increased the percentage of waste sorted correctly, specifically in S4, to 94 % in low-density areas and 97 % in high-population-density areas. The average percentage of properly sorted

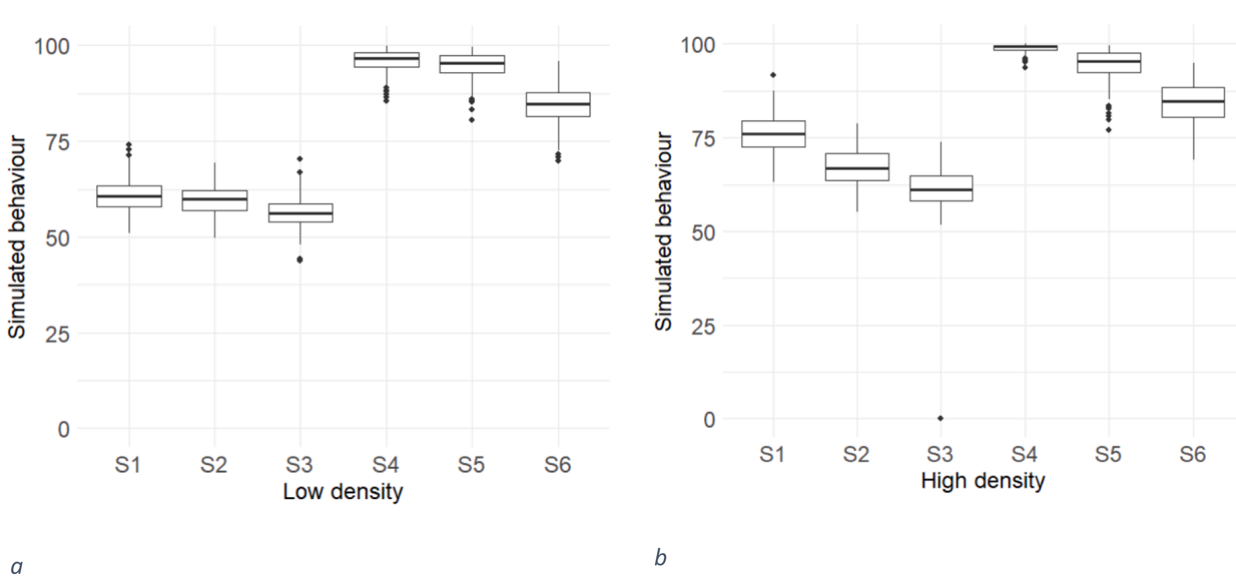

Fig. 6. Average waste sorting behaviour under different urban scenarios: Panel a) low population density scenarios; Panel b) high population density scenarios.

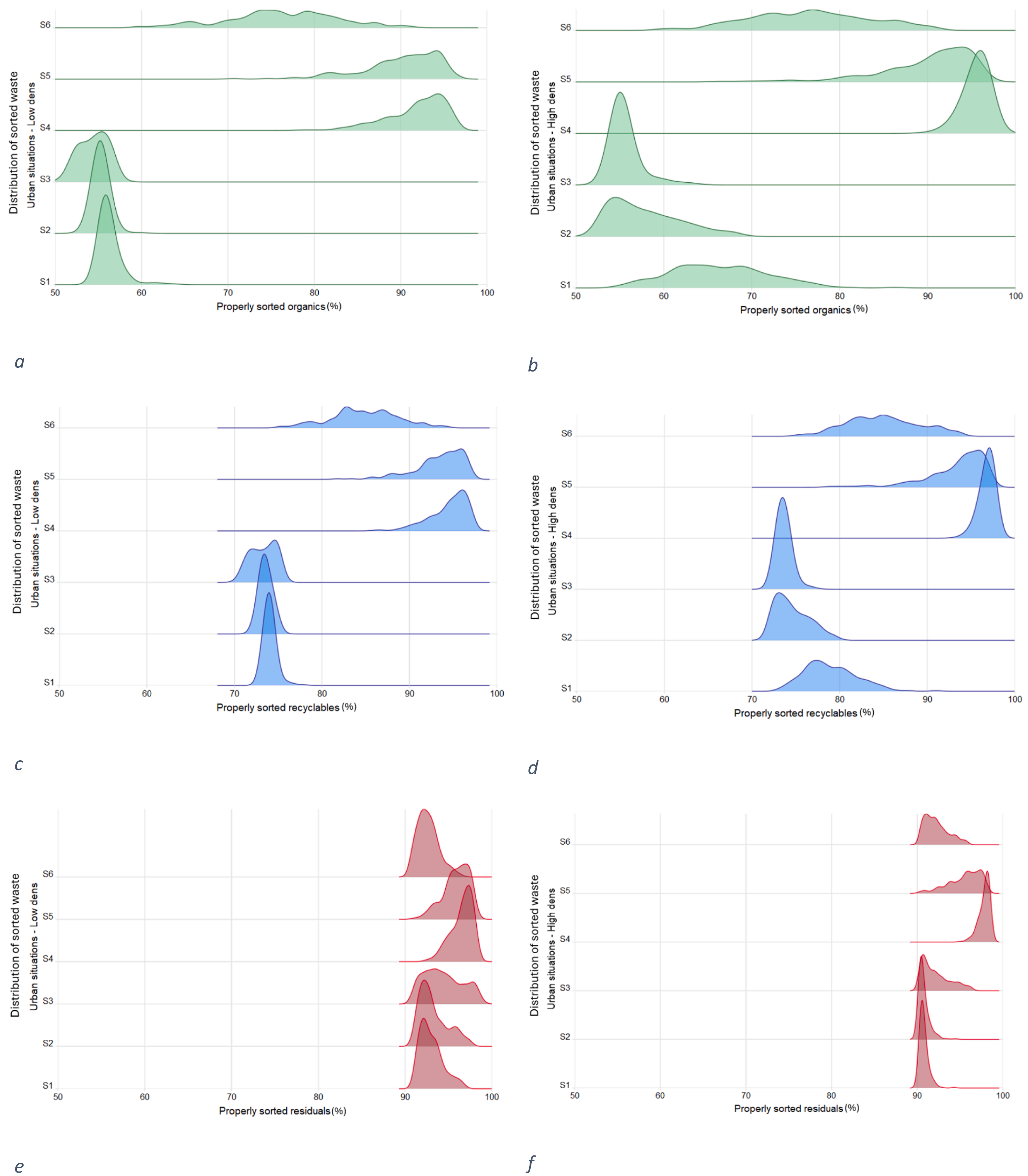

Fig. 7. Density distribution of the percentage of adequately sorted waste in low- and high- density scenarios. Panels 7a, 7c, and 7e present results of low-density scenarios for organic (green), recyclable (blue), and residual (red) waste streams, respectively. Panels 7b, 7d, and 7f present results of high-density scenarios for the same waste streams. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

waste decreased in the low-density area as waste bins were located further away from residential units. 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 regarding organic and recyclables in the high-density urban area.

6. Discussion

The behaviour of waste sorting is usually dichotomous: individuals sort or do not sort (or recycle) their waste (X. Zhang, 2023). The ABM simulations in this work incorporate a TPB model of waste sorting and model how residents behave differently for different waste streams, i.e., organic, residual, and recyclable. Improvements in how waste sorting behaviour is modelled 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 indicate that improvements in the spatial distribution and number of recyclable waste collection points can also yield improvements in properly sorted residuals and organics.

6.1. Theoretical contributions

By developing an ABM of individual waste sorting, this study contributes to addressing the following research gaps: (i) Agents in the model are residents, allowing for a one-to-one integration with TPB; (ii) the ABM contributes to bridging the gap between individual waste sorting behaviour extracted by TPB and outcomes quantifiable through waste sorting metrics; and (iii) the ABM is spatially explicit, enabling the exploration of various urban situations.

First, the agents in the model are individual residents instead of households, harmonising the unit of analysis between TPB and its implementation in an ABM setting. This modelling characteristic does not require further assumptions regarding how an individual behaviour of waste sorting can be used at the household level (Longhi, 2013).

Second, the model formalises the relationship between behaviour and percentages of properly sorted waste, demonstrating a direct relationship between TPB and waste sorting. By incorporating the results of a TPB survey into an ABM, this study showcases how behaviour determines waste sorting metrics at the neighbourhood level.

Third, the ABM advances agent-based modelling for waste sorting by explicitly modelling space and 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 about waste sorting. As shown in this article, by changing the location of bins, the ABM for individual waste sorting can be used to explore urban scenarios as a virtual laboratory.

In this case, the simulations showed that although placing more bins leads to better waste sorting, planners can decide how many waste bins, what kind, and where they should be placed. An outcome of the study suggests a relationship between organic, residual, and recyclable waste bins as suggested in (Gellynck et al., 2011; Schüch et al., 2017): more recyclable bins increase the proportion of adequately sorted waste for recyclables and residual waste.

As suggested by (Pauliuk et al., 2015), to increase the quality and transparency of modelling, the model is open-source and can be found online with an ODD protocol that can help users adapt the model to fit other urban contexts or TPB formalisations. Researchers and city planners can use this ABM to analyse how urban scenarios affect residential waste sorting. The model is generalisable as long as three main inputs are provided: coefficients to model the behaviour of waste sorting as TPB (survey data and SEM estimation), the location of homes with their population, and the location of different waste bins. Future research will be able to look at the programmed functions in detail, allowing for discussion, improvement, and expansion of the model.

6.2. Practical implications

This study's scope has been to present a spatially explicit ABM for individual residential waste sorting and showcase its potential and practical implications for urban planning.

First, such a simulation tool can be used to support the design of new neighbourhoods. The developed model allows for testing various designs in terms of residential building typology, layout and density, including specific population profiles, and evaluating the potential residential waste sorting outcomes. Secondly, such a tool can support the development or improvement of neighbourhoods to study potential outcomes in terms of waste sorting. For instance, future city plans can be used as inputs and by varying the location and waste bins typologies, urban planners would be able to study waste sorting outcomes. Because this model estimates the percentage of adequately sorted waste, the results could be complemented with waste management logistics to reduce the extension of routes or other unwanted externalities from the collecting activity (Feil et al., 2017; Rousta & Ekström, 2013).

Although the model's heuristics and architecture are open-source, its usability depends on the technical capabilities of waste management institutions. Namely, in terms of geospatial data processing and GIS to prepare the inputs for the model, statistical analysis to interpret the results, and eventually prepare location specific parameters, such as waste sorting behaviour coefficients and waste sorting quantities, and finally object-oriented programming to modify the code related to some of the model's parameters. Moreover, a precondition for using the ABM is to develop a TPB study that extracts the specific coefficients of waste sorting behaviour for the given location and population, or to have supporting evidence to assume the value of these coefficients.

Finally, in terms of validation and future calibration of the model, waste characterisation studies will be needed to adjust the model so that it can be used to inform the previously mentioned decision-making. For example, such a study in Gothenburg would involve the quantification of the waste from the different streams disposed of by the population in various neighbourhoods, and an analysis of waste sorting quantity and quality in those neighbourhoods. Moreover, TPB survey and estimation of parameters should be estimated for specific locations.

6.3. Limitations and future research

In the ABM presented, 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.

Moreover, the present model architecture could be integrated with other models that focus on the location and allocation problem (Nevrlý et al., 2021; Viktorin et al., 2023). Since the present study focused on the exploration of the effect of waste bin location on individual waste sorting percentages, the model could be coupled with models assessing the performance of collection activities, or analytic models searching for optimal bin placement solutions, for defining optimal waste collection routes. Future research efforts should take a holistic approach by integrating the various components of the waste management system.

Another aspect 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. 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 (Cohen et al., 2024) 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. The model can be extended to incorporate other socio-economic characteristics that determine how residents dispose of their waste – gender, socio-economic status, age or religion (Knussen et al., 2004; Lou et al., 2022). Future models could use synthetic populations to explore this heterogeneity.

This study evaluated specific urban scenarios; however, other variables not explored in those scenarios can also determine waste sorting outcomes. The information available at waste bins, how clean the waste bins are, and the amount of household space are encoded in the proposed ABM and can be set as parameters for testing 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 defines the amount of waste residents generate in the ABM. 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.

Finally, the study did not measure the quantities of waste disposed of in the scenario locations, therefore, the model could not adequately be validated with real data. This is a challenge especially when testing alternative scenarios since real world changes are not always possible to implement. This is a crucial aspect to consider in future research, which should focus on providing more evidence to validate the outcomes of ABM models. Ideally, a comprehensive study of waste sorting should determine the behavioural aspects of a specific population, develop or implement a similar ABM to virtualise that behaviour, and engage with various activities in the field to characterise and quantify waste outcomes to further calibrate and validate the simulations.

7. Conclusion

This study presented an Agent-Based Model (ABM) to study waste sorting outcomes under various urban scenarios. The ABM showcases how the Theory of Planned Behaviour (TPB) can enrich the agents' behavioural framework in the simulations and successfully advances the modelling for waste sorting in various ways. The developed ABM offers a direct integration between TPB and individuals, reducing the complexity of how an individual behavioural theory can be instrumented at the household level. By integrating TPB into the ABM, the simulation offers an alternative to establishing a link (virtual) between waste sorting behaviours and outcomes quantifiable through waste sorting metrics. The developed ABM is spatially explicit, which enables urban planners to test different what-if scenarios and evaluate waste sorting levels. Finally, the study's open-source model enables future research to investigate how waste sorting might change under various conditions or locations and to further improve and expand the model.

CRediT authorship contribution statement

Jonathan Cohen: . **Jorge Gil:** Writing – review & editing, Supervision, Funding acquisition. **Leonardo Rosado:** Writing – review & editing, Conceptualization.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wasman.2024.12.020.

Data availability

Data will be made available on request.

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