Testing a norm-based policy for waste management:

An agent-based modeling simulation on nudging recycling behavior

Highlights

- Using an ABM approach to investigate the effects of social norms (SN) on recycling behavior
- Nudges inspired by descriptive SN are powerful if preceded by nudges inspired by injunctive SN.
- The level of waste present in the environment moderates the effects of nudging policies on recycling behavior.

ABSTRACT

The present study uses agent-based modeling (ABM) to examine the effectiveness of a nudge policy for improving recycling behavior. In our simulation, agents' recycling behavior is computed by components of the Theory of Planned Behaviour (i.e., attitudes, perceived behavioral control, social norms) and influenced by other agents as well as their surrounding (i.e., amount of waste in the area). The simulation, based on real data from a Taiwan community district, confirms realistic recycling trends and demonstrates the usefulness and reliability of ABM as a method to examine the effectiveness of waste management policies. An additional step in our simulation was to manipulate the amount of waste in the community to test the effect of a nudge policy based on social norms. Results showed that the policy increases recycling activity, but predominantly in low waste scenarios. This suggests that nudges, in the form of norm-based policies, can be an effective solution to enhancing people's recycling behavior under specific circumstances.

Keywords: *Recycling Behavior; Nudges; Norm-Based Policy; Agent Based Modelling; Theory of planned behavior; Social Norms*

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1. Introduction

Considerable evidence exists that the amount of waste produced by our societies will continue to increase because of population growth, accelerating resource exploitation and increasing consumption. According to the 2019 World Bank report, the amount of urban waste being produced is growing faster than the rate of urbanization. By 2025, there will be 1.4 billion more people living in cities worldwide, with each person producing more than double the current average solid waste. The core of the waste problem mostly relates to emerging countries and South and East Asia, which now produce about 33 percent of the world's total amount of waste (Idris et al., 2004; Kapur et al., 2003). In response to this, some Asian countries have developed effective waste management policies, which have resulted in Japan, South Korea and Singapore becoming leaders in the recycling industry (Shekdar, 2009). Another case in point is Taiwan, and its established recycling measures known as "Four-in-One Recycling" and "Keep Trash Off the Ground" (KTOG[1]), which aimed to reduce municipal solid waste, increase recycling, and improve the efficiency of the recycling industry. Under these policies, the recycling rate in Taiwan increased from 2 percent in 1999 to 17 percent in 2014 (Hsu & Kuo, 2005).

The implementation of strategies for managing the generation and recycling of waste is therefore a pressing problem for public policy. Over decades, recycling procedures have become increasingly effective (Prothero et al., 2011), and the public sector is continually examining appropriate incentives to encourage recycling behavior (Rainford & Tinkler, 2011). Some of these public policy approaches are more technical in nature, and others relate to the psychological aspects of people's behavior. Like for the KTOG, the overall success of a recycling stream is a favorable combination of different solutions. This includes prompting recycling by copying other people's

[1] In 1997 the Taiwanese government started this experimental Four-in-One Recycling Plan, which includes a set of policies aimed at developing responsibility among communities for recycling activities. The "Keep Trash Off the Ground" measure requires all citizens to keep their household waste at home until the garbage pick-up trucks come to a designated spot in each community twice a week.

behavior, following social norms, as well as forging attitudes, beliefs, and values that are useful for developing a sustainable community (Griskevicius et al., 2012). The core of KTOG was indeed the community network: the Tsu-Chi Foundation (a Buddhist organization), the Homemakers United Foundation, and the Conservation Mothers Foundation are all social communities directly engaged in promoting recycling behavior. For this reason, KTOG can be defined primarily as a policy based on social norms (i.e., norm-based policy, see Chao, 2008; Derksen & Gartrell, 1993).

From this perspective, recycling can be understood primarily as a social behavior Individual waste management is observable by other people and each household witnesses what others do. The social nature of recycling has inspired a field of research that bases its roots on Ajzen and Fishbein’s Theory of Planned Behavior (1980) and seeks to shed light on pro-environmental behavior by taking into account the relevance of social approval, peer effects and “warm glow” patterns in individual motives (Abbott et al., 2013; Viscusi et al., 2014).

Our simulation analysis uses a similar approach by taking the social nature of recycling as well as environmental attitudes, perceived moral obligation, and perceived behavioral control into account when implementing public policies designed to increase recycling. The originality of our paper lies in dynamically modeling the interactions between neighborhood units that allow and endorse beliefs about recycling and related norms. We demonstrate how subjective decisions about recycling depend on social interactions and how this affects the effectiveness of public policies.

Given the prominent role of social norms in influencing recycling behavior, communities and governments need to identify ways to develop and estimate the impact of norm-based policies. One such possibility is to create so-called “nudges” to motivate people to show the desired behavior (Gregor & Lee-Archer, 2016; Weinmann et al., 2016; Wilson et al., 2016). Still, the implementation of a policy is a delicate matter, and in some documented cases has failed, or worse, backfired (e.g., Baldwin, 2015; Spiegler, 2015). Studies show that the impact of norm-based policies does not follow predictable linear trends, with periodic decreases in recyclables production (Chao, 2008). Evaluating the impact of norm-based recycling policies should therefore also focus on the psychological drivers of people's recycling decisions, including environmental beliefs and introjected morality concerning sustainability as well as contextual factors like environmental degradation. Indeed, research on social norms and littering confirms that people in a 'dirty' environment tend to recycle less than those exposed to a 'clean' environment (Cialdini et al., 1990; Drackner, 2005; Fiorillo, 2013).

In the current paper, we propose a novel and integrative way of testing norm-based policies using an agent-based modeling (ABM) simulation. We first present a brief overview of the theoretical framework leading to the current research on recycling behavior, and then examine the effectiveness of a norm-based policy in specific conditions. Under a set of assumptions based on theories of social norms, planned behavior and psychological modeling, we recreate interactions in the waste chain (i.e., householders, garbage trucks, and collection centers). The results of the ABM simulation are used to examine and estimate the potential extent of the recycling policy effects and are compared with time series statistics derived from Taiwan recyclables production data. Moreover, the simulation tests policy efficacy in a highly degraded environmental scenario by taking into account the impending forces operating in such a setting.

2. Theory

2.1 Psychological modeling: Surrounding and peer influence

Research shows that the surrounding environment has a crucial influence on people's recycling behavior. For example, individuals recycle less in dirty settings (Fiorillo, 2013; Drackner, 2005) and litter on the street is seen as a disincentive to using appropriate bins for recycling (Geller et al., 1977; Keizer et al., 2008; Krauss et al., 1996; Ramos & Torgler, 2012; Reiter & Samuel, 1980). Recycling functions in a conditionally collaborative way, such that people are discouraged from recycling if they observe enviromental degradation (i.e., surrounding influence). A similar dynamic can occur when observing other people's behavior directly (Cialdini et al., 1990), resulting in demotivation to recycle as a consequence of the norm set by others (i.e., peer conformity). These behavioral spillover effects are based on peer and surrounding influences (Bandura, 2001) and can start negative littering feedback loops that turn a community into a dirty neighborhood (Dur & Vollaard, 2015). In this process, the key determinants for reproducing others' (lack of) recycling behavior depend on the sensitivity towards social norms.

2.2 From social norms to a policy for improving recycling

Social norms signal what is typical or normal behavior, and motivate action by providing evidence of what is likely to be effective, adaptive, and appropriate in a social setting (Göckeritz et al., 2010). Social norms can influence individuals' behavior by observing others (i.e., descriptive norms) and beliefs about what is the right course of action (i.e., injunctive norms). Government institutions increasingly apply strategies that use social norms to activate recycling behavior, which appearto be even more effective than financial incentives (Mannetti et al., 2004).

Social norms are the theoretical building blocks of policies based on nudge strategies. The concept of nudging (Thaler and Sunstein (2008) refers to any aspect of the choice architecture that alters people's behavior in a predictable way, without forbidding any option or significantly changing their economic incentives. In the context of recycling, providing households feedback about their own recycling performance in relation to the communities' performance can increase people's sensitivity towards social norms regarding recycling (Milford, Øvrum, & Helgesen, 2015; John et al., 2013) and subsequently increase recycling behaviour. . The study by Nomura, John, & Cotterill (2011) showed that when feedback is given on the recycling performance of the entire community (i.e., nudge based on descriptive norms) rather than for each individual household (i.e., nudge based on injunctive norms),it increases the likelihood of participation in the recycling scheme. These findings support the notion that the inner personal circle relating to individual and moral values exerted by family, friends and neighbors plays an important role in increasing the likelihood to recycle (Aceti, 2002). Reviews of results collected in laboratories show that the average increase in recycling rates due to social norm nudges is close to 19 percent (Cialdini et al., 1990; Hansen & Jespersen, 2013; John et al., 2013; Schultz, 1999)..

The scientific literature also suggests that in order to better understand the impact of public policies on human behavior, social norms should be modeled jointly with behavioral components such as psychological drivers (Fishbein & Yzer, 2003; Rivis & Sheeran, 2003). It is difficult to determine the precise impact of a norm-based policy on recycling behavior without considering the multifaceted psychological nature of it, including the role of attitudes and behavioral control. In the current paper we adopt a multi-causal framework for recycling behavior, which models both psychological drivers as well as the influence of social norms (i.e., Theory of Planned Behavior, Ajzen 1991).

2.3 Theory of Planned Behavior and Recycling

The Theory of Planned Behavior (TPB) is one of the most widely used theories in environmental psychology for explaining and predicting the psychological components of recycling behavior (Botetzagias et al., 2015; Chan & Bishop, 2013; Chen & Tung, 2010; Cheung et al., 1999; Kaiser & Gutscher, 2003; Mannetti et al., 2004; Pakpour et al., 2014; Ramayah et al., 2012; Tonglet et al., 2004; Tonglet et al., 2004; Valle et al., 2005; Vicente & Reis, 2008). The TPB in its original form (Ajzen, 1991) includes three constructs, namely Attitude (*AT*), Subjective Norm (*SN*), defined as the level of Social Norms embedded in a person, and Perceived Behavior Control (*PBC*). These three constructs subsequently explain the Behavioral Intention (*BI*), which, under favorable conditions, translates to Behavior (*B*). Within the current study, we focus on the model developed by Chu and Chiu (2003)[2], emanating from Taylor and Todd's (1995) work on ways to influence recycling behavior. The factors weigh (*w*) the original constructs of the TPB in addition to the

[2] The SEM model developed by Chu and Chiu (2003) is optimal for this simulation since it is based on a survey conducted in Kaohsiung district (Taiwan) during the implementation of the KTOG program. The survey was developed in accordance with the TPB principles suggested by Ajzen (1991).

perceived moral obligation to recycle (PMO_r). The mathematical expression of the model can be presented as follows:

$$B_r \cong w_{BI} BI_r \propto [w_{AT}(AT_r) + w_{SN}(SN_r) + w_{PBC}(PBC_r) + w_{PMO}(PMO_r)]$$

We assume that the actual behavior is an expression of the intention to recycle, where B_r and BI_r denote the actual behavior and the behavioral intention to recycle, respectively. The behavioral intention is proportional to the influence exercised by relevant others and the perceived barriers to the actual performance of a certain behavior. As a formula, recycling behavior is the mediated expression of BI_r and other TPB latent components (i.e., SN_r, AT_r, PBC_r, PMO_r). Research suggests that along with the influence of others, the intention to recycle is further predicted by psychological factors, namely personal drivers such as AT_r and PBC_r (Boldero, 1995). Behavioral attitudes are defined as a person's expectations of the consequences of a certain behavior and control beliefs refer to people's expectations about the impediments of performing a certain behavior and the resulting degree of success. Lastly, the PMO_r component reflects the perception that engaging in recycling is morally correct or incorrect, and also represents internalized pressure to be consistent with one's set of values (Lam, 1999). Since such a component is conceptually very close to beliefs in subjective norms, it appears to be also affected by policies based on social norms (Thøgersen, 1996; White et al., 2009).

INSERT FIGURE 1

Although the TPB framework incorporates variables that contribute to predicting individual behavior (Ajzen, 1991; Fishbein & Ajzen, 2011), at the macro level it is still unclear how the policy implementation of TPB fosters recycling for a bigger community in the long run (Knussen et al., 2004).

In view of the missing link between laboratory results and policy data, the present study introduces a methodological approach that incorporates (longitudinal) dynamics with agent based modeling (ABM). The nucleus of the current research approach is a stochastic simulation model in the framework of the TPB theory. A computed society with agents, waste generation, and collection processes is modeled, and the set of outputs examined. In order to build a realistic model, the key parameters of the ABM simulation and the macro results of the norm-based recycling policy are derived from field data (from Taiwan), whereas the estimated effects of social norm intervention come from the scientific literature relating to nudge programs. Although some of these parameters are taken from a specific city district in Taiwan (i.e., Kaohsiung) the model represents a general approach that is not geographically limited.

In the present study we first aim to test the policy simulation procedure by comparing second-order approximation output data from the ABM model with data retrieved in the field (Schubring et al., 2016). In our model, agents with strong environmental attitudes (AT_r), perceived moral obligation (PMO_r), and perceived behavioral control (PBC_r) should have a high intention to recycle and a high probability to engage in such behavior, whereas agents who are low in these drivers tend to avoid recycling. The same linear relationship can be observed with subjective norms, an agent's social norms (SN_r) relating to their beliefs concerning recycling, but also to less stable factors, such as the influence of other agents' recycling behavior (i.e., peer influence) and more in general the virtual community's surrounding environment (i.e., surrounding influence). Consequently, a policy based on social norms would influence introjected rules, but also through social norms of psychological modeling by enhacing the simulated recycling behavior (i.e., expressed as an increasing of recyclables production over waste).

We further predict that implementing a norm-based policy should increase recycling behavior (H1). In addition to the norm-based policy, we also predict that the presence of a critical waste level in the simulation influences recycling behavior, such that agents' recycling rate is higher when waste levels are low (H2). We assume that in scenarios with high waste levels the agents' intention to engage in recycling is weaker because of the discouraging influence of the environmental surroundings, and in scenarios with low waste levels the agent's recycling activities should be stronger. Moreover, we examine whether the effect of the policy on agents' recycling behavior persists with the same magnitude even in the presence of a critical level of waste in the simulation.

Finally, we also assume that the presence of a critical level of waste has a different effect on the agents' surrounding influence. Whereas the level of rubbish should greatly affect a community's surrounding influence (H3a), the levels of peer influence should be more affected by the presence of the policy because it is based on social norms (H3b).

3. Material and methods

3.1 Procedure for Agent-Based Modeling simulation

Agent-Based Modeling (ABM) simulations range from highly structured artificial worlds with few simple rules and constraints (Kohler & Gummerman, 2001), to complex models[3] in which agents' behavioral components interact with different structural environments (Ghali et al., 2017; Stinchcombe, 2001). Agent behavioral components are modeled into a heterogeneous artificial population in order to simulate a specific behavior (Richetin et al., 2010). Considering the high predictive power as well as the computability of the TPB and its components, ABM is a suitable empirical technique relating to this framework. Prior research has suggested procedures to transpose TPB models into computer simulations (Hesan et al., 2014; Orr et al., 2013; Richetin et al., 2010; Sogani et al., 2005). These approaches are neither strictly based on simulation nor entirely statistical, but a mixture of the two; they make it possible to evaluate the outcome of the simulation with traditional statistical techniques, whilst maintaining ABM's strengths. Of particular interest is

[3] Here we mean "complex" in the sense of a complex system, that is to say, a system with non-trivial self-organizing and emergent behaviors (see, for example, Mitchell, 2009), instead of the more mundane definition of "complex" as a synonym for "difficult" (see, for example, Papadimitriou, 2020).

the procedure suggested by Richetin et al. (2010), in which the operationalization of the TPB components into ABM are extracted and added, starting with the standardized coefficients of the corresponding statistical model. A similar method used in this study is derived from the PLS path model (Schubring et al., 2016) for specifying agent action behavior.

The agent's behavior is an interpretation of the target construct, which describes an agent's activity (in this case recycling), and where the agent derives probabilities regarding performing this action. The ABM defines the components of agent reasoning, which are derived from a structural model consisting of a latent-variables causal network a (i.e., structural equation model). In the PLS agent concept, the agent acts by interacting with their environment, which may be environmental conditions or a neighbor's behavior model influencing their action (Schubring et al., 2016). Each exogenous variable of the PLS path model represents one component. Concerning the TPB, the exogenous variables represent the average score of the indicators used to measure the components: environment attitudes (AT_r), moral obligation (PMO_r), subjective norms (SN_r), and perceived behavioral control (PBC_r). These components may have varying values within simulation experiments, representing distinguishable product characteristics. High component values of personal drivers (AT_r and PBC_r) increase the probability of action (i.e., recycling), while others (SN_r) are highly dependent on environmental conditions. The calculation includes the total effect values to account for the specific agent, in this case normally distributed, and the latent variable scores to account for the product component values. The total effect values are the strengths of each criterion's influence. For the TPB, its components determine the latent variable BI_r score. Consequently, they depend on the agent type and the strength of the criteria in terms of the total impact in the same circumstances (Schubring et al., 2016).

3.2 The Planned Recycling Behavior model (PRB_1.2)

We developed an ABM simulation model of Planned Recycling Behavior (PRB_1.2)[4] aiming to reproduce a district community in a square plane space measuring 5000*5000 points. The individuals and objects of the simulation are modelled as agents $i \in \Theta$, where Θ denotes the population or set of agents. The population is closed in time, such that the set of agents does not change during the simulation. In the plane, they can perceive other agents inside the Euclidean ball of radius $\delta > 0$ centered on the agent. We call this radius the area of influence, and it is equal for all agents. Agents' activities, based on their type, consist of producing rubbish, producing recyclables, transporting/moving rubbish, and eliminating it from the system; in these behaviors they can be reciprocally influenced by others. The activities are performed by three different types of agents: *householders, garbage trucks*, and *waste processing plants*. For this specific simulation, agent parameters (number of householders, garbage trucks, daily waste production, etc.) come from scaling the actual data from a Kaohsiung (TW) community district (Diong, 2012). The scaling of the agents' characteristics is derived from coefficients related to the TPB and taken from a Structural Equation Model (SEM) on motivations for recycling behavior developed by Chu and Chiu (2003), also based on a Kaohsiung survey. The SEM values of these constructs are assigned to the agents' decision-making process through a stochastic computation and used in the simulation as probabilistic factors of behaving. The SEM presents four important coefficients which determine recycling behavior: environmental attitudes (AT_r), moral obligation (PMO_r), subjective norms (SN_r), and perceived behavioral control (PBC_r). The simulation is designed to explore different scenarios in which two independent variables were manipulated. The first independent variable is the presence of the nudge policy. The public policy employed in the current model is based on social norms, which diversely affect the values of the TPB determinants of recycling. The policy nudges

[4] The entire model, code and documentation are available on the www.comses.net website. For more information, please see Scalco, A., et al. 2017. It should be noted that other cities can be simulated by changing the parameters.

the agents to be influenced by others' behavior or by simply working on norm values, also influencing agents' moral obligation and subjective norms. Coefficients and the increment of recycling rates (i.e., higher production of recyclables over rubbish) are extracted from a literature review of experiments about nudging social norms in recycling behavior (Cialdini et al., 1990; Hansen & Jespersen, 2013; John et al., 2013; Schultz, 1999).

INSERT TABLE 1

Householders. Under the KTOG policy, citizens keep their household waste at home until garbage pick-up trucks come, and so residents are modeled as householders (one for each building). All the household agents present in the community produce rubbish or recyclables. Every householder $i \in \Theta$ has an initial amount $\xi_i \in \mathbb{R}$ of rubbish and $\rho_j \in \mathbb{R}$ of recyclables. At every time t, every householder $i \in \Theta$ increases their level of rubbish or recyclables by a certain amount ξ_i^+ and ρ_i^+, normally distributed in the population, so that $\xi_i(t+1) = \xi_i(t) + \xi_i^+ \; or \; \rho_i(t+1) = \rho_i(t) + \rho_i^+$. At each time $t \in \mathbb{N}$, the agent selects a strategy to follow until the next step based on the algorithm Planned Recycling Behavior (PRB_1.2) described in Schema 1. In the following section, we describe the details for each part of these processes.

INSERT HERE SCHEMA 1

Garbage trucks. The model includes a transportation system which removes garbage from household agents and transports it to the collection points. These pick-up trucks heuristically design their routes by going to the agent that minimizes the ratio of distance divided by the amount of garbage (recycled or non-recycled). For this reason, two different types of trucks were designed: one type collects only recycled rubbish, and the other collects only non-recycled rubbish. Both garbage trucks give priority to resident agents with higher rubbish levels. After a certain amount of rubbish is collected, garbage trucks go to the nearest waste processing plant.

Waste processing plants. There are two types of collection points in the simulation: one for unseparated (i.e., non-recycled) garbage and one for recycled garbage. The waste processing plant progressively eliminates the garbage deposited by the trucks following a linear decay function. Note that the waste processing plants are designed to operate like waste incineration plants, thereby removing garbage over time (not just storing it). This feature was applied to establish a sustainability limit in the model.

4. RESULTS

Data was collected for 15 simulation runs for each of the four experimental conditions to ensure sufficiently reliable outcome values. After an initial simulation assessment (t=100 units), we found the variability of outcome parameters was reasonable. Each time unit represents one of the twice-a-week collection days in the simulation, and each simulation lasts for a period equal to 741-time units, the equivalent of 6 years.[5] This should be long enough to observe the effects of the norm-based policy and compare them with the time series analyses obtained in the field. For each of the four environmental situations, we observed three variables: the recyclable production as the outcome of recycling behavior, the surrounding influence level (*SI*), and the peer influence level (*PI*).

4.1 Validation of the simulation results based on second-order approximation

Graph 1 compares the evolution of the average value of recyclables production in the simulation when the norm-based policy is applied (vs. not applied) and waste levels are not critical.

[5] The first 100 time units were for assessment simulation training.

The vertical axis represents units of recyclables production and the horizontal axis represents the timeline. The agents' surroundings and peer levels (average values) are presented below in the graph. A comparison of the conditions when the policy is applied versus when not applied shows that the surrounding influence is similar in both conditions and remains relatively stable over time, whereas peer influence changes considerably and is higher when the policy is applied. Recyclables production also shows a similar and meaningful difference between scenarios due to the policy effect. The increase in recyclables is about 15 percent when the policy is applied, indicating an increased probability that an agent recycles in that condition. This is in line with data collected in the field during the application of the KGOT policy in Kaohsiung. Data from a time series study by Chao (2008) suggests that the impact on the long-term growth of recyclables production is only marginally significant. The effect of the policy may therefore be short-lived, as Chao explains: "*At the time the KGOT sorting had just begun, the amount of recyclables increased rapidly but then dropped down*" (p. 867). This indicates that the simulation closely replicates circumstances with policy implementation in the field.

INSERT GRAPH 1

Graph 2 compares the evolution of the average value of recyclables production in settings when the state of rubbish equates to a critical level but differs in whether the policy is applied or not. A clear difference is visible when the policy is applied but remains relatively stable over time. Compared to the growth curve for the conditions without a critical rubbish level (Graph 1), the effect of the policy is smaller. Both surrounding and peer influence show similar differences between the two conditions (policy applied or not) in the two scenarios (critical rubbish level or not). On the other hand, growth trends slightly differ in the second scenario. The surrounding influence exhibits a logarithmic trend over time. It starts off flat, but as agents repeatedly observe recycling in action, recyclables production increases gradually. Once rubbish piles up, the value of surrounding influence is boosted by the strong impact of recycling activity. Peer influence behaves similarly, but the increase seems much more stable compared to the surrounding influence. Such observations can be subsequently statistically explored to confirm the hypotheses.

INSERT GRAPH 2

4.2 Statistical Analysis

In order to statistically test the hypotheses, we conducted a 2 Nudge (present vs. not present) × 2 Rubbish (present vs. not present) between-subjects analysis of variance (ANOVA) that treated each of the 15 data runs in each of the four settings as independent observations. The dependent variable was the average recyclables production in each simulation. The results revealed main effects for both Nudge, $F(1,56) = 45.4$, $p < .001$, $\eta^2 = .448$, and Rubbish conditions, $F(1,56) = 16.5$, $p < .001$, $\eta^2 = .227$, which were qualified by a significant interaction, $F(1,56) = 7.5$, $p = .008$, $\eta^2 = .118$ (see Table 2). The interaction indicates that the nudge policy had a stronger effect when no rubbish was present.

To account for changes in recyclables production over time, we also conducted a 2 (Nudge) x 2 (Rubbish) x 4 (Years) repeated-measures ANOVA which grouped outcomes by years. This revealed that, although recyclables production decreased over time, $F(3,168) = 3102.1$, $p <.001$, $\eta^2 = .982$, the main effect of policy nudge was present and did not differ by years, as indicated by a non-significant interaction between Nudge and Years, $F(3,168) = 1.62$, $p =.187$, $\eta^2 = .028$. Morevoer, although the pattern of the interaction between Nudge and Rubbish changes slightly over the years, as indicated by a three-way interaction, $F(3, 168) = 7.44$, $p <.001$, $\eta^2 = .117$, the positive effect of Nudge policy on recyclables production is always stronger when initially no rubbish was present; the policy only had a slight effect if rubbish was initially present.

INSERT TABLE 2

To test the effect of policy and rubbish levels on surrounding and peer influence, we conducted two separate 2 (Nudge) x 2 (Rubbish) ANOVAs. For surrounding influence, we only found a main effect of the initial rubbish level, with a stronger surrounding influence when no rubbish was present, $F(1,56) = 3137.8$, $p < .001$, $\eta^2 = .982$, confirming H3a. The policy did not affect the surrounding influence, nor did the interaction between policy and rubbish levels ($p > .37$). For peer influence, mean levels were higher when the nudge policy was present, $F(1,56) = 152.5$, $p < .001$, η2 = .731], confirming H3b. Neither the level of rubbish nor the interaction was a significant predictor for peer influence (*ps* > .11).

Finally, we also investigated the relationships between recyclables production and the peer and surrounding influence by calculating the correlation coefficients for the individual 15 runs in each of the four conditions. Average correlations are displayed in Table 3. Results suggest that the relationship between peer influence and recyclables production is generally positive but rather weak, regardless of whether the policy is applied or whether rubbish is present or not. Contrary to this, the relationship between surrounding influence and recyclables production is much stronger in simulations when no rubbish is present. It is also of note that the nudge policy seems to increase the relationship between recyclables production and both peer and surrounding influence regardless of whether rubbish is present or not.

INSERT TABLE 3

5. DISCUSSION

The implementation of strategies for managing the generation and recycling of waste is a paramount topic for public policy. Many interventions are being tested worldwide to probe the effectiveness of such policies . The public sector is continually examining appropriate incentives to encourage recycling behavior (Rainford & Tinkler, 2011). This current research was designed to examine the effectiveness of norm-based policies to increase recycling behavior by using an ABM simulation. According to our simulation results, the norm-based policy significantly increases the amount of recyclables. As such, our findings are consistent both with the mainstream literature on experimental nudge recycling as well as with actual attempts to create successful public policies in order to address the recycling challenge (Dobson, 2011; Ramayah et al., 2012). The 15 percent increase in recyclables registered when the policy was introduced in the no-rubbish scenario corresponded with the results obtained in the field with the implementation of KTOG (Cialdini et al., 1990; Hansen & Jespersen, 2013; John et al., 2013; Schultz, 1999). The time series analysis based on the KTOG effect showed that the policy measure indeed exerted a substantial influence, but also in different ways in terms of recycling growth. The cities involved showed different trends, such as an initial boost in recycling, or a declining long-term trend, mostly depending on the environmental conditions and social mindset towards recycling. According to Derksen & Gartrell (1993), people are surrounded by a social context that has a significant effect on recycling behaviors. Additionally, pro-environment attitudes enhance the effect of context on separate collection behaviors, and that is the reason why a policy-based program can change the subjective proneness towards recycling on a neighborhood basis.

Indeed, the KTOG measure is based on social context influence. It is the impact of social norms that facilitates a community to participate in recycling (Hopper & Nielsen, 1991). However, using a model and computational simulations, our results show that the peer effect is not systematically positive. In fact, this effect depends on the environmental policies implemented, and on the composition of the considered population, as well as households' beliefs about whether society is more environmentally friendly than it is self-indulgent and greedy (Kirakozian & Charlier, 2016).

Both our simulation as well as data collected in the field show that the growth of recycling rates is not linear. Norm-based policies seem to ignite a recycling boost, but the growth rates decline over time. If recycling is based only on progressive imitation behavior, it is unclear why in the first scenario the norm-based policy only increases the amount of recyclables in the beginning. Similar evidence from data in the field shows an immediate boost in recycling in the initial stage, and in the later period a declining trend in recyclables production followed by an assessment. It is possible that after a certain point of engagement, people grow tired of participating in recycling activities. An alternative explanation that is based on our simulation is that the amount of rubbish sitting idle in the system also has a (negative) impact on recycling activity. The norm-based policy increases recycling to a greater extent in normal environmental conditions compared to conditions when the amount of rubbish is at a critical level. In our model, this effect is attributed to the state of the surrounding community influence. The visual impact of seeing too much garbage around immediately lowers the motivation to recycle, embodied in a double-edge effect of descriptive social norms (Botetzagias et al., 2015; Eriksson et al., 2015; Hansen & Jespersen, 2013). This explains the initially decreasing production of recyclables in Graph 2, which eventually increased again as the simulation progressed and the environment started to become cleaner.

The fact that rubbish affects recycling trends is also confirmed by time series statistics for Taiwan cities where KTOG has been applied. Cities like Taichung and Taipei, considered highly contaminated at the time, showed a different recycling trend compared to Kaohsiung. In those cities, the policy was not effective initially, and it took years before seeing any results. Social norms, especially descriptive ones, weakened policy development because the most prevalent behavior was oriented towards not recycling and, more importantly, because the presence of litter on the street was a disincentive for recycling. By the time the policy started to achieve some results, the processes underlying psychological modeling had become an incentive to recycle. The fact that the impact of the policy is reduced by the state of the surroundings is supported by the idea that injunctive social norms are a pre-requisite for the smooth implementation of policies based on descriptive social norms. The combined results of our simulation suggest that the impact of the policy is slightly noticeable in the level of peer influence, whereas the impact of rubbish is particularly visible in the surrounding influence. Both policy and rubbish levels affect recycling behavior, with public policies based on social norms working particularly well when rubbish is present at a normal level.

5.1 Practical implications: an integrative policy method

Our study investigated the determinants of recycling behavior through simulation, performed via agent-based modeling. The practical implication concerns policy development – specifically, testing the effectiveness of a norm-based policy to be used in waste management. Agent-based models allow the simulation of the effectiveness of various recycling campaigns under identical conditions (a macro or top-down analysis) and, at a later stage, specific public policies under different conditions (a micro or bottom-up analysis). Starting with the results obtained in the laboratory, we recreated similar effects to those obtained with KTOG by considering a specific Taiwan scenario. We stress that realistic policy modeling should always take into consideration the intricacy of the cognitive mechanisms of the agents it simulates, as well as the external environmental factors. This is arguably one of the strengths of ABM that interactions with multilayered inputs can be integrated with existing models. Importantly, ABMs do not use linear dynamics without considering the basis of psychophysics (Weber, 1834). Considering all these aspects makes the model somewhat elaborate but also closer to reality and more predictive for policy modeling.

The stochastic simulation, combined with more standard statistical analyses, revealed that both the nudge policy strategy and the initial level of rubbish affect recycling. Public policies designed to motivate recycling behavior by nudging people's social norms need to take into account that such policies do not readily work in environments with high waste levels. It is not enough to increase the awareness of environmental issues or remind people that recycling is a good idea per se. Likewise, public policies and social marketing campaigns that put a sustainable lifestyle at the center of residents' focus of attention are unlikely to be successful in the long-term if these policies are implemented in a dirty environment. These recommendations are in response to the call by

Prothero et al. (2011), who contend that more knowledge about public policies (and how they influence residents) is needed to effectively engineer sustainable consumption on a macro-level.

Although the current paper effectively links laboratory studies on recycling nudges to norm-based public policy, the results of our simulation need to be evaluated bearing in mind several potential limitations. The first is the critique intrinsic to any family of models, including agent-based models. Human beings are more complicated than the agents stylized in the stochastic model. Yet, by reducing community residents' motivations to those of stylized agents, complex interactions can be codified. The second limitation is the number and choice of variables in the model. In order to make the model manageable, we restricted the number of independent variables, even though we are aware that variables like education, income, age and the household demographic and socio-economic characteristics can play an important role in predicting recycling behavior (Ma et al., 2019). Likewise, other aspects such as local customs and culture, lifestyles as well as consumption habits impact recycling behavior (Gu et al., 2018) and could have been included in a more complex model. The choice of variables in our study was informed by the object of interest: nudges based on social norms. Future studies could also include other nudges such as administrative and economic incentives to recycle (Mak et al., 2018). The third limitation is the quantification of the parameters used in the model. These parameters were elaborated based on the Chu and Chiu (2003) model and refer to a specific region of Taiwan, therefore might not fully reflect the peculiarities of other areas on the planet. The employed methodology, however, is not geographically limited as other cities can be readily simulated with different parameter values.

6. CONCLUSIONS

Using an ABM approach, we investigated the effects of social norms on recycling behavior. Although social norms represent a potent source for increasing people's motivation to recycle, our results also support the notion that the amount waste already present in the streets is an important moderator variable that policy makers need to take into consideration. We recommend that future research on the interplay between the psychological drivers and surrounding influences makes use of similar simulation techniques to examine the effects of public policies. One potential avenue would be to distinguish between injunctive and descriptive norms, which in our simulation were both targeted by the implemented public policy approaches. Moreover, the sequence in which different types of nudges are applied can potentially matter: nudges inspired by descriptive social norms could be more powerful if preceded by nudges inspired by injunctive social norms.

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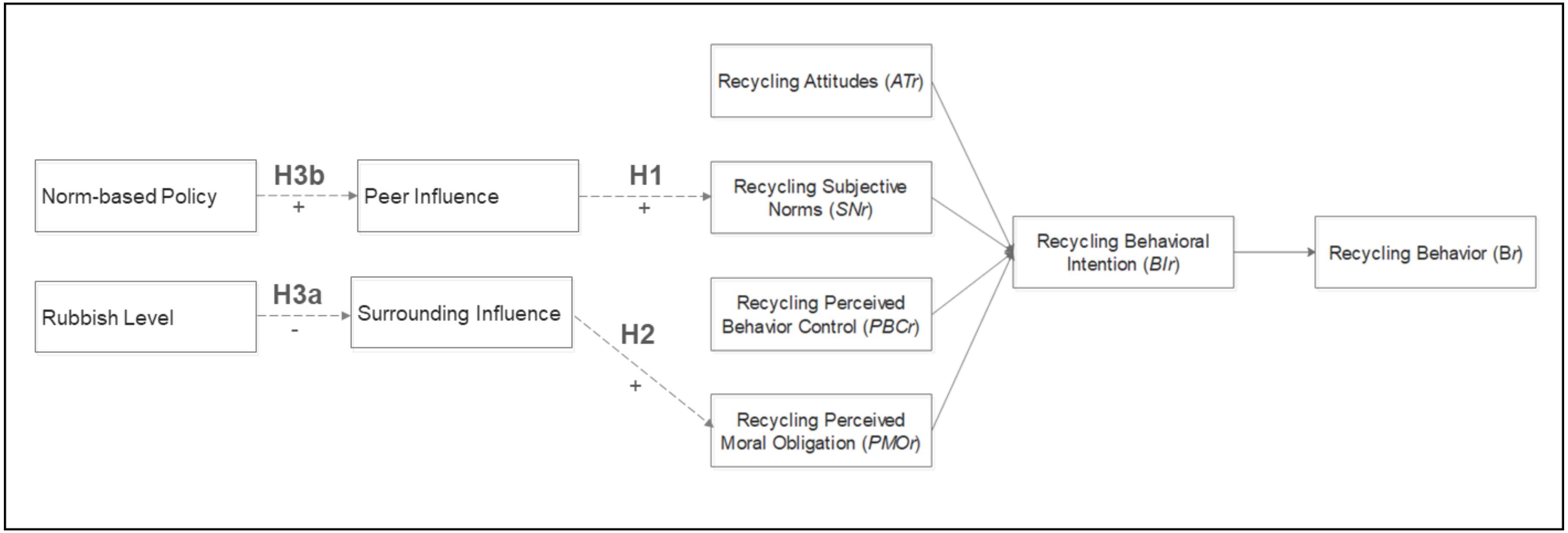
Figure 1: The psychological determinants of the recycling behavior based on the Theory of Planned Behavior (TPB).



Schema 1: Example of an agent's reasoning in the simulation, based on algorithm PRB_1.2: Process I: the agent's behavior is driven by social norms (SN_r) because these are higher than personal drivers (EA_r, PMO_r, PBC_r). Process II: the agent's behavior is steered by personal drivers because these are higher than social norms. Process III: based on high levels of EA_r, PMO_r, and PBC_r the agent produces more recyclables than rubbish. Process IV: based on low levels of personal drivers, the agent does not recycle. Process V: the agent, by observing other agent behaviors and the garbage level of the simulation, computes the "peer influence" in recycling (PI), the "surrounding influence" (SI), and relative

probabilities via two decay functions, based on human sensitivity characteristics. Process VI: due to the low level of p(PI) and p(SI), the agent does not recycle.

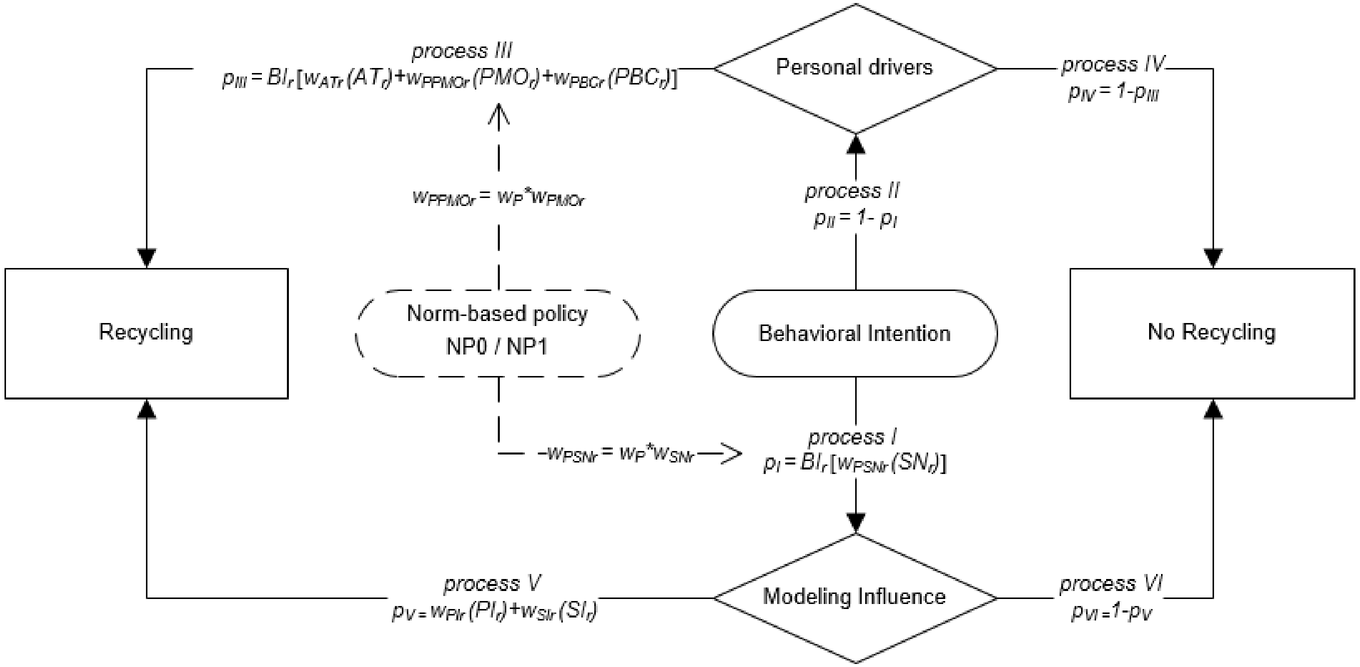


Table 1. Coefficients and parameters used in the simulation.

Variable	Scale values	Data source and references
Total number of household agents present in a community	1,100	Parameters for a Kaohsiung City district (Diong, 2012)
Starting twice a week average recyclables production per household	4.8 kg	
Critical rubbish (CR) level per household	25 kg	
Coefficient of environmental attitudes (AT_r)	0.18	Standardized and normalized regression coefficients extracted from Chu and Chiu 's study (2003)
Coefficient of subjective norms (SN_r)	0.12	
Coefficient of perceived behavioral control (PBC_r)	0.33	
Coefficient of perceived moral obligation (PMO_r).	0.10	
Average increase in recycling rate as a result of social norm nudge experiments	≈ 0.19	Increase estimated based on several nudge's experimental studies (see Cialdini et al., 1990; Hansen & Jespersen, 2013; John et al., 2013; Schultz, 1999)

Table 2: Effects of Nudge and Rubbish on Recyclables Production, Surrounding and Peer Influence

	No Rubbish Present		Rubbish Present	
	No Nudge	Nudge	No Nudge	Nudge
Recycables (Year 1)	5.55 (0.67)	6.30 (0.19)	7.89 (0.17)	8.01 (0.12)
Recycables (Year 2)	4.85 (0.48)	5.64 (0.20)	4.20 (0.21)	4.50 (0.22)
Recycables (Year 3)	4.55 (.042)	5.23 (0.21)	4.59 (0.27)	4.94 (0.19)
Recycables (Year 4)	4.62 (0.43)	5.18 (0.19)	4.88 (0.29)	5.28 (0.12)
Recycables (Total)	4.89 (0.49)	5.59 (0.17)	5.39 (0.20)	5.68 (0.11)
Surrounding Influence	0.51 (0.002)	0.51 (0.001)	0.48 (0.002)	0.48 (0.003)
Peer Influence	0.12 (0.001)	0.15 (0.007)	0.13 (0.012)	0.15 (0.001)

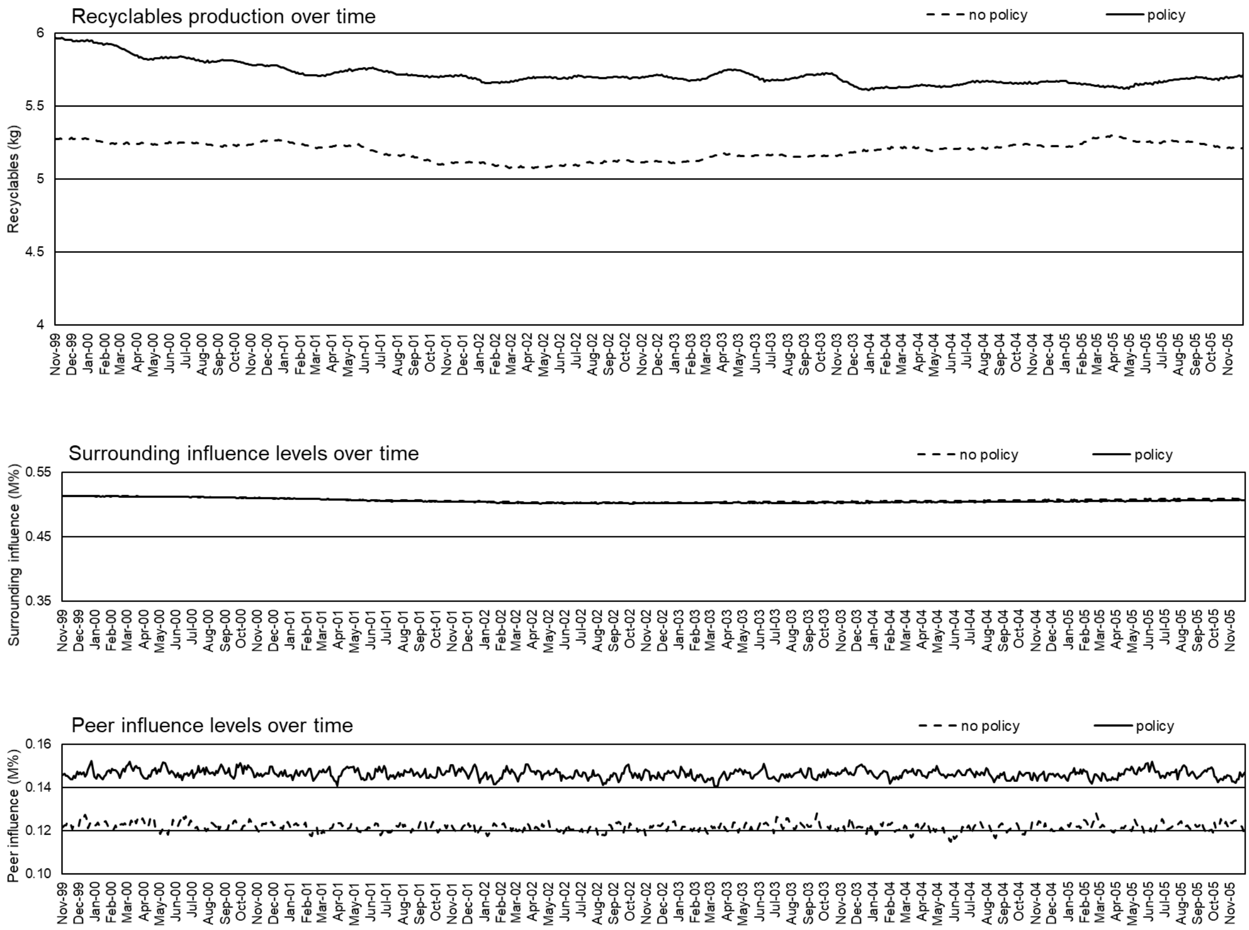
Note: Averages are shown. Standard deviations are in parentheses.

Table 3: Correlations of Recyclables Production with Surrounding and Peer Influence

	No Rubbish Present		Rubbish Present	
	No Nudge	Nudge	No Nudge	Nudge
Surrounding Influence	.685	.762	.161	.194
Peer Influence	.107	.176	.178	.202

Note: Average correlations were computed after aggregating across all 15 runs in the respective conditions. All *p*s <.001.

Graph 1. Recyclables production, and peer and surrounding influence levels over time when norm-based policy is applied or not and rubbish levels are not critical.



Graph 2. Recyclables production, and peer and surrounding influence levels over time when rubbish equates to a critical level but differs in whether the policy is applied or not.