

# 1 Exploring urban scenarios with an agent- 2 based model to assess residential waste 3 sorting

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## 9 Abstract

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

## 22 Keywords:

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

25

## 26 1. Introduction

27 Under the current linear economic system, waste materials are an unavoidable and  
28 undesirable by-product of daily activities that need adequate management. Globally, it is  
29 estimated that by 2050, waste generation will grow to 3.4 billion tons, and municipal waste  
30 management (MWM) related emissions will grow to 2.6 billion tons of CO<sub>2</sub>e (i.e. 5% of global  
31 emissions) (Kaza et al., 2018). As environmental concern continues to increase, waste-related  
32 issues are gaining attention and ranking high in priority worldwide (Matiuk & Liobikienė,  
33 2021).

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

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

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

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

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

68 Several studies advocate the integration of TPB and ABMs (Jager, 2017; Muelder & Filatova,  
69 2018; Scalco et al., 2018) since TPB offers a behavioural model for the agents. However, more  
70 applications for residential waste sorting and recycling are needed. First, we need to  
71 understand how individual behaviours result at a household or city level. Moreover,

72 simulations are often non-spatial(Chen & Gao, 2022; Meng et al., 2018; Tucker & Smith,  
73 1999), or space and location of different urban elements related to waste sorting are  
74 abstracted (Tong et al., 2018), making the models unsuitable for urban planning.

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

82 The remainder of this paper is structured as follows. Section 2 introduces the state of the art  
83 on TPB and ABM for waste sorting. Section 3 describes the methodology and the proposed  
84 ABM. Section 4 describes the data and case study of Gothenburg. Section 5 presents the  
85 application of the ABM to different urban scenarios, which is discussed in Section 5. Section  
86 6 concludes by highlighting the main findings.

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

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

95 2.1. Waste Sorting and Theory of Planned Behaviour

96 According to the TPB, people’s behaviour (BEH) is determined by four primary constructs:  
97 intention (INT), social norm (SN), attitude (ATT), and perceived behavioural control (PBC)  
98 (Ajzen, 1991). ATT refers to an individual’s evaluation of performing a particular behaviour. It  
99 encompasses beliefs, knowledge, and a subjective valuation of performance. SN refers to the  
100 perceived social pressure or influence by other individuals to perform a behaviour. Finally,  
101 PBC refers to the perceived ease or difficulty of performing the behaviour. It encompasses  
102 internal and external factors such as skills, resources, opportunities, and barriers. Combined,  
103 ATT, SN and PBC are used to determine the INT that (with PCB) leads to a specific BEH. Figure  
104 1 presents the original conceptualisation proposed by Ajzen. It can be noted that the  
105 constructs are determined using observable variables (att1, att2, att3, sn1 ..., beh3).

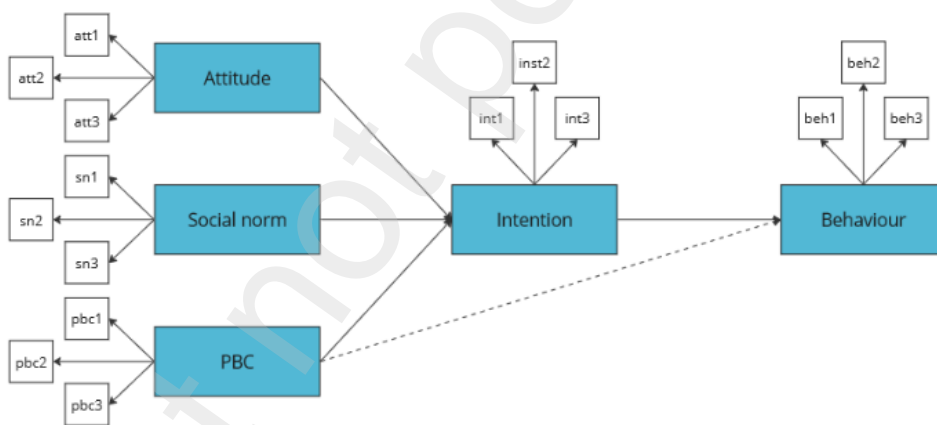


Figure 1 Conceptualisation of the Theory of Planned Behaviour (Ajzen, 1991).

106 TPB allows the inclusion of other constructs in addition to these primary constructs, and  
107 previous research has shown evidence that awareness of consequences (Hu et al., 2021;  
108 Tonglet et al., 2004; Wang et al., 2020), situational factors (Azlina et al., 2013; Govindan et  
109 al., 2022; Tonglet et al., 2004; Zhang et al., 2019), self-identification (Issock Issock et al., 2020;  
110 Knussen et al., 2004) or past behaviour (Knussen et al., 2004; Lakhan, 2018) are relevant

111 constructs in specific contexts. Empirically, to evaluate the validity of a TPB model,  
112 researchers design a survey that captures various aspects of each construct.

113 Existing studies usually consider the behaviour of individual waste sorting or recycling as a  
114 single phenomenon. For instance, specific studies have focused on food waste (Abdelradi,  
115 2018; Azlina et al., 2013) and the return of packaging (Struk, 2017b). Moreover, research  
116 shows that perceived increased distance towards waste bins can reduce how residents sort  
117 their waste. Li, et al. (2020) provide evidence that distance does not play a significant role in  
118 participation in recycling, while other studies found that shorter distances to bins are  
119 associated with more involvement in recycling and pro-environmental attitudes (Cohen et al.,  
120 2024; Ibrahim, 2020; Lange et al., 2014; Roustae et al., 2020; Struk, 2017a).

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

## 127 2.2. Waste sorting and Agent-Based Models

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

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

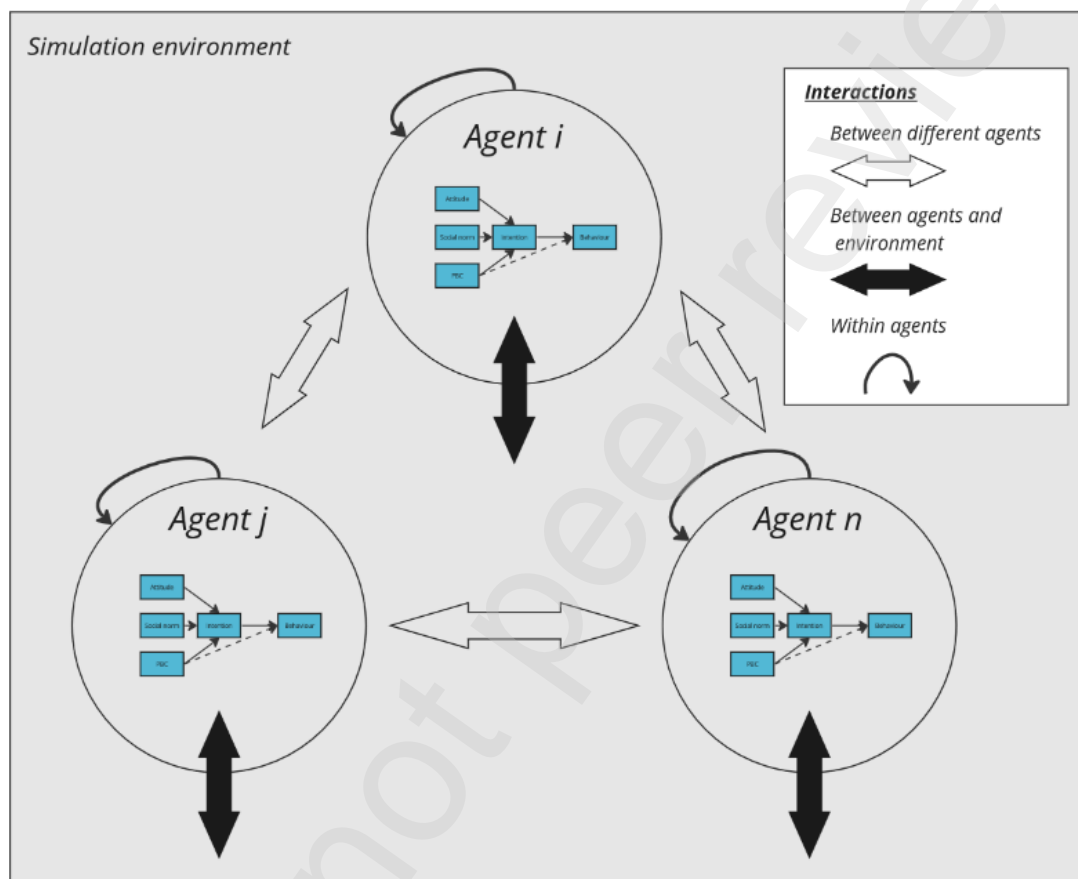


Figure 2 Integration of TPB and Agent-Based Models.

137 Researchers have approached the topic of waste recycling using ABM to explore the role of  
 138 the informal waste system (Chen & Gao, 2021) and the introduction of taxes (Meng et al.,  
 139 2018). In both ABMs, the agents include psychological variables and a utility function is used  
 140 to determine their behaviour. Tong et al. (2018) ran a social experiment using technology to  
 141 affect residents' incentives for waste recycling, and TPB was used as a baseline mechanism to  
 142 represent their behaviour. Results showed that Social Norms played a crucial role in their  
 143 context. An ABM was then developed to explore different waste disposal possibilities and

144 study the level of recycling participation, using an abstract representation of the town divided  
145 into zones with other demographics. Finally, Ceschi et al. (2021) developed an ABM  
146 incorporating the TPB primary constructs for waste recycling to evaluate norm-nudging  
147 policies. Although the ABM was able to reproduce historical data and provide evidence of  
148 how TPB can be used in an ABM setting, the model takes advantage of two simplifications:  
149 first, it is spatially abstract by representing households as grid cells, and second, the TPB  
150 individual behaviour is applied at the household level.

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

### 158 3. Methodology

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



162 (1.4.0).”<sup>1</sup>. First, following the TPB, a set of equations is described to estimate the behaviour  
163 of waste sorting. Second, the agents and the heuristics of the ABM are presented.

### 164 3.1. Determining the behaviour of waste sorting

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

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

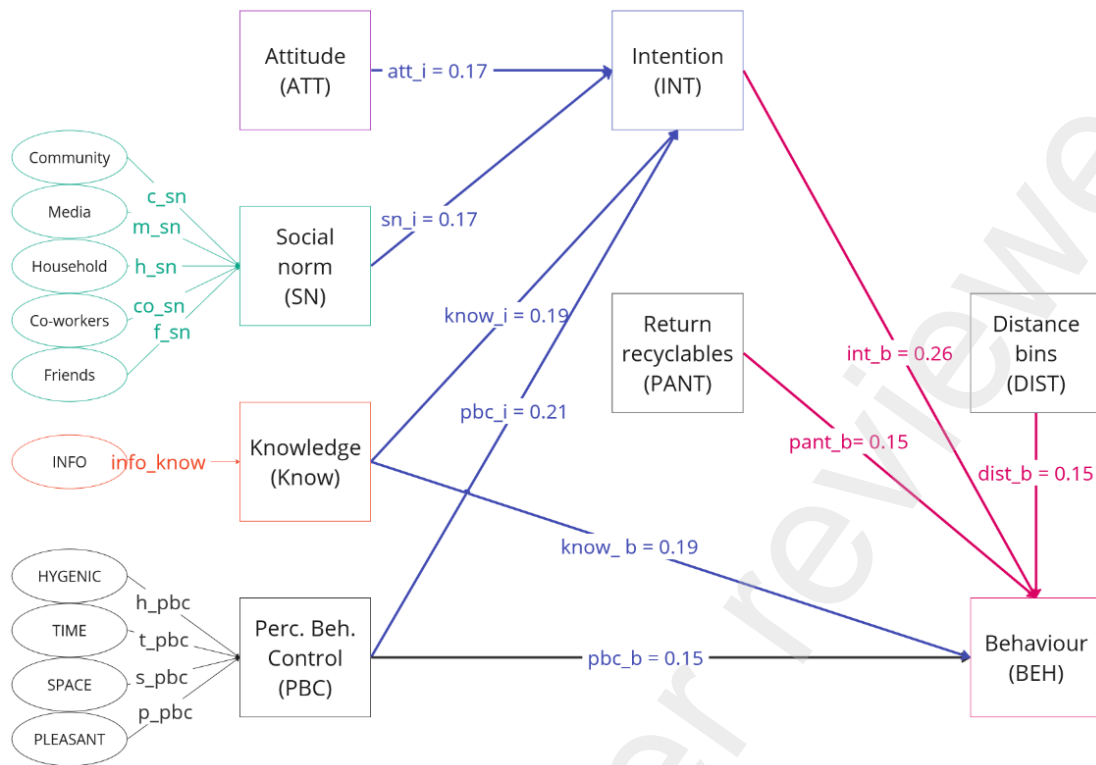


Figure 3 Path analysis of TPB coefficients. Source: adapted from (Cohen et al., 2024).

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

$$BEH = constant_b + int_b \times INT + pbc_b \times PBC + know_b \times KNOW + dist_b \times DIST + ret_b \times PANT \quad Eq 1$$

178 In the equation above, DIST accounts for the average distance (meters) that a resident travels  
 179 to dispose of organics, residuals, and recyclable waste. PANT is a dummy variable that  
 180 identifies whether a resident exchanges packages for their economic value at supermarkets.  
 181 Also, following the path analysis, intention (INT) is estimated using Eq 4 and includes SN, ATT,  
 182 PBC and KNOW, with their associated estimated coefficients ( $att_i$ ,  $sn_i$ ,  $pbc_i$ ,  $know_i$ ).

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

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

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

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

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

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

$$PBC = constant_{pbc} + h_{pbc} \times HYGENIC + t_{pbc} \times TIME + p_{pbc} \times PLEASURABLE + s_{pbc} \times SPACE \quad \text{Eq 5}$$

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

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

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

### 201 3.2. The ABM of residential waste sorting

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

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

#### 212 3.2.1. Residential buildings

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

#### 216 3.2.2. Households

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

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

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

### 227 3.2.3. Public waste bins

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

### 234 1.1.1. Workplaces

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

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

### 243 1.1.2. Residents

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

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

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

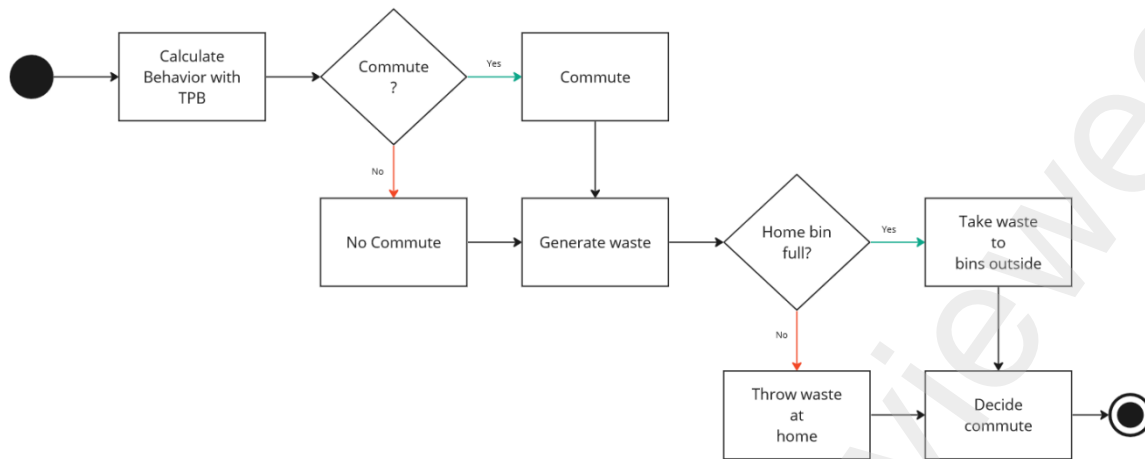


Figure 4 Routine of residents

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

262 If the waste bins at home are found to be full, or the waste has been standing for a certain  
 263 number of days, one resident of the household proceeds to empty the household waste bins  
 264 and the waste amount is transferred to the public waste bins. For instance, when a resident  
 265 has a positive amount of organic waste, it accesses the behaviour score. Let us imagine this is  
 266 65, which, according to the model, represents "Good" behaviour. The agent is assigned an  
 267 80% to 95% probability of throwing the organic waste into the organic waste bin and a 10%  
 268 to 30% probability of throwing the organic waste into the residual waste bin. The cut-off  
 269 values of what defines very bad, bad, or good behaviour are based on the results presented  
 270 in the appendix **Error! Reference source not found..**

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

	Behaviour			
	0-30 Very bad	30-55 Bad	55-75 Good	75-100 Very good
<u>Disposal of organic</u>				

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

273

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

## 277 2. [Simulation of residential waste sorting in Gothenburg](#)

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

### 283 [2.1. Data inputs](#)

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

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



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

295 To determine the four types of behaviour (very bad to very good) and the probabilities of how  
296 to dispose of waste, empirical data from the survey was used. In this case, the respondents  
297 indicated a percentage of properly sorted waste for organic, residual, and recyclable waste.  
298 These three values were averaged, and the calculation of quartiles of the averaged behaviour  
299 gave the ranges of four distinguishable groups, which are presented in the appendix in **Error!**

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

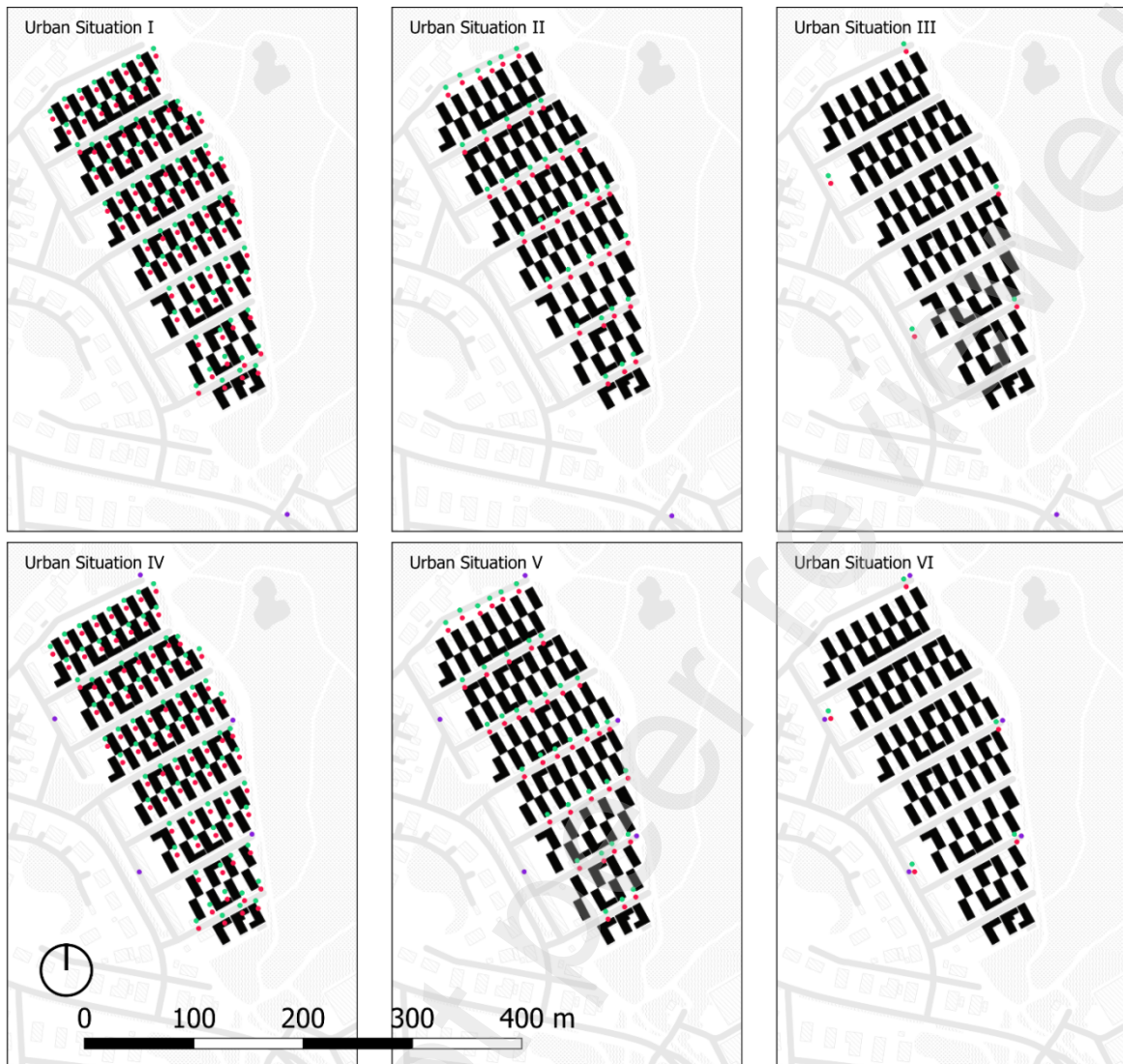
308 In Sweden, residents are expected to dispose of plastics, metals, glass, papers, and other  
309 recyclable materials in recycling stations. The location of these recycling stations was used to  
310 identify two distinct urban areas in terms of population density. Google Street View was used  
311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

## 314 2.2. Urban scenarios

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

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

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



Panel a

Selected area

Low density

Waste bin

- Residual
- Organic
- Recyclable

Residents: 129

Buildings: 79

Number of bins

	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



Panel 5b

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

## 336 2.3. Simulation and analysis

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

## 343 3. Results

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

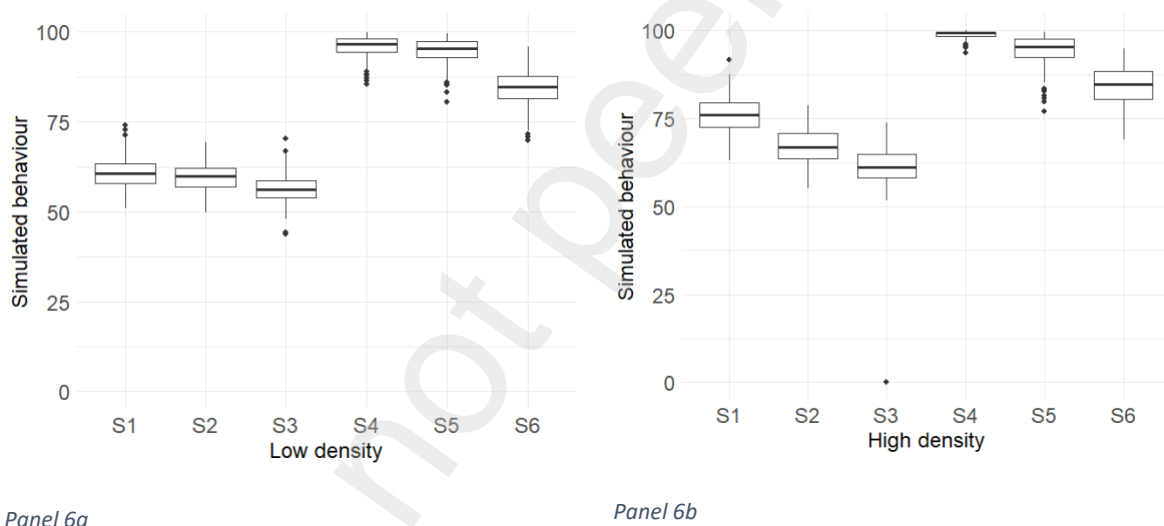
### 350 3.1. Residents' waste sorting behaviour

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

357 In the low-density area, the initial scenario (S1) produced an average behaviour of 60 with a  
358 standard deviation of 4. As expected, the simulated behaviour decreases when residual and

359 organic bins decrease in S2 and S3 to an average of 59 and 56, respectively. S4, the scenario  
 360 with the most waste bins, presents the best-behaved simulated agents with a score of 96.  
 361 Again, moving to scenarios S5 and S6, where the number of residual and organic bins  
 362 decreases, so does the average waste sorting behaviour, to 94 and 84, respectively.

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

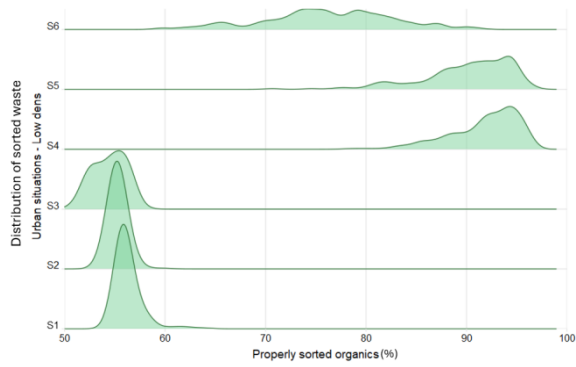


Panel 6a  
 Panel 6b

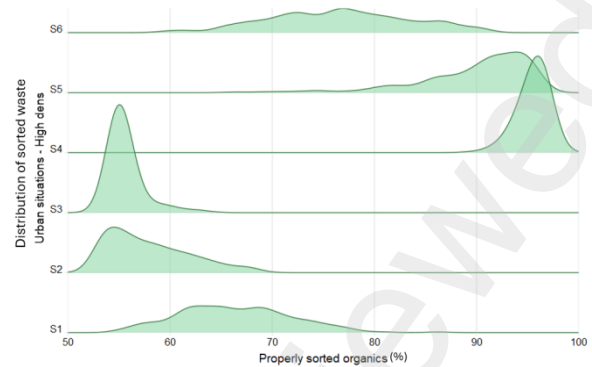
Figure 6 Average waste sorting behaviour under different urban scenarios: a) low population density scenarios; b) high population density scenarios.

### 368 3.2. Properly sorted waste percentages

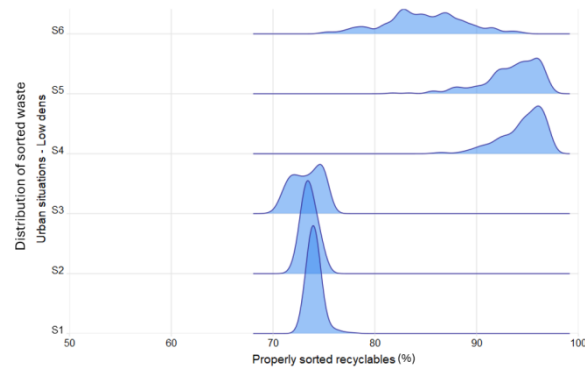
369 Besides tracking the residents' waste sorting behaviour, the model follows the amounts of  
 370 adequately sorted waste. Figure 7 shows plots of the distribution of the percentage of  
 371 adequately sorted waste for three waste streams (i.e., organic, residual, and recyclable) in  
 372 each urban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



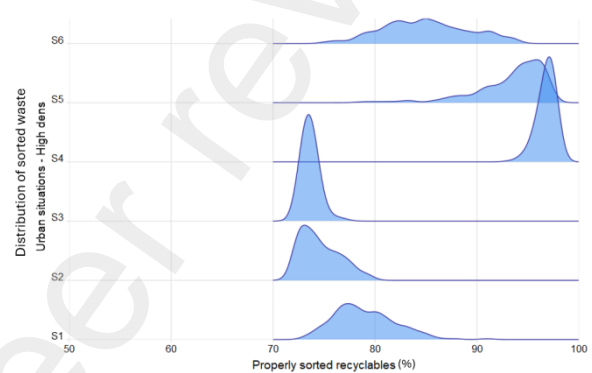
Panel 7a



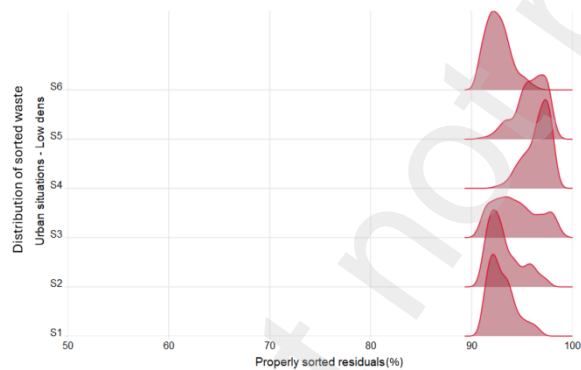
Panel 7b



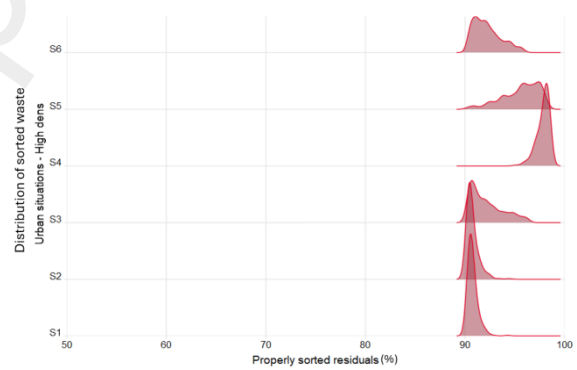
Panel 7c



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.

374 The results presented in Panel 7a and Panel 7b show that in all urban scenarios, at least 50%  
 375 of organic waste is correctly sorted. However, scenarios S4 to S6 (top) perform better than

376 scenarios S1 to S3 (bottom). In high-density scenarios (Panel 7b), there is more variability than  
377 in low-density scenarios (Panel 7a).

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

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

387 When it comes to recyclable waste (as shown in Panel 7c and Panel 7d), every scenario (S1 to  
388 S6) has an average of over 70% of adequately sorted waste. Even in low-density scenarios  
389 (Panel 7c), sorting accuracy ranges from 70% to 78% in S1 to S3. However, when the bins for  
390 organic and residual waste are reduced (S2 and S3), the percentage of correctly sorted  
391 recyclables decreases slightly. Equivalent results were observed in high-density areas (Panel  
392 7d), where S1 had an average of 79%. However, reducing the number of bins (S2 and S3) led  
393 to a decrease in the percentage to 71%. In both urban areas, placing more accessible bins for  
394 recyclable materials increased the percentage of waste that was sorted correctly, specifically  
395 in S4, to 94% in low-density areas and 97% in high-population-density areas. In the low-  
396 density area, as waste bins were located further away from residential units, the average  
397 percentage of properly sorted waste decreased. S5 has, on average, 93% of correctly sorted



398 recyclable waste, while S6 has only 84%. The high-density scenario produced comparable  
399 results.

400 Proper waste sorting is highest with residual waste (Panel 7e and Panel 7f), with more than  
401 90% properly sorted in all urban scenarios. The distributions follow a similar trend to the  
402 previous waste types, with scenario S4 performing the best. However, the changes observed  
403 between scenarios are small, and introducing more recyclable bins may not necessarily  
404 increase the proper waste sorting of residual waste.

405 In summary, the results indicate that waste is being appropriately sorted by more than 50%  
406 in all scenarios and that there are significant differences across waste streams and scenarios.  
407 The percentage of properly sorted residual waste has minor variability, ranging from 90% to  
408 100% in all scenarios; recyclable waste varies from 70% to 100% depending on the urban  
409 scenario, and organic waste displays the most variability across all scenarios. Lastly, the  
410 baseline scenario (S1) presents more significant variability in the high-density urban area  
411 when it comes to organic and recyclables.

#### 412 4. Discussion

413 The behaviour of waste sorting is usually considered dichotomous: individuals recycle or do  
414 not sort (or recycle) their waste. The ABM simulations in this work, incorporating a TPB model  
415 of waste sorting, have shown that residents behave differently for different waste streams.  
416 Improvements in how the waste sorting behaviour is measured are critical to understanding  
417 how municipalities can increase the amount of waste purity or material circularity. The  
418 relationship between individual behaviour and waste streams is not independent of the built  
419 environment or each other. After 200 simulations in each urban scenario, it was possible to  
420 extract the effect of different waste bin scenarios. The results seem to indicate that

421 improvements in the spatial distribution and number of recyclable material collection points  
422 can also yield improvements in properly sorted residuals and organics.

#### 423 4.1. Contributions

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

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

442 Finally, the simulations reveal the effect of various waste bin quantities and locations on  
443 waste sorting quality. Since the model was calibrated using results from a survey study, the

444 simulation results follow the main trends from the statistical model. The results show that  
445 although placing more bins leads to better waste sorting, there is room for planners to make  
446 decisions regarding how many waste bins, of what kind, and where they should be placed. A  
447 critical outcome of the study is showing the relationship between organic, residual, and  
448 recycling waste bins. More recyclable bins increase the proportion of adequately sorted waste  
449 for recyclables and for residual waste. The results show that high-density urban areas perform  
450 better than low-density ones, reflecting the fact that bins are positioned closer to the  
451 residents. However, these results require further research as socio-demographics and  
452 population density are not independent.

#### 453 4.2. Limitations and future research

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

465 Another aspect of the study that needs to be further developed is the dynamic aspects of TPB.  
466 While the behaviour of individual agents can change during the simulation, given the

467 interactions with the environment, the coefficients of TPB used in the ABM stay constant over  
468 time, and this assumption can be challenged. Future research involving longitudinal surveys  
469 would make it possible to assess changes in behaviour and TPB constructs, addressing this  
470 knowledge gap.

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

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

482 In this study, the ABM operationalised TPB to model waste sorting behaviour. While this  
483 theory is widely used in waste sorting research, future studies should explore how to  
484 incorporate other relevant behavioural models, such as social contagion theory. (Griliches,  
485 1957; Mansfield, 1961).

486 A stochastic process in the global section of the ABM defines the amount of waste generated  
487 by residents. As a result, waste reduction strategies relevant to the Circular Economy and  
488 environmental sustainability in general are beyond the scope of this model. This aspect of

489 waste management is essential, and future studies should also focus on researching how  
490 effective waste reduction strategies are.

## 491 5. Conclusion

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

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

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