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Beyond social experiments: Simulation of descriptive littering norms through agent-based modelling

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Abstract

Littering is an increasingly problematic phenomenon in urban settings that is exacerbated by global tourism. Littering behaviour is typically explained in the focus theory of normative conduct, which details how different categories of norms are communicated between people and how they affect behaviour. Research into littering behaviour is obstructed by practical limitations, particularly with respect to spatially disparate and densely crowded areas. Simulation through agent-based modelling lends itself well to experimentation with such variables and is therefore presented as a method to expand littering research with. In this project, a model is developed that simulates the effect of the descriptive norm on pedestrian littering in two spatially distinct streets in Amsterdam. A main finding is that the configuration of personal norms as stochastic variables and activated norms as corresponding multipliers is a valid interpretation of the theory through which it seems empirical data can be reproduced. Furthermore, several incomplete assumptions with regard to littering-specific and general norm theory are exhibited.

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1: Introduction

1.1: Background

As one of the main sources of non-degradable pollution, littering harms the environment, animals and people (Torgler, García-Valiñas, & Macintyre, 2012). While it was initially treated as a mere aesthetic problem, litter is now considered an environmental threat (Ong & Sovacool, 2012). It can degrade water quality, endanger wildlife and even contribute to flooding by blocking drainage systems. Some types of litter may even harm people directly, particularly sharp objects. Litter is not only considered one of the greatest nuisances in living areas but also a costly business: the Dutch government spent €250 million on cleaning public spaces nationally in 2010 (Milieucentraal, n.d.).

Global tourism exacerbates the problem of litter even further, especially in popular tourist destinations such as Amsterdam. The Dutch capital of roughly 850.000 inhabitants accommodated almost ten times as many tourists last year (OIS, 2018). Since continuously crowded areas could not be kept litter-free by regular cleaning services anymore, the city recently even introduced unorthodox anti-litter measures. These include nightly 'sweeping breaks', in which busy night life streets are briefly closed to be cleaned, and mobile bins mounted on moving bicycles (Van Lieshout, 2018).

Littering behaviour has been a relatively common social research subject since the 1970s (Cialdini, Kallgren, & Reno, 1991). It was soon associated with urban sociology concepts such as the broken windows theory, which describes how visual disorder instigates more disorder in built environments (Bateson et al., 2015). Through social experimentation, littering behaviour has been linked to more detailed theories regarding norms. Cialdini, Reno, & Kallgren's (1990) theory of normative conduct has been influential in explaining social norms as distinctly descriptive, injunctive and later personal. The litterer's age and proximity to bins have furthermore been found to affect littering rates (Bator, Bryan, & Schultz, 2011), while other socio-economic and demographic characteristics were not found to be as important (Bamberg & Möser, 2007).

However well designed the experiments from which they are derived and however sound the reasoning upon which they are based, littering theories can usually not be thoroughly tested in real-world settings. In experiments, subjects are typically isolated and monitored in manipulated settings intended to influence their behaviour and subsequently given a chance to litter (e.g. Cialdini et al., 1990; Reno, Cialdini, & Kallgren, 1993; Sibley & Liu, 2003; Ernest-Jones, Nettle, & Bateson, 2011; Keizer, Lindenberg, & Steg, 2011). Such methods are highly effective for testing hypotheses on a small scale, though carrying them out in more realistic, large scale settings is often virtually impossible due to practical or moral constraints. Moreover, as important as other people indirectly are to the behaviour of the subject in littering theory, they are often excluded from experiments for the same reasons.

Agent-based modelling (ABM) might prove instrumental in overcoming some constraints of studying littering behaviour in natural settings. By describing behaviour on the level of artificial agents, the researcher can use ABM to simulate social patterns, increase understanding in underlying mechanisms and experiment with parameters (Eberlen, Scholtz, & Gagliano, 2017). ABM has proven especially useful in addressing the sociological micro-macro problem, which concerns the difference between individual's actions on the micro level and behavioural patterns that arise on the macro scale (Bruch & Atwell, 2015). The analysis of normative influence on littering behaviour in crowded areas (i.e. non-isolated individuals) could be facilitated by ABM concepts such as emergence. Furthermore, the effects of variables such as the amount of litter present in the environment, the position of bins and agents' line of sight could all be controlled easily because the technique is spatially explicit.

This research project aims to contribute to littering research through (the process of) agent-based modelling. Theoretical implications will be investigated in simulation, while the modelling methodology for this type of explorative research will also be examined. More generally, the research will aim to explore the value of agent-based modelling in resolving some of the practical limitations of social experimentation in littering research.

1.2: Objectives

The main objective of this research is *to gain insight into littering behaviour through agent-based modelling by simulating theoretical assumptions in settings that are otherwise difficult to examine in practice*. In order to meet that aim, the following sub-questions will be answered.

1.2.1: Research questions

What theory explains littering behaviour most effectively? The theory that can most consistently explain findings, but that is also most focused, i.e. draws upon the fewest variables possible (following the principle that a model should be as simple as possible, but not simpler [Helbing & Balietti, 2012]) should be used as a framework for the model.

How can ABM be used to increase understanding about littering? It is necessary to address this issue in a sub-objective because it dictates exactly how findings can be interpreted and what conclusions may be drawn from the modelling process and the finished model.

How can littering behaviour plausibly be captured in an ABM? The theory that is used should be condensed in a most basic set of behavioural and environmental rules that can be operationalised in an ABM. The subsequent processes of creating and reporting on the model are also addressed in this sub-question, as well as model evaluation.

How does the physical environment affect littering rates? *How do population size and composition affect littering rates?* These questions are to be used as leading research questions to be explored with the finalised agent-based model. These will likely generate some insight into potential interventions but are certainly not exhaustive with respect to possible topics that may be experimented with.

1.2.2: Scope

The final model should be good enough to generate plausible patterns that can provide insights into data but should not aim to perfectly replicate empirical data by including too many variables. Firstly, 'over-fitting' empirical datasets often leads to the inclusion of noise or irrelevant details in the model, undermining the believability of the model (Helbing & Balietti, 2012). Secondly, models suffering from the 'curse of dimensionality', i.e. having too many variables are often hard to interpret in a meaningful way (Eberlen et al., 2017). The principle of Occam's Razor, which states that the explanation with least assumptions is most likely, is also to be kept in mind.

The model should furthermore be used to replicate empirical behavioural patterns and explore the workings of theoretical mechanisms in different settings, so as to guide future research and potential interventions, but not to produce directly usable quantitative findings. The identification of potential measures (such as the capacity or location of bins) is a research aim, but it would not be meaningful to quantify such findings because these would not be realistic when derived from a relatively simple model. Finally, experimentation with, and synthesis of existing theory and finding is a greater focus of this research than the formulation of new littering theory.

1.2.3: Overview

This report details the research and modelling processes that were critical in developing the agent-based model. Chapter two will span a theoretical background of littering behaviour through descriptions of behavioural models, social norms, and individual and environmental characteristics, and research limitations, as well as a short theoretical review of agent-based modelling. In chapter three, the conceptual model on which the ABM was based is described, as well as the implementation and evaluation phases. The experimentation that was carried out with the model is described in chapter four. In chapter five, the central research aim is addressed and potential applications of the model are proposed. The limitations of the project are discussed in chapter six. The report will be concluded by a reference list in chapter seven. Additionally, several appendices are provided in the digital version of the report.

2: Theoretical framework

This chapter will consist of two parts: a synthesis of littering behaviour in theory in 2.1, and a review of agent-based modelling in sub-chapter 2.2. The first part comprises sections about behavioural, norms, norm activation, interpretations of those theories, other factors, and limitations of research methods. The second part is divided in sections detailing ABM history, complexity, epistemology, and a previously developed ABM about littering.

2.1: Littering behaviour

2.1.1: Attitude, intention and behaviour

Littering is commonly defined as "the careless, incorrect disposal of minor amounts of waste" (Hansmann & Scholz, 2003: p. 753). In their large-scale study, Schultz, Bator, Large, Bruni, & Tabanico (2013) observed that littering occurred among 17% of pedestrians in the USA, and even among 65% for cigarette butts specifically. Yet Campbell, Paterson de Heer and Kinslow (2014) reported that only 9% of their research population admitted to occasional littering. A distinction can be made between active and passive littering; failure to notice your littering could explain this difference between reported and observed littering rates (Sibley & Liu, 2003). However, three fourths of Campbell et al.'s research population stated that they felt guilty about littering and moreover, 81% of observed littering occurred with intent (Schultz, 2013). Sheer carelessness or mechanical reasons thus cannot explain littering behaviour entirely.

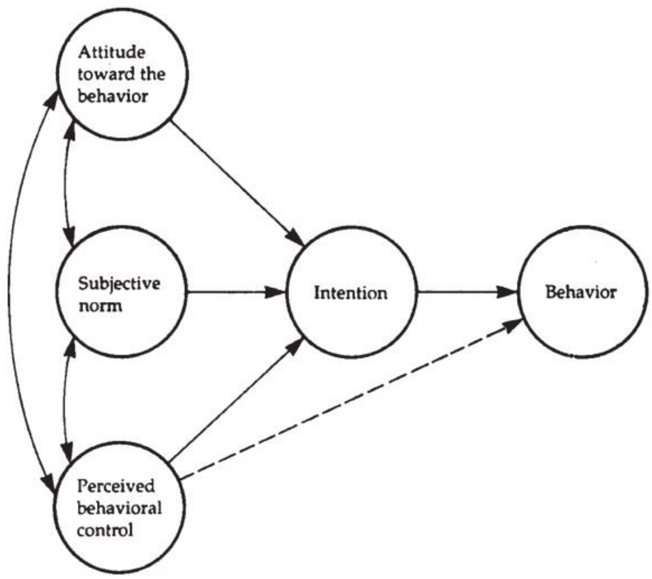


Figure 2.1: Theory of planned behaviour (Ajzen, 1991).

The gap between a person's (stated) attitude and their behaviour has been the subject of a great many psychological and sociological studies. Of particular relevance here is that pro-environmental attitudes are frequently not translated to pro-environmental behaviours (Smith & Louis, 2009). Ajzen's (1991) *theory of planned behaviour* has provided a highly influential framework for explaining people's actions in specific contexts. The theory states that intentions are the strongest determinant for behaviour, as has been backed by numerous statistical reports (Bamberg & Möser, 2007). Intention is in turn shaped by attitudes, subjective norms, and perceived behavioural control (see figure 2.1 above).

Subjective norms refer here to a person's perceived social pressure while behavioural control describes the perceived difficulty of carrying out a behaviour.

The theory of planned behaviour explains that most variance in behaviour is explained by 'internal' variables (attitude and behavioural control) rather than 'external' norms. The opposite has been found as well, however. The *economics of crime* perspective aims to explain behaviour by arguing that people take into consideration possible penalties for their actions while maximising utility (Torgler et al., 2012). Littering is then explained by the amount of time and energy that is saved by the litterer in relation to the fine that would be issued if they are caught. Such theories are only rarely properly supported by evidence as people persistently comply more with rules than would be expected. This high degree of cooperation is explained by social norms. Negative consequences of misconduct (i.e. littering) include more than legal punishment through fines; internal sanctions such as guilt and remorse and social sanctions such as gossip and disapproval seem to have much higher prices than expected. Besides its likely underestimation of the importance of norms, the theory of planned behaviour may lack the flexibility to capture the dynamic processes observed in littering, as well as the influence of people's environment (Eberlen et al., 2017).

2.1.2: Broken windows and other norms

An older, less formalised theory that sheds light on the workings of littering behaviour in the context of social norms is the *broken windows theory* (Wilson & Kelling, 1982). It describes how signs of disorder in the built environment (such as litter, graffiti or the titular broken windows) are visual cues that communicate information about the quality of social environments which stimulate more disorderly behaviour. If individuals perceive that residents of a neighbourhood are antisocial, they are more likely to behave antisocially themselves (Weaver, 2015). Littered environments thusly attract more littering. Cialdini et al. (1991) tested this in controlled settings, where they reported a 32% littering rate in littered environments but only 14% in tidy environments. Similarly, for every unit of increase in the amount of litter (on a 1-10 scale) in non-experimental settings, the littering rate was found to increase by 2% (Schultz et al., 2003). The 'spreading of disorder' as described in the broken windows theory makes littering problematic beyond its potential environmental detriment: the prevalence of social problems can increase the presence of litter but also vice versa (Bateson et al., 2015).

Note the different meaning of 'norms' in the broken windows theory and the theory of planned behaviour. In the former, it denotes the behaviour that is 'normal' or followed by a majority of other people, while in the latter it is meant to indicate the social pressure behind acting in a certain way. Cialdini, Reno and Kallgren conducted a series of studies in the 1990s that together constitute the *focus theory of normative conduct* to increase understanding about social norms. The distinction between the two categories of norms is a basic principle in their research. The writers termed them 'descriptive' and 'injunctive'. Descriptive norms indicate what others commonly do, while injunctive norms relate to people's perception of what behaviour is expected of them (Cialdini et al., 1990). The broken windows theory the refers to how the descriptive norm shapes behaviour, which is demonstrated by increased littering in dirty environments. The injunctive norm is rather used in paradigms such as the theory of planned behaviour or the economics of crime, where it guides behaviour with the threat of social sanctions for (not) behaving in a certain way. In regard to littering behaviour, descriptive norms influence one through the amount of litter in a specific environment, while injunctive norms usually keep one from littering. In more poetic terms, we may speak of norms of *is* and norms of *ought*, respectively (Kallgren, Reno, & Cialdini, 2000).

In the academic literature, the term 'norm' usually refers to injunctive norms. A common theme in norm-related littering research is when and in what context littering is allowed or frowned upon. For instance, some types of litter have been found to be more socially accepted than others. Discarding cigarettes in urban areas and organic litter in green areas are not frowned upon as much as other items in those settings (Torgler et al., 2012). Sibley and Liu (2003) showed that cigarette butts are more tolerated than many other types of litter – sometimes even in legal terms. Littering is also considered more acceptable when the responsibility of keeping areas tidy is not felt strongly. In many western countries, cleaning or keeping areas tidy are expected to be solved by the public sector or cleaning services. Ong & Sovacool (2012) contrast western littering with the Japanese urban environment, which is kept much cleaner because of the societal injunctive norm that prescribes that everybody is equally responsible for the cleanliness of their environment.

Nonetheless, the widespread injunctive norm in western societies is anti-littering. People in Amsterdam, for instance, generally believe they ought not to litter, whether their motivation is to preserve an aesthetic, the environment, or to avoid a fine. Still, when an environment is littered, this will affect further littering behaviour through descriptive norms. This contradiction between the beliefs of injunctive norms and the behaviour of descriptive norms is supported by the costly information hypothesis that stems from *cultural evolutionary theory*. The hypothesis states that attaining accurate context-specific behavioural information is costly to individuals in terms of time and effort because there are so many factors that could be taken into account in different socio-spatial situations (Weaver, 2015). Acting in accordance with the descriptive norm (or effectively copying others' behaviour) gives people an information processing advantage and decisional shortcut when choosing how to behave (Cialdini et al., 1990). Following the descriptive norm provides a less accurate but also much less costly solution and have therefore been favoured by evolution, so the cultural evolutionary theory postulates. This phenomenon is described in a multitude of well-known idioms, perhaps most popularly: 'when in Rome, do as the Romans do'.

2.1.3: Norm activation

Cialdini et al.'s series of studies is mostly cited for a novel finding, rather than their elucidation of categories of norms. In their 1990 research, the writers found that the influence of both descriptive and injunctive norms on littering behaviour is limited unless the norms are salient or activated in the subject. In other words, litterers will behave according to the descriptive or injunctive norm especially if their attention is focused on either. The researchers came to these findings in controlled settings, initially in an experiment about the descriptive norm. They provided their research subjects with an unwanted item in littered and clean settings and observed their behaviour. In some test runs, a confederate littered the object in the subjects' view, while in other runs, the person merely walked by. Seeing somebody littering led to a much higher littering rate among the subjects in unclean settings. The opposite was shown to have the reverse effect: a litterer in a clean environment stimulated *not* littering. Where the broken windows theory described the influence of the state of the environment on a person's behaviour, it was now shown that being exposed to somebody else in the act of littering activates the descriptive norm. The results of this particular study are depicted in figure 2.2. The difference in littering rates in conditions of low norm salience (14% versus 32%) has not been replicated consistently and is instead usually reported as roughly equal (Reno et al., 1993). The difference in this study may have been due to an already activated descriptive norm. Nevertheless, the pattern that active descriptive norms lead individuals to adjust their behaviour to existing litter is significant.

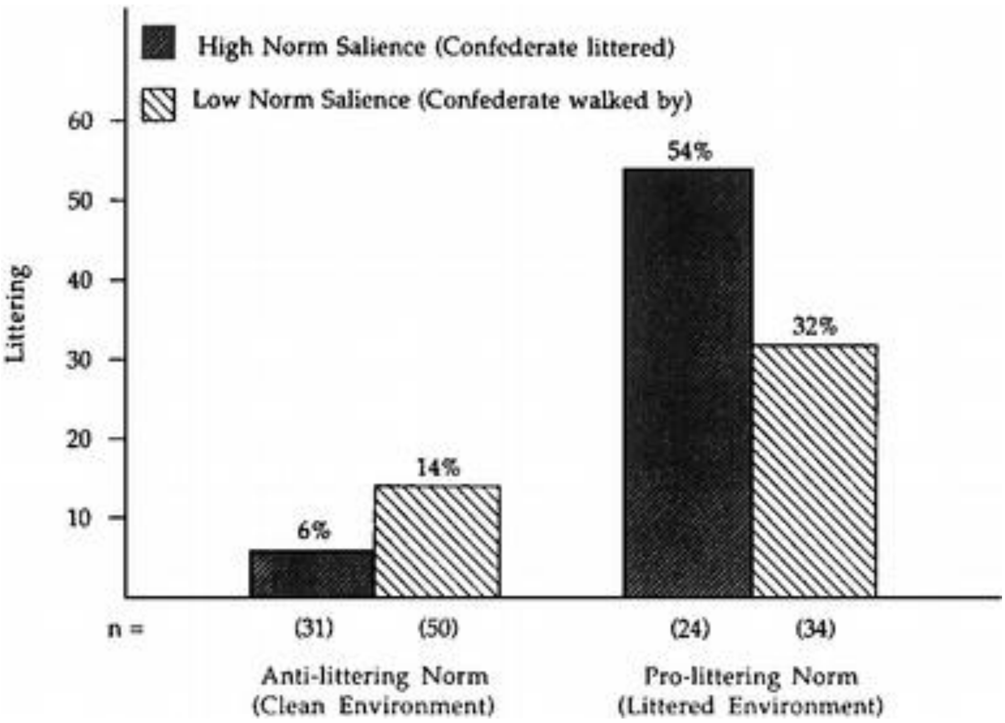


Figure 2.2: Descriptive norm activation experiment results: bars depict the percentage of research subjects littering in the given settings (Cialdini et al., 1990).

While it is intuitive that seeing somebody littering stimulates littering (as imitating others' behaviour has been described as an efficient way to choose the appropriate behaviour in a setting), it seems that it merely draws a person's attention to the state of the environment. Exposure to littering in a clean environment led to less littering, which indicates that the state of the environment represents the descriptive norm rather than a single other person's littering. Although the effects of correct waste disposal have not been studied as thoroughly as those of littering, Reno et al. (1993) found that observing somebody disposing of litter properly also activates the descriptive norm. Seeing someone throwing litter in a bin thus increases the likelihood of littering in an unclean setting. This counterintuitive finding is explained by the lack of social sanctions it exhibits. Others' correct or incorrect waste disposal is seen as personal behaviour, which does not directly inform subjects about what others will think of them and their behaviour (i.e. the injunctive norm) but rather only draws attention to the state of the environment.

As a defining characteristic of injunctive norms, the suggestion of social (dis)approval was found to be a prompt for injunctive norm activation. The manner in which this is suggested has been more continually researched since the dawn of the theory of normative conduct. Cialdini et al. (1991) found that observing somebody picking up litter (rather than disposing of it, properly or improperly) activated the injunctive norm in subjects, which led them to litter significantly less, regardless of the cleanliness of the environment. Signs with normative messages were shown to have the same effect, even if the norm they communicated is not directly related to littering (Kallgren et al., 2000). Well-worded signs that for instance appealed to people's help in keeping an area clean proved particularly effective (Torgler et al., 2012; Schultz, Nolan, Cialdini, Goldstein, & Griskevicius, 2007). This effect lasted longer than that of descriptive norms: while the latter refers to a specific setting, injunctive norms seemed to remain active even outside of the area where they were made salient. Injunctive norms were furthermore found to be activated through others' facial expressions, particularly those showing disapproval through anger (Hareli, Moran-Amir, David, & Hess, 2013). The extent to which injunctive norms are activated by different prompts is not quite clear yet, however. Moreover, there is evidence that different norms can be active simultaneously, but Cialdini et al. (1990; 1991) could not account for their dual influence properly and other studies produced yet different results about the effect of conflicting norms (Hamann, Reese, Seewald, & Loeschinger, 2015).

2.1.4: Personal norms and interpretation of normative conduct

While the notion of personal norms is older than the focus theory of normative conduct, the concept later expanded the theory as a third type of norm (Kallgren et al., 2000). Personal norms are defined as internalised injunctive norms (Bamberg & Möser, 2007). They relate to what is deemed important to people themselves rather than what they perceived as important to others. The threat of not following personal norms is therefore not shaped by potential social sanctions but by a threat of shame or guilt if personal values are not followed (De Kort, McCalley, & Midden, 2008). This is witnessed by the previously described widespread feelings of guilt after littering (Campbell et al., 2014). A weak personal norm against littering should not be interpreted as pro-littering, however. Rather, motives such as carelessness and laziness (which were found as indicators for littering in Torgler et al.'s [2012] survey) seem to justify littering to people with a less dominant personal anti-littering norm.

Personal norms are also subject to activation. In the words of Kallgren et al. (2000, p. 1010): "The data indicate that mere possession of a personal norm does not lead routinely to norm-based action. Rather, internal or external focus of attention importantly moderates the degree to which the personal norm is likely to guide such action". However, the functioning of personal norm activation is not well described in the cited studies. Kallgren et al. (2000) focused subjects on their personal values through filling in surveys about their own littering standards and by exposing subjects to their own image on a TV monitor. Such prompts do not occur naturally, yet personal norm has been described as highly indicative of a person's behaviour, notably in the aforementioned theory of planned behaviour (where it is termed 'attitude'). Individual rates of littering rate have also been correlated with personal values or disposition (Bator et al., 2011). Whether personal values lead to routine behaviour with regard to (refraining from) littering, or whether they are active more commonly than suggested in Kallgren et al.'s (2000) research, it seems that their influence on littering should not be underestimated.

The focus theory of normative conduct is sometimes cited or expanded on to explain environmental behaviour in general or littering specifically, but the two categories of social norms are commonly confused in spite of Cialdini et al.'s (1990) warning that they are conceptually and motivationally distinct. For instance, in research about the impact of signs with normative messages, Keizer et al. (2011) use the term 'norm' inconsistently, not distinguishing between descriptive and injunctive norms but rather drawing from the *goal frame theory*, formulated by two of the same authors (Lindenberg & Steg, 2007). This theory describes environmental behaviour as determined by goal frames, which frame the way people process information and act upon it. Normative, hedonic and goal frames are distinguished, which correspond to people's aim to comply with injunctive norms, personal convenience, or personal gain, respectively. However, Keizer et al.'s (2011) research design is very similar to one of Cialdini et al.'s (1991) studies aimed precisely at explaining the difference between descriptive and injunctive norms. The results of both studies were similar as well, but there seems to be some struggle in explaining them coherently with the newer theory, particularly because it does not account for descriptive norms. This criticism is particularly relevant to the present research because inspiration will be drawn from Rangoni and Jager's (2017) agent-based model, which is partly based on Keizer et al.'s (2011) study. Rangoni and Jager's (2017) research will be further explained in chapter 3.2.4.

2.1.5: Individual characteristics, social context and environment

Besides analysing relatively concealed mechanics such as injunctive norms, most littering studies also test for correlations between littering and demographic patterns. Little difference in littering is usually found between the genders. Men sometimes seem to litter more than women (Cialdini et al., 1990; Torgler et al., 2012), but the majority of studies find no significant evidence for this pattern (Cialdini et al., 1991; Reno et al., 1993; Bator et al., 2011; Schultz et al., 2013). Age seems to impact littering behaviour to a much larger extent: the age group 18-32 is reported to admit to littering the most (Arafat, Al-Khatib, Daoud, & Shwahneh, 2007; Torgler et al., 2012; Campbell et al., 2014), and was even observed to litter at a 26% rate, compared to an average of 14% for other categories (Schultz et al., 2013). This phenomenon is reasoned to be caused by less developed (injunctive) normative sensibility among young adults (Torgler et al., 2012; Schultz et al., 2013). Furthermore, the level of formal education has not been found to affect littering behaviour (Arafat et al., 2007; Torgler et al., 2012).

Group dynamics are another variable that should intuitively influence littering behaviour. Pro-social behaviour has long been theorised to decrease with larger group sizes because of diffusion of responsibility. An illustrative example is that people are less likely to act in emergency situations in crowded places (Bator et al., 2011). Contrarily, the presence of other people nearby is also described as having an encouraging effect on pro-social behaviour (e.g. decreasing littering rates). This is in line with classic urban geography literature, where it was termed *natural surveillance* (Bateson et al., 2015). Furthermore, the size of the immediate social circle has experimentally been found to decrease littering rates in groups of up to four people (Ernest-Jones et al., 2011; Al-Mosa, Parkinson, & Rundle-Thiele, 2017). No significant correlations between crowdedness or group size and littering were found in real-world observations, however (Schultz et al., 2013). The 'openness' or degree of publicity of Schultz et al.'s studied locations could be used as a reason for this pattern (for instance, Keizer et al. [2011] found higher littering rates than expected in their research area – a quiet alley), but the divergent direction of the suggested relationship between crowdedness and littering in the academic literature demands further research. Notably, there seems to be an absence of explicitly descriptive or injunctive norms in the research subject, one that is recommended to be elaborated on.

Tourism is frequently associated with littering (Weaver & Lawton, 2001; Santos, Friedrich, Wallner-Kersanach, & Fillmann, 2005). Tourists as well as non-resident workers are typically described as lacking a connection to place, which leads to criticism regarding anti-social behaviour such as littering, especially from residents. Campbell et al. (2014) found evidence to the contrary, however: tourists littered equally to residents and claimed to be similarly concerned for the environment. In a large-scale survey on criminal behaviour, problems of littering were strongly associated with drunk or rowdy behaviour, such as through littered fast food waste and cans or bottles (Upson, 2006). In Amsterdam, intoxicated tourists have also been identified as a problematic source of littering. Groups of men between the ages of 18-34 who originate from the Netherlands and the United Kingdom and travel to Amsterdam for short stays, were recently identified as a troublesome target group for littering while publicly intoxicated, among other offences (I Amsterdam, 2018). The effect of neither tourism nor intoxication on norms seems to have been researched academically. It seems evident, however, that tourism is associated with intoxication, and that intoxication leads to higher littering rates.

It was already shown by the great influence of the descriptive norm in littering that "individual behavio[u]r is characteri[s]ed by significant plasticity in response to variations in geographic context" (Weaver, 2015: p.142). The layout and design of the built environment have been shown to affect littering rates critically as well (Bator et al., 2011). Although the average distance to a bin at the time of littering is nine meters (Schultz et al., 2013; Al-Mosa et al., 2017), the sheer number of bins is not as important in influencing littering rates as their placement (Pon & Becherucci, 2012). Wever, Van Kuijk, & Boks (2008) found that disposed items are piled onto full bins if those are placed more conveniently than other bins, regardless of how full those are. This phenomenon likely embodies conflicting norms, in which neatly placed litter is still considered unclean but also communicates some injunctive value of keeping the environment tidy (Cialdini et al., 1990). The extent to which environmental factors explain variance in littering differ: Schultz et al. (2013) claim individual factors are much more predictive, while Al-Mosa et al. (2017) emphasise the importance of environmental settings. The extent of the influence of bins is likely context-specific, but regardless of setting, people have generally shown to be willing to walk small distances to dispose of their litter in bins in public areas.

2.1.6: Practical limitations of littering research

In conclusion, although a great body of knowledge has been gathered about littering behaviour, the research domain is subject to several practical limitations. Large-scale observations have the capacity to provide highly accurate data, but they are costly and usually do not expose complex or concealed phenomena. Gathering data through surveys or interviews is never completely accurate because people have been shown to be unconscious about a degree of their littering, their passive littering. Additionally, they may only remember instances of littering or disposing of their thrash in a bin if any norm was activated, which in the case of injunctive and personal norms would mean when they disposed of litter properly. However, if they are conscious about improper littering, the injunctive anti-litter norm could lead them to embellish the truth when self-reporting on their behaviour in a survey.

By observing people in field experiments rather than letting them describe their behaviour themselves, these issues are circumvented. Field experiments have been proven instrumental in the analysis of individual littering behaviour, but they also lead to a number of issues. Firstly, people are often isolated so that they do not influence each other lest it may affect the data, but this very influence is of great interest in mechanisms that are affected by social phenomena such as norms. Secondly, controlling an environment as part of an experiment is often costly, impractical or simply impossible. The settings that are used in controlled environments often have little to do with realistic situations, such as when research subjects are given the chance to litter by means of a flyer that is attached to their vehicle. Finally, the scale of field experiments is often rather small – both in number of observations and, as mentioned, number of subjects observed simultaneously.

"Instead, we might set up a model (in this case, a computer program) which embodies some plausible assumptions and see what happens, comparing the behaviour of the program with the observed patterns" (Gilbert & Troitzsch, 2005: p. 2). Serendipitous findings, such as Cialdini et al.'s (1990) accidental discovery of how neatly swept piles of litter exhibit conflicting norms, are unlikely to come by when all rules of a behaviour are pre-imposed, but through computer simulation, we may have the capacity to surmount the abovementioned obstacles to littering research.

2.1.7: Summary

To recap, littering behaviour seems strongly correlated with multiple categories of norms. This is reflected in the famous broken windows theory, which states how descriptive norms in the environment affect behaviour. The focus theory of normative conduct provides a clearly defined theoretical framework for the influence of social norms on littering behaviour. Other influential theories, such as the theory of planned behaviour or the goal frame theory include more elements with which a generalised explanation of behaviour is perhaps more properly given, but they do not capture the social and spatial dynamics that are evidently important to littering. While the activation of injunctive and personal norms is not as clearly defined in the focus theory of normative conduct, it should provide a realistic foundation for a littering ABM. The first sub-question, *what theory explains littering behaviour most effectively*, has hereby been answered.

2.2: Simulation in social research

2.2.1: Agent-based modelling

The first university research computers in the 1960s were already used for modelling social processes. Simulations were initially used in social research as they were in exact sciences: to predict future patterns and behaviours. The necessity of strong empirical evidence for quantifying model assumptions and the inherent complexity of social systems made this a problematic aim (Gilbert & Troitzsch, 2005). Save for a handful of influential studies (e.g. Schelling's model of residential segregation [1971]), computer simulation was not common in the social sciences until the advent of multi-agent simulation in the 1990s, and specifically agent-based modelling.

Agent-based models are defined as "computer programs in which artificial agents interact based on a set of rules and within an environment specified by the researcher" (Bruch & Atwell, 2015: p.1). Such artificial agents are characterised by heterogeneity, autonomy, the capacity to interact with other agents and to adapt their behaviour to changing settings (Macal, 2016). During simulation, agents act autonomously based on a set of theoretically justified rules programmed by the scientist. As such, ABM can be used as a virtual environment in which to test well-elaborated theory and experiment with mechanisms and parameters (Eberlen et al., 2017). Furthermore, ABM has been proven useful in sharpening the researcher's thinking about empirical problems because all underlying assumptions need to be made explicit in order to be programmed. With multi-agent models and ABM specifically, the aim of modelling in the social sciences has thus shifted from predicting to understanding the target system. Bruch and Atwell (2015) wrote of agent-based modelling that it bridges the gap between formal but restrictive quantitative models, and rich but imprecise qualitative descriptions of phenomena.

ABM has been proven especially useful in addressing the sociological micro-macro problem, which concerns the difference between individual's actions on the micro level and behavioural patterns that arise on the macro scale. Actions of individuals often give rise to social organisation and dynamics rather than simple aggregations of individual characteristics and behaviour. Social phenomena in turn also affect choices on the level of the individual, establishing a feedback mechanism between the micro and macro levels. Individuals constantly respond to their (social) environments while the accumulation of their choices or behaviour will eventually change their (social) environment (Bruch & Atwell, 2015).

2.2.2: Complexity

The modelling concept of 'emergence' – the manifestation of phenomena as an unintended aggregate result of designed individual behaviour – is a key concept in agent-based modelling and helps address the micro-macro problem (Eberlen et al., 2017). The possibility of emergence sets ABM apart from most other modelling techniques that assume linear relationships between variables, i.e. when dependent variables are proportional to the sum of independent variables. Complexity theory is the overarching domain concerning emergence of complex behaviour from relatively simple activities. The degree of interconnectedness of a system's elements rather than their sheer number make a system complex and may cause emergence (Gilbert & Troitzsch, 2005).

Besides model complexity, the degree to which the model is based on empirical findings, or empirical realism, is a central concern in agent-based modelling (Bruch & Atwell, 2015). Model complexity can range from abstract to high dimensional worlds, which refer to models with respectively singular agent attributes and deterministic rules, and those with a multitude of agent characteristics and dynamic environments. The degree of empirical realism, in turn, makes models range from virtual laboratories that are as grounded in empirical findings as possible, to abstract models that are focused on the clarification of theories more than the replication of empirical data. On the intersection between the two concepts' extremes, a model could be characterised as a simple world (with only several agent attributes) with low dimensional realism (using some empiricism and some abstraction). The appropriate levels of both issues should be dictated by the research goals.

When the aggregate consequences of strongly assumed micro-level behaviour are explored in simulation, as in this research, low-dimensional realism simple worlds are often most successful. This relates to the notion that a model's success should be measured by its usefulness to increasing understanding of the research problem rather than its level of similarity to the real world, which can usually already be achieved through more abstract models. Too much empirical realism is furthermore very rarely suitable in social research.

Data and knowledge of human behaviour are often not completely available or suitable, leaving key interactions unexplained. However, if policy recommendations are intended to be made, or even if manipulation mechanisms are merely to be identified, some grounding in empiricism will likely be necessary (Bruch & Atwell, 2015). Gilbert and Troitzsch (2005) write that accuracy of model output is an advantage in models that aim at prediction while simplicity is a virtue in models that are used to increase understanding.

2.2.3: Uncertainties and epistemology

Whatever the level of complexity and empirical realism, models must reflect the target system properly. Through the process of verification, it is examined whether a model functions as intended. Comparison with the conceptual model and debugging are core elements to the process. Verification is difficult to carry out for ABMs, but it is highly necessary. Only with mathematical proof can a model be fully verified, but since this is impossible to achieve in models with a qualitative focus (Gräbner, 2018), the researcher's intuition is typically relied on to establish sufficient verification (Gilbert & Troitzsch, 2005).

The basic aim of simulation is to create a model that is simpler to study than the target system itself. If it is a correct representation of the target system, conclusions drawn from the model should also hold for the target (Gilbert & Troitzsch, 2005). Besides testing whether the model works as designed in the process of verification, scrutiny with regard to its value as a representation of the target system is also essential, which is carried out through validation. Several aspects of a model can be tested for validity. A distinction is commonly made between its capacity to replicate existing patterns, to predict future patterns, and the accuracy of its structure. Only the latter is always pursued in the social sciences as a result of the ubiquity of limited or vague data in the field. A model is generally considered structurally sound if its programmed 'microstructures' have the capacity to emerge in macrostructures as postulated by the theory, and if both structural levels reasonably resemble real-world processes (Troitzsch, 2004). In practice, full verification and validation is impossible because real-world systems are never closed; there will always be external behaviour that outside of the model scope (Oreskes, Shrader-Frechette, & Belitz, 1994).

There is no agreement about a single 'best' tool for verification and validation (Gräbner, 2018). A model's complexity, structure and purpose should guide the choice of an appropriate method. Similarly, various criteria for how knowledge is created by models are used in different scientific communities. An elementary understanding across communities, however, is that models are not intrinsically representations of targets but are rather made so by the intentions of the researcher. Frigg and Nguyen's (2016) DEKI account (an acronym for denotation, exemplification, keying up, and imputation) may aid in the description of what model features make them representations of their targets, and essentially how knowledge is derived from specific models. Gräbner's (2018) concise table of the DEKI account (including this researcher's intentions with the model in development) is depicted in table 2.1.

Concept	*Explanation*	*Littering model*
Target of the model	The real or fictional system/object that the model intends to represent	Pedestrians' littering behaviour in western urban settings

Scope	Clarification of what features of the target the model intends to represent	The influence of the descriptive norm and its activation to individuals' littering behaviour in variously crowded areas
Assignment	Clarification of which part in the model corresponds to which part in the target, and which parts of the model are to be ignored	Agents represent individuals - litter represents litter – bins represent bins – environments are based on actual streets and squares in Amsterdam.
Kind of explanation attempted	Which kind of explanation does the model user attempt here? A full explanation, a partial explanation, or a potential explanation?	Potential explanation: this refers to a description of how descriptive norms could possibly lead to observed patterns – full or partial explanations could not be properly validated on account of lacking datasets
Exemplified properties of model and the key	The main relevant properties of interest and how they should correspond to properties of the target	The agents' generation of litter refers to a chance that real pedestrians have litter to dispose of – personal norms in the model are intended to represent the effects of actual personal and injunctive norms, their coincidental activation, and any other coincidental effect on people's littering behaviour
Imputed properties	The properties that the model (truly or falsely) imputes on its denoted target.	The effects of the personal and descriptive norm (and the activation of the latter) and of the accessibility of bins on littering behaviour
Attempted dynamic sufficiency	The degree of structural sophistication a model must have to produce an output reasonably similar to that of its target	Patterns in the model output should be qualitatively plausible but quantitative prediction is not an aim – rough calibration could help in this respect
Attempted mechanistic adequacy	The degree of structural sophistication a model must have to mimic the causal of its target adequately	The functioning of the descriptive norm and its activation should be captured adequately as well as their interaction with the personal norm

Table 2.1: Epistemological considerations of the DEKI framework that should be clarified (Gräbner (2018) and the account of this research.

2.2.4: Littering in ABM

No more than a single ABM project about littering behaviour seems to have been published academically: by Rangoni and Jager (2017). The researchers based their model on Keizer et al.'s (2011) interpretation of the goal frame theory (Lindenberg & Steg, 2007), which was touched upon in chapter 2.1.4. The goal frame theory places (injunctive) normative influence in a wider motivational framework (Jager, 2017). Behavioural goals are theorised to be framed as normative or one of two other goals, one emphasising hedonism and the other gain. The theory was formulated to explain environmental conduct: behaviour was interpreted as being motivated by social norms, personal convenience, and/or personal financial gain, respectively.

In an empirical study related to littering behaviour, Keizer et al. (2011) used the goal frame theory (or rather hedonic and normative motives) to explain littering behaviour. The goal frame theory does not explicitly incorporate descriptive norms, but since these have been found as critical to littering behaviour, the theory does not seem suitable for explaining littering. In the process of accounting for the observed behavioural patterns, the researchers seem to have interpreted 'norms' as descriptive rather than injunctive as they were originally intended in the goal frame theory. In the final analysis, littering behaviour was thus explained as a trade-off between hedonic and descriptive goals, which do not exist together in either theory.

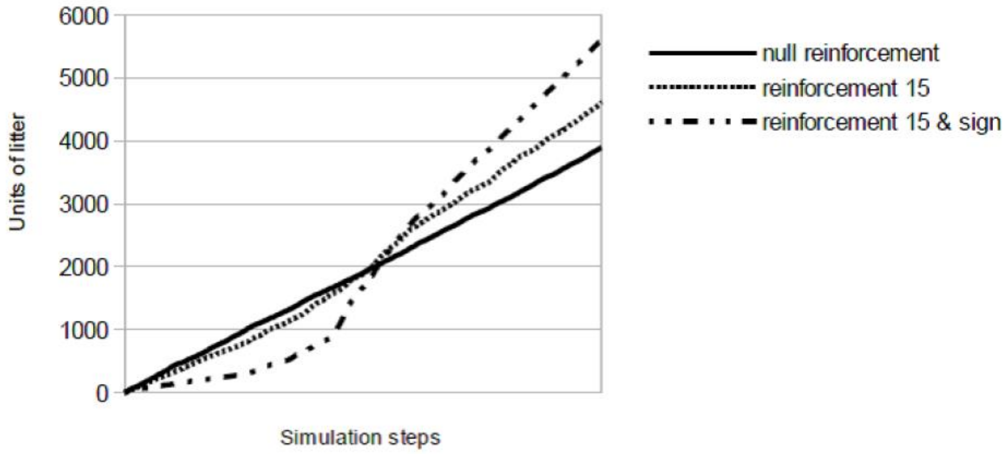


Figure 2.3: ABM-derived littering rates for different strengths of descriptive norm (reinforcement) (Rangoni & Jager, 2017).

Rangoni and Jager (2017) skilfully captured Keizer et al.'s (2011) explanation of littering behaviour in an ABM. Every agent is conceptualised as having a static hedonic score, and a dynamic normative score, which changes according to the density of litter on the surrounding tiles. The effect of signs with normative anti-litter messages are also incorporated eventually (see figure 2.3); they were shown to have effects similar to descriptive norm activation (Cialdini et al., 1990), although their influence is explained differently. This part of the model was calibrated using Keizer et al.'s (2011) experimental data. Bins were graciously programmed in the model under the assumption that the attractiveness of disposing of litter properly is a function of the proximity of the agent to the bin, where the attractiveness score must weigh up to both of the agent's goal frame scores. The model was ultimately used to investigate the cost-effectiveness of various cleaning strategies, i.e. how many cleaners should clean how often and following which patterns. However, the incoherent framework upon which the model was based demands another attempt at capturing littering behaviour and normative influence in ABM.

2.2.5: Summary

In conclusion, agent-based modelling seems to be a very suitable simulation method for researching littering dynamics; particularly because of the agents' capacity for autonomous acting and the praised link between micro and macro patterns. Even though a model of little complexity should suffice in researching littering behaviour, the model will likely be of limited validity because of incomplete datasets and the general difficulty of validating social models. Yet knowledge can certainly be derived from the modelling process and the end-product because underlying assumptions will be made explicit, parameters can be experimented with and future research could be facilitated, particularly with transparently described models. The only agent-based model about littering that has been developed has produced several usable insights into cleaning strategies and assumptions about littering behaviour but was based on a theory of limited reliability. The second sub-question, *how can ABM be used to increase understanding about littering*, has hereby been answered.

3: Methodology

Based on the theory about littering, norms and ABM, a model will be developed. This chapter will detail the development process, spanning the conception, implementation and evaluation of the model. The final versions of the model will be set in the Dam and Kalverstraat, two of the most popular tourist destinations in the Amsterdam city centre that attract much litter. While both are pedestrian zones, the former is a large square surrounded by bicycle paths, tram rails and automobile lanes around which crowded museums and shops are located. The latter is a relatively narrow street that houses a large number of stores on both sides, and is crossed halfway by a similar street, Hartenstraat, at a right angle. The differences in accessibility and visibility between the two areas are hypothesised to affect littering rates, as will be explained later in this chapter. Both research areas are shown in their topographic context (derived from OpenStreetMap) in figure 3.1.

Figure 3.1: Dam and Kalverstraat in their topographic context.

3.1: Conceptual model

3.1.1: Overview

In broad lines, littering behaviour is attempted to be elucidated by simulating individual agents that move through an area and potentially generate an unwanted item that is littered, pocketed, or disposed of in a bin. Agents have heterogeneous dispositions with regard to litter, some being more prone to disposing of it improperly than others. If they see each other disposing of litter, the descriptive norm will activate for them, leading them to adjust their chance to litter to the amount of existing environmental litter (see the 'reinforced' lines in figure 2.3). As explained in chapter 2.1.3, the activation of injunctive norms seems to occur much less predictably and in a greater multitude of ways. Therefore, to preserve mechanistic adequacy, its effect is omitted from the model.

The model is different from the existing ABM (Rangoni & Jager, 2017) in several ways. Most importantly, it has been attempted to be based on a more theoretically grounded framework: the theory of normative conduct. Secondly, descriptive norm activation by communication of visible behaviour is attempted to be described by the model. This is assumed to be both more dynamic and realistic than introducing a global reinforcement factor which represents anti-littering messages on signs (as done by Rangoni and Jager [2017]). Finally, more variables are intended to be programmed as stochastic rather than deterministic because it represents people's limited rationalism. Where Rangoni and Jager (2017) used stochastic variables, they assumed them to be normally distributed and duly described as an average and a standard deviation. This approach will be used in the present model as well. The following sections will explain the preliminary assumptions behind the model's agents, interactions and environments. The most important model variables are summed in a table for each category (3.1-3.3).

3.1.2: Agents

The agents in the model represent individual pedestrians. Their defining characteristic is a personal norm that explains a great portion of variation between individuals' littering behaviours, which should be reflected by a large standard deviation. Norms, even personal ones, have been described as wholly unimportant to behaviour unless they are activated (Kallgren et al., 2000). Yet an uneven littering rate is sometimes reported for different environmental conditions when norms are understood to be inactive (e.g. figure 3.2). Therefore, the variance from the average personal norm should be high to account for coincidental injunctive norm activation, which can even be carried over from settings outside of the research area (Reno et al., 1993). The average personal norm should be valued around a 0.35 chance to litter (Cialdini et al., 1991; Reno et al., 1993; Keizer et al., 2011). In all these studies, no bins were available to the subjects. Therefore, this number (a mean of all littering rates in the studies, regardless of normative influence) could be taken as an approximation of the average personal norm independent of other factors. Because the accompanying standard deviation will reflect differences in personal norms, as well as accidental norm activation and factors outside of the scope of this research, a value of 0.1 is presumed to be appropriately large.

All agents belong to an age group. They can be either between the ages of 18-32, a group that was found to litter 1.5x more than average (26% versus 17% in real-world settings), or non-18-32, who littered at 0.8x the average rate (14% versus 17% [Schultz et al., 2013]). These values will be reflected as multipliers to agent' personal norms. A third of the individuals described by Schultz et al. (2013) were part of the younger age group. Agents are furthermore represented as walking through the environment, one step per model step, which corresponds to a real-world second. Their walking speed is assigned a random value between 0.85 and 1.35 meters per second; a range that is intended to represent varying pedestrian behaviour as a result of individual differences in movement speed and motives for walking (e.g. commuting or strolling leisurely).

With every step, agents have a chance to generate litter. Schultz et al. (2013) reported that only 28% of the people in their observations left the research area without pocketing an item or disposing of it. However, no detailed description of their research area is available and nor is data about littering rates in the research areas of this study. Therefore, every pedestrian in the model is programmed to litter once on average during their transversal following the formula: 1 / *average steps to walk through the area*.

When litter is generated, agents will first locate the nearest bin. They will move towards the bin and dispose of their litter there according to a chance calculated by a function of their personal norm (since the stronger the personal norm against littering, the more willing one is expected to be to walk to a bin) and the distance to the bin. If the agents choose not to walk to the bin, they will either litter or pocket the waste following the chance represented by their personal norm. Schultz et al. (2013) show that littering rates increase by roughly 2.3% per meter from a bin, with littering rates of 12% at 0-1.5 meters and 30% at 18 meters or more. The mean distance from a bin at the time of littering was around 8.5 meters in their survey. While insightful, these data cannot be used directly to calculate the function between the personal norm and the distance to a bin because they are highly aggregated both across research areas and scales of measuring. Furthermore, they describe several more mechanisms than merely the effect of distance on a person's willingness to walk to a bin (such as descriptive norms and the visibility of a bin).

Although intoxication and tourism have neither been controlled for in the works cited in this study, nor are their implications to littering or norms clearly explained on a theoretical level, a hypothetical variable could be designed to implement them in the model. A very liberal assumption could be that tourists in Amsterdam display above average rates of intoxication and therefore have a higher chance to litter as per their personal norm, as well as higher chances to generate litter per step. A variable of sorts should merely be used to illustrate extreme cases but is omitted in this model because the same effect can be achieved by adjusting the 'age' variable, as will be done in chapter 4.

Variable	*Value*	*Influence*	*Reference*
personal norm	mean: 0.35, standard deviation: 0.1	choice to drop or pocket litter and willingness to move to bin	Cialdini et al., 1991; Reno et al., 1993; Keizer et al., 2011
age	age 18-32: 1.5, age 32<: 0.8	multiplier to personal norm	Schultz et al., 2013
walking speed	random: 0.85-1.35 m/s	movement	-

generate litter	1 / average steps in the area	prompts agent to choose disposal behaviour	-
bin proximity	< 9 meters	max distance at which agents are willing to move to bin	Schultz et al., 2013

Table 3.1: Most important agent variables.

3.1.3: Interactions

The descriptive norm has been shown to activate in individuals who observe others disposing of litter (properly or improperly). While in reality holding on to litter when it is generated is more common than either type of disposal (Schultz et al., 2013), the action is not nearly as visible and is therefore not understood to activate descriptive norms. In the model, agents also sense the amount of litter in the environment and visible behaviour of the agents around them. Norms were activated at 5 meters from the individual in experiments (Cialdini et al., 1990), but it would presumably also happen at greater distances (up to 12 meters seems reasonable). An agent that litters or throws litter in a bin will signal to all agents in whose view it is that the descriptive norm should be activated for them.

The descriptive norm is a multiplier based on the amount of litter in the environment (which is a ratio as will be discussed shortly). It has no effect on the model behaviour or the agents unless it is activated for them. If it is active, it will act as a multiplier to the personal norm. When there is little litter, the ratio should be a fraction, thusly decreasing the agent's chance to litter. In littered scenarios, the active descriptive norm will increase the likelihood that an agent will litter. The descriptive norm will remain active for as long as an agent is in the study area (Reno et al., 1993). In the real world, the descriptive norm may be active in individuals even when they have not been exposed to another's behaviour. Therefore, an unknown portion of agents should spawn with an active descriptive norm.

Variable	*Value*	*Influence*	*Reference*
viewing distance	12 meters	area in which disposal and environmental litter are sensed	-
descriptive norm	clean areas: 0.5, dirty areas: 1.5 (approx.)	multiplier to personal norm and willingness to walk to bin	Cialdini et al., 1990

Table 3.2: Most important interaction variables.

3.1.4: Environments

A key environmental feature in the model will be disposed litter. Although the behaviour behind littering and its material contents are clearly defined in theory, there is no singular description of what constitutes a 'littered' area. In one Cialdini et al. (1990) study (the results of which are depicted in figure 2.2), a parking lot floor in 'heavily littered' condition is described as containing "an assortment of handbills, candy wrappers, cigarette butts, and paper cups" (p. 1016). The littering rate for inactive descriptive norms in that setting is 32%.

Schultz et al. (2013) scored their surveyed areas on a 1-10 scale from 'not at all littered' to 'extremely littered', the average rating being 2.4. Every scale point increase was shown to lead to a 2% increase in littering (at a 17% littering average), which means in 'extremely littered' areas the littering rate averaged at 32%, too. These opaque yet surprisingly consistent terms suggest an intuitive value could be used for weighing the abundance of litter in the model. An assumed value of 10 units of litter in the agents' 12-meter radius may be a plausible number to represent 'normally' littered environments – in between clean and untidy. It is derived from Cialdini et al.'s (1991) third study, where environments with more than 8 pieces of litter attracted above-average littering rates. However, since the increments in amount of litter in that study were distributed unevenly, the value is rounded upwards to 10 units of litter.

A variable for agents' tolerance to litter in the environment was used in Rangoni and Jager's (2017) ABM, which leads to a different interpretation of 'littered' for every agent, affecting the descriptive norm if it is active. This seems a sensible assumption to make, given the unclear definition of the condition in empirical research, and the plausibility that people would heterogeneously perceive areas as (un)tidy. However, the variable might be too hypothetical to include in a model given the vagueness of the term 'littered' in empirical studies in the first place. It is therefore omitted from this research but a recommendation for future research regarding individual tolerance to litter is in order.

Bins are another important feature of the modelled environment. They will have a given capacity (assumed to be 100 items in Rangoni and Jager [2017]) and will push any additionally deposited litter onto neighbouring tiles. A likely emergent phenomenon is the clustering of litter around bins – probably mostly around well-placed bins (Wever et al., 2008). Figure 3.2 depicts the phenomenon in Rangoni and Jager's (2017) model. The placement of litters will be based on real-world locations in one scenario; in others finding an optimal location or capacity will be an experimentational objective.

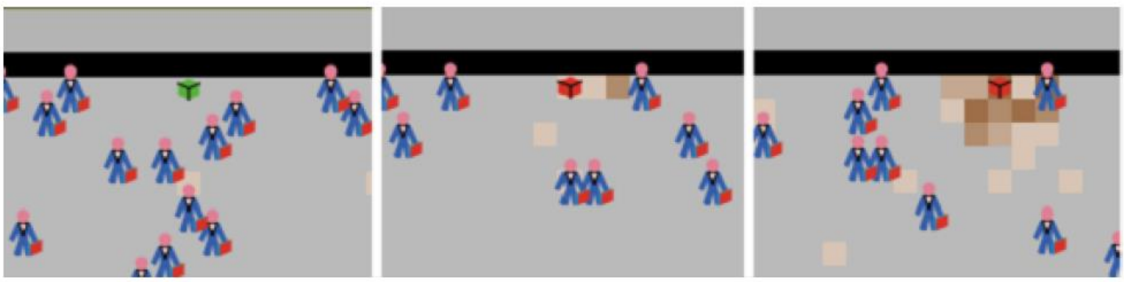


Figure 3.2: Litter emergently clustering around bins: the ABM at 40, 160 and 320 simulation steps (Rangoni & Jager, 2017).

It is one of the aims of this research to experiment with patterns of littering behaviour in varying street layouts. The wideness of streets may affect agents' distance to bins or how many agents can be sensed at once, while corners may even prevent norm activation behaviour completely if visibility proves to be limited. The Dam and Kalverstraat are among the most crowded and tourist-dense streets in Amsterdam and they have distinctive street layouts. Experimentation with different environment layouts could identify the underlying causes of litter bottlenecks, for instance.

Variable	*Value*	*Influence*	*Reference*
clean/littered	10 pieces of litter within viewing distance	strength of descriptive norm multiplier	Cialdini et al., 1990; 1991; Schultz et al., 2013
bin capacity	100	amount of litter initially kept off the ground	Rangoni & Jager, 2017
street layout	variously shaped study areas	viewing distance and bin positioning	-

Table 3.3: Most important environment variables.

3.2: Implementation

3.2.1: Materials

The modelling process was carried out in GAMA 1.7, a free-to-use agent-based modelling platform. The software is spatially explicit and supports shapefiles, ESRI's ubiquitous vector-based data format. Besides GAMA's intuitive programming language, the platform facilitates carrying out multiple simulation runs at once, a feature that is highly useful for models that require many permutations because of stochastic variables. The numerical model output was furthermore edited and visualised using Microsoft Excel.

In the advanced versions of the littering model, street layouts of two Amsterdam streets were used. These were derived from the Dutch national open-source topographic registration (Basisregistratie Topografie, BRT). The datasets were accessed through the ESRI geodata portal and adjusted using ArcGIS Pro. Of the roads ('wegdeel') dataset, objects with the pedestrian ('voetpad') attribute in the research areas were isolated. Whenever necessary, features were merged using the ArcGIS tool of the same name.

Additional line-feature shapefiles were created to designate the entrances and exits of the research areas, the shapes of which were hand-drawn. The litter heatmaps were created by running GAMA shapefile output through the ArcGIS Pro 'Kernel Density'-function. Finally, Google Maps satellite view was used to locate the real-world bin positions in the study areas.

3.2.2: The modelling process

3.2.2.1: Agent movement and norms

In the first version of the littering ABM, a geography has not been defined yet. Instead, agents spawn anywhere on either edge in width of a 70 * 25 meter rectangle and define anywhere on the opposing edge as their goal to move to. If their goal is reached, they disappear from the area. Agents have a 0.33 chance to be below the age of 32, in which case they are depicted as green circles; if they are above that age they spawn as purple circles. With every step, the agents have a chance to generate litter, which leads them to calculate whether they will keep the litter with them, turning pink, or dropping the litter and colouring orange. In the latter case, an inert piece of litter (visualised as a small red dot) will spawn at their location.

The chance that generated litter is dropped rather than pocketed corresponds to the agent's personal norm value. The mean personal norm is 0.35, which means that on average 35% of all generated litter will be dropped on the street. However, as established in theory, this behaviour is also affected by the litter in the environment if the descriptive norm is activated. Although the extent of the effect has not been irrefutably reported on, clean areas typically decrease littering rates by 50%, where littered areas seem to increase them by 50% (Cialdini et al., 1991). The distribution of this effect is approximated in the graph of figure 3.3. The corresponding function is as follows:

$$N_a(L) = \frac{1.7}{1 + 2.4e^{-0.13L}}$$

with active descriptive norm N_a and visible environmental litter L.

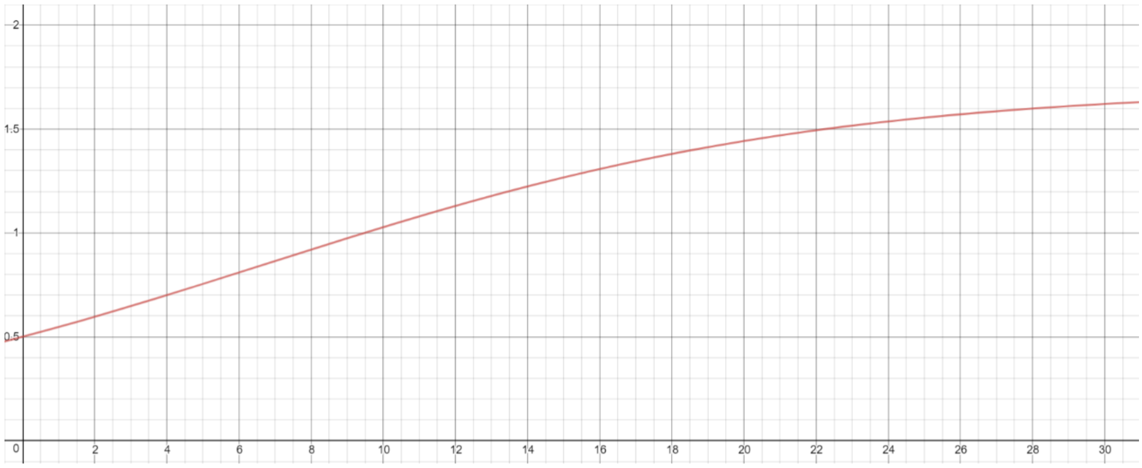


Figure 3.3: The effect of the descriptive norm (y) as a function of the amount of visible environmental litter (x).

The descriptive norm functions as a multiplier to the personal norm. When an agent litters, it signals to other agents within viewing distance that their descriptive norm should be activated. With every step, agents also count the number of pieces of litter around them. In practice, this means that an agent with an activated descriptive norm and a personal norm of 0.35 will on average have a (0.35 * 0.5 =) 17.5% chance of dropping litter in areas devoid of litter and a (0.35 * 1.44 =) 50% chance of littering when surrounded by 20 pieces of litter. Note surrounding litter is counted locally rather than globally. This reflects the real-world pattern that an evenly littered area is perceived as less clean than an equally littered area where litter is piled up. Furthermore, to account for pedestrians' coincidentally active descriptive norms, all agents will have a 10% chance to spawn with an active descriptive norm. Agents with an active descriptive norm are indicated by a light green outline. A screenshot of this version of the model is shown in figure 3.4.

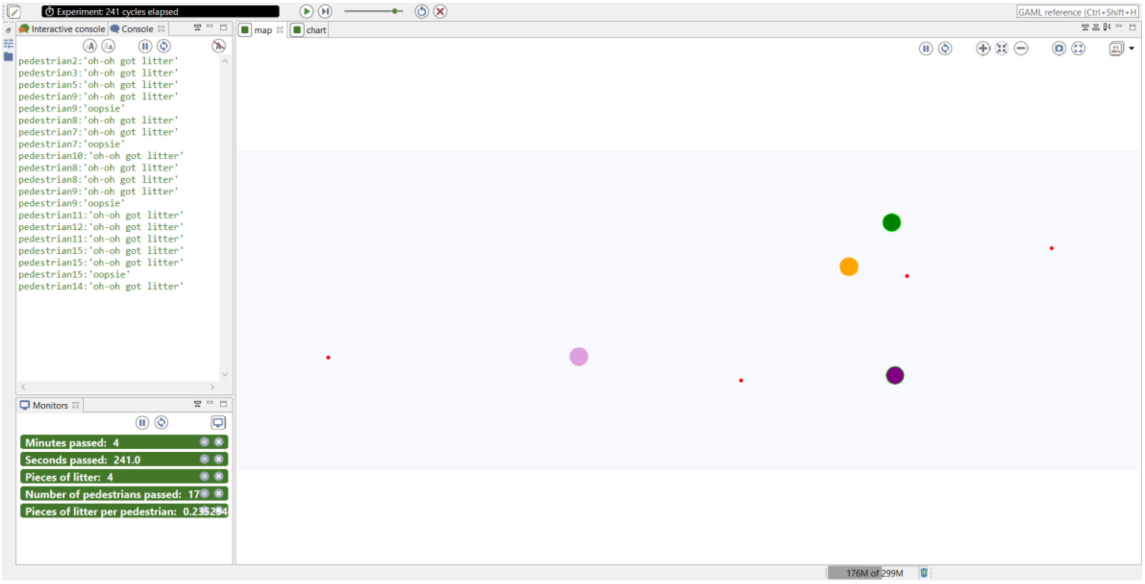
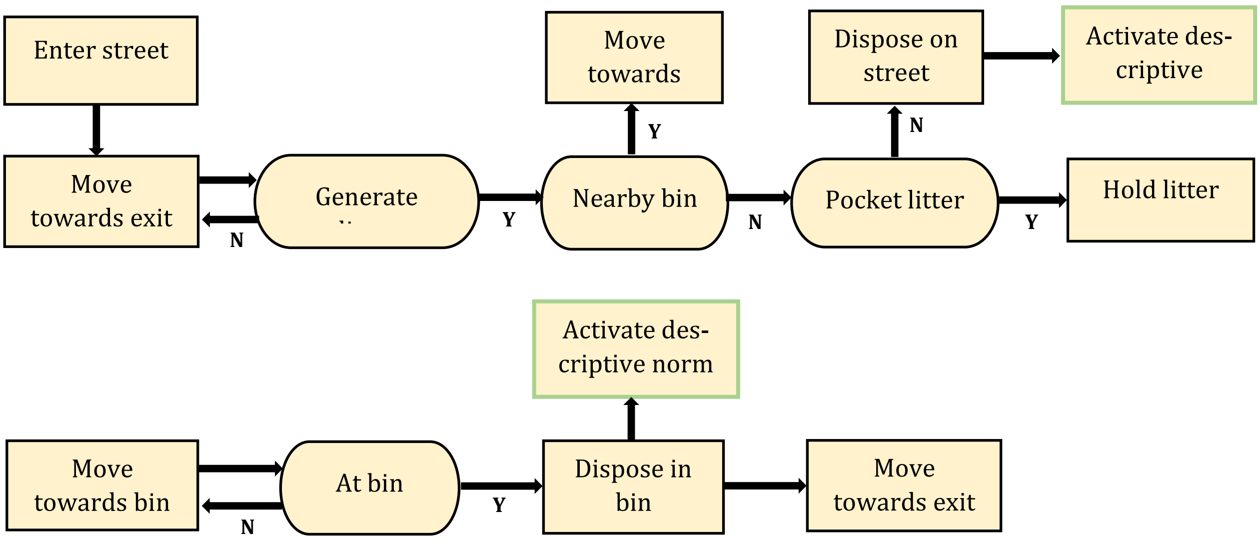


Figure 3.4: A simulation of the initial littering ABM in GAMA. The green and purple agents were within the visible radius and have witnessed the orange agent dispose of litter, which has activated the descriptive norm for them. The pink agent has generated litter but pocketed the item rather than littering it. Four pieces of litter can be seen lying on the floor.

3.2.2.2: Inclusion of bins

In the next modelling stage, bins are introduced. They are depicted as dark orange squares and are defined by the amount of litter they contain, as well as a maximum capacity. With the addition of bins to the model, agents have a third option when they generate litter: disposing of it in a bin. Whenever they generate litter, agents will locate the nearest bin. If it is outside their tolerated distance, they have a chance to drop litter, which is calculated as before. If they pocket the potential litter, it now means they will calculate which bin is closest with every step. If a bin presents itself within their tolerated distance and litter has been generated or is held, agents will replace their movement goal with that bin. Upon reaching the bin, they ask the bin to update its contained litter by one piece and revert their movement goal back to their initial destination. A schematic overview of the most important previously explained agent behaviour is depicted in figure 3.5.



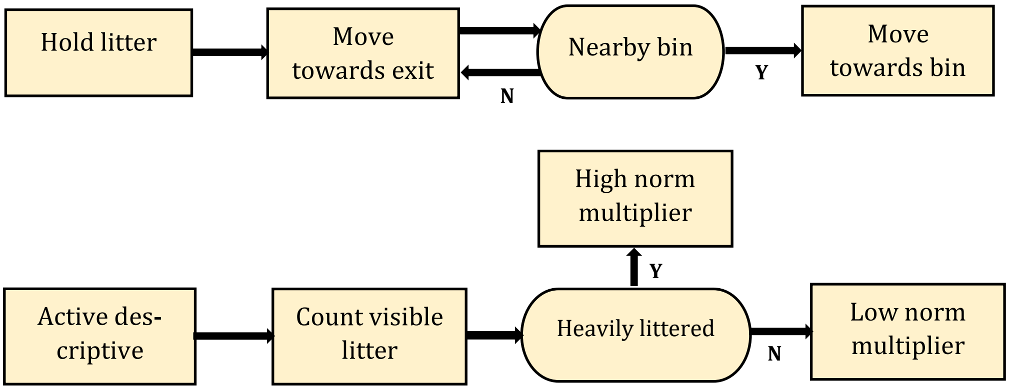


Figure 3.5: Schematic overview of key pedestrian littering behaviour in the ABM. Blocks with a green outline are communicated to surrounding pedestrian agents.

Whenever a bin is asked to update its containing litter beyond the maximum capacity, a piece of litter spawns anywhere beside it instead. In Rangoni and Jager's (2017) ABM, this phenomenon was not included but rather emerged from the model's behaviour. In that model, agents recalculated the distance to the closest bin upon reaching a full bin, and instead tended to litter next to the bin if that distance was overly large. While that programming solution is arguably more elegant than the one applied in this research, it assumes people cannot see how full a bin is from a distance. The difference between the effects of the two programming assumptions is most pronounced in situations where a bin is full, but not much litter has accumulated around it: In Rangoni and Jager's model, agents would still have a reasonable chance of moving towards the next bin instead, whereas in this new ABM, agents always dispose of litter in the bin regardless of its contents. In the real people routinely and willingly dispose of their litter on top of or next to full bins world rather than finding the next closest bin (Wever et al., 2008). Bin behaviour is therefore kept simpler in this model, even if it is possibly less robust without the emergence present in Rangoni and Jager's design choice.

Critical in the agents' behaviour regarding bins is their heterogeneous interpretation of proximity. Although the positive correlation between littering rates and the distance to a bin has been widely reported on (Bator et al., 2011; Schultz et al., 2013; Al-Mosa et al., 2017), the extent of interpersonal heterogeneity regarding this correlation is unclear. A mean distance of around 8.5 meters to a bin at the time of littering could be coupled to the mean personal norm of 0.35 in this model. A logarithmic relation could plausibly exist between the variables, where people with a stronger anti-litter personal norm are willing to walk unproportionally further than people with weaker norms. In this suggested relationship, personal norms of one standard deviation below mean could correspond to a willingness to walk up to 12.5 meters to the nearest bin, while one standard deviation above mean would not walk farther than 4.5 meters. The graph in figure 3.6 and the formula below approximate the suggested relationship. A screenshot of this version of the model is furthermore shown in figure 3.7. This version of the model is included in appendix 8.1.

$$P_n(D) = \frac{20}{1 + 0.08e^{8.2D}}$$

with personal norm P_n and distance to bin D.

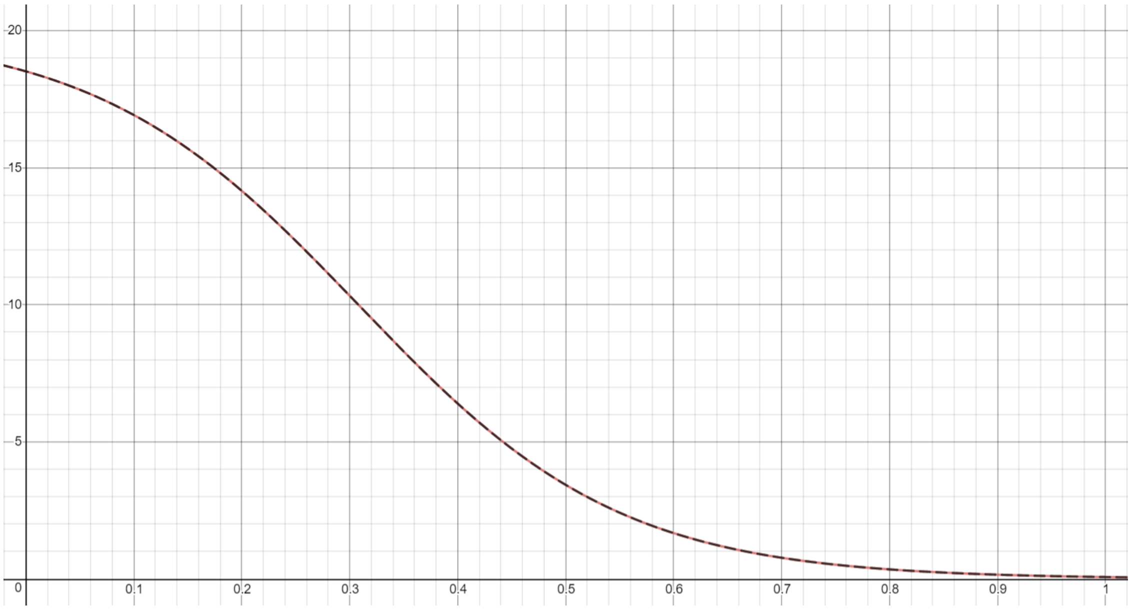


Figure 3.6: The maximum distance in meters agents are willing to travel for disposal in a bin (y) as a function of their personal norm (x).

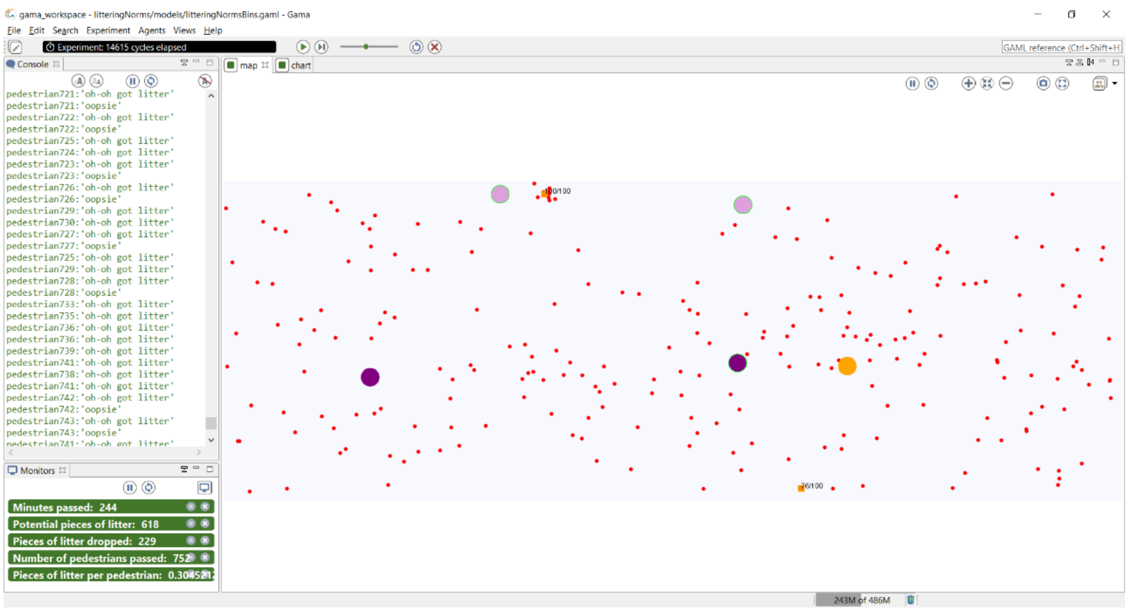


Figure 3.7: A simulation of the second version of the littering ABM in GAMA. After 244 in-model minutes, the global littering rate is 30.45%. The top bin has been filled beyond maximum capacity and some litter has begun to cluster around it, while the bottom one has not been entirely filled yet.

3.2.2.3: Street layouts

In the final versions of the model, the geometries of the Dam and Kalverstraat are added along with the real-world locations of their bins. Together with the newly built entrance/exit shapefiles, this change requires an overhaul in agent movement. Agents now spawn anywhere on the entrance/exit lines and define their movement goal as any other location defined in that geometry. Particularly in the windy Kalverstraat geometry, this leads to the issue of agent pathfinding. Where agents could not move outside of the study area in earlier model versions because of the rectangular environment, they must now restrict their movement to the shape of the street in question. Because no simple built-in pathfinding mechanism is available in GAMA, agents are programmed to check whether the line between their location and their destination intersects with any of the street's edges upon spawning. If so, their ad hoc movement goal is a widely accessible point in the middle of the street geometry, which they will move to until they can reach their original destination without crossing the edges of the street. This solution is not applicable to all possible spatial scenarios because a central point that is accessible from every location in the geometry is not always available. It is nonetheless free of bugs in the current scenarios and requires relatively little processing power.

Since the 8200 m² surface of the Dam is 4.7 times that of the stand-in rectangle, and the Kalverstraat's 2800 m² surface 1.6 times, the chances of pedestrians spawning per model step are multiplied accordingly. The chance that agents generate litter is also correspondingly adjusted. Where the average number of steps was calculated as a Pythagorean equation of the width and half the height of the rectangle's sides in the previous model geometry, it is now defined as the average distance of the entrances/exits to the central ad hoc destination point times two, or 1 / (59 * 2) for the Dam setting and 1 / (81.5 * 2) for Kalverstraat. (These calculations proved inaccurate, consequently the chance that agents generate litter was later adjusted; see section 4.2 for details.) Because of the Kalverstraat's length, this number of steps is higher and consequently its agents have a lower chance to generate litter per step.

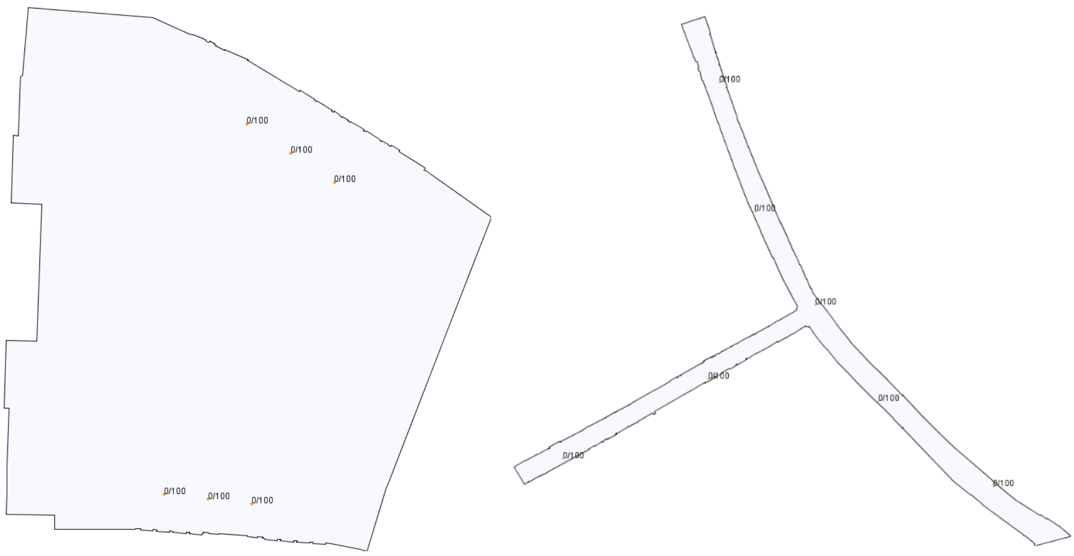


Figure 3.8: The initial states of the Dam and Kalverstraat simulations with bins in their real-world locations.

Besides the agents' movement, their field of view should also be limited by the boundaries of the street. Upon calculating the distance to the nearest bin and when counting the surrounding litter, agents leave out objects that are obstructed from their field of view using the same intersect procedure. In order to make the efficiency of the model, agents no longer count the litter surrounding them with every step (which was the case to keep the descriptive norm updated), but only do so when litter is generated in case their descriptive norm is active. Screenshots of the Dam and Kalverstraat simulations are displayed in figure 3.8. This version of the Kalverstraat model is included in appendix 8.2.

3.3: Evaluation

3.3.1: Face and expert validation

To increase the usability and reliability of the model, face validation is typically carried out as an elementary step towards model validity (Klügl, 2008). The process is composed of three sub-methods. Animation assessment is a visual inspection of the model behaviour during simulation. Immersive assessment follows a single agent during a model run. With output assessment, the plausibility of absolute model output is tested. For additional reliability, these assessments are often carried out with supervision of an expert in modelling or the field of study. The expert validation of this ABM was carried by Daan Goppel, an urban planning scientist who has designed new garbage cans for the municipality of Amsterdam based on insights from behavioural studies.

When the model is run, agents move as intended between randomly selected entrances and exits. They sometimes generate litter and correctly follow the decisional process described in figure 3.5. Litter initially does not appear close to bins frequently, but as the bins fill up, it increasingly does. Mr Goppel finds the general processes in the model realistic, but comments that pedestrian movement is not as linear as depicted in tourist squares such as Dam. People wander more and often sit down, thereby littering passively, he adds. Agents leaving their litter next to or on top of a bin when it is full strikes him as very realistic. Many do not consider leaving their trash near a full bin littering because they feel it is the responsibility of the municipality to maintain the bins. Although litter next to bins is more convenient to clean than far from them, it is a concerning behavioural pattern because litter is often carried back into the street through wind and weather, thereby certainly contributing to the littering rate.

On the agent level, behavioural choices are made in line with the conceptual model. Mr Goppel agrees with the conception of personal norm as a probability of littering. In the real world, even people with the strongest anti-littering disposition are sometimes preoccupied and litter regardless, he remarks. Furthermore, norm activation is communicated properly between agents and if their descriptive norm is activated, the multiplier is duly informed by the amount of litter surrounding them. The distance they are willing to move to a bin is rather disparate as a result of the selected function – particularly when the descriptive norm is active. A willingness to move 8.5 meters to the closest bin on average seems reasonable to Mr Goppel, since agents are already moving. If agent movement were more realistic (i.e. with the inclusion of sitting or wandering agents), an average of 8.5 might be too high. A visible area of 12 meters in radius also seems realistic, but Mr Goppel adds that fields of view should be obstructed by other agents; in a more widely applicable model agents should not be able to see as far when surrounded by others.

Comparison of model output to empirical data is problematic because many empirical studies are aggregated or produce varying results, which was the reason for using hypothetical values for parameters such as the chance to generate litter. Yet assessment of dependent variables during the simulation shows that the results are not far from the empirical evidence. When streets are clean, the global littering rate is around 20%; when dirty it typically increases by roughly 10%. Controlling for activated descriptive norms shows very different results. Regardless of the state of the environment, the littering rate lies somewhere between those values when the descriptive norm is omitted. On the other hand, a 'reinforcement' effect (Keizer et al., 2011; Rangoni & Jager, 2017) of littering rates of around 12% in clean, and 40% in littered settings can be observed when the descriptive norm is permanently activated for all agents. This output, though not accurately comparable to empirical data in itself, suggests that the model is capable of consistently producing realistic patterns.

3.3.2: Sensitivity analysis

3.3.2.1: Method

In order to gain insight into the relationships between parameters, a sensitivity analysis will be carried out. Whether sensitivity analysis is understood to be part of the verification process because it only refers to the workings of the model (Gräbner, 2018) or of its validation (Leombruni, Richiardi, Saam, & Sonnessa, 2006), it is highly useful for exploring the allocation of uncertainty in model output as a result of different inputs (Bruch & Atwell, 2015). Although sensitivity analysis is typically recommended to be carried out over small parameter variations, larger adjustment steps are more appropriate in this analysis. The ABM in development is probabilistic rather than deterministic because many key variables regarding agent behaviour are stochastic. This implies that not only are no two model runs the same, but the average of 100 runs still differs slightly from another 100-run average. Therefore, the relative effect of small parameter adjustments could be mistaken for inevitable inherent simulation variations.

Several parameters will be excluded from sensitivity analysis. The chance that agents generate litter per step is not based on real-world rates, but rather calculated in order to make all agents decide what to do with their litter once (on average) in their traversal through the street. This was programmed with the intention of reflecting littering rates in real-world experiments where every subject is given a chance to litter. Similarly, the capacity of bins has been given a value that is meant to be exceeded in the late model run, rather than reflect a realistic value. Furthermore, the mean personal norm and the effect of the activated descriptive norm are based on empirical data. It is therefore not meaningful to analyse the effects of these variables in a sensitivity analysis. The chance of agents entering the street, their age distribution, and bin positions are experimented with through different scenarios in chapter 4.

Four parameters remain, all of which were based on estimated values because empirical evidence was missing or not reported on. These comprise:

- the standard deviation of the personal norm distribution,
- agents' viewing distance,
- the fraction of agents that enter the area with an active descriptive norm, and
- the relationship between personal norm and bin proximity.

The effect of the three variables is tested by means of a 'one-at-a-time' (OAT) sensitivity analysis. This entails that the variations on a parameter are applied while all other variable values are kept constant (using the original value). The model is run 100 times per variable configuration; the average global littering rate (the most important quantitative dependent variable) for each parameter configuration is calculated over five timesteps. In addition, the percentage of agents whose descriptive norm activates during their traversal will be monitored for the viewing distance variations, since that is another factor the parameter is reasoned to affect. Finally, to preserve computing speed, the sensitivity analysis will be conducted on the second model version, which includes garbage bins but no street layouts. The effect of the street layout on littering rates will be discussed in the next chapter.

3.3.2.2: Results

Variations in personal norm distribution were explored for standard deviations of 0.05 and 0.15 around the previously established mean of 0.35. The original, rather high value of 0.1 was selected to reflect Schultz et al.'s (2013) observation that individual differences in littering behaviour have a significantly larger effect on littering rates than environmental factors. However, the results of the three configurations do not differ much in this model, as can be seen in figure 3.9. The greatest divergence shows after the model has run for some time, but still does not span much more than a single percentage point. The difference between the dependent variable values likely increases over time because the ground is highly littered in all scenarios and therefore the activated norm multiplier is at its maximum in almost all locations of the street. Higher personal norms (which occur more often when the standard deviation is higher) are then multiplied disproportionally to lower personal norms, leading the absolute littering rate to increase with them.

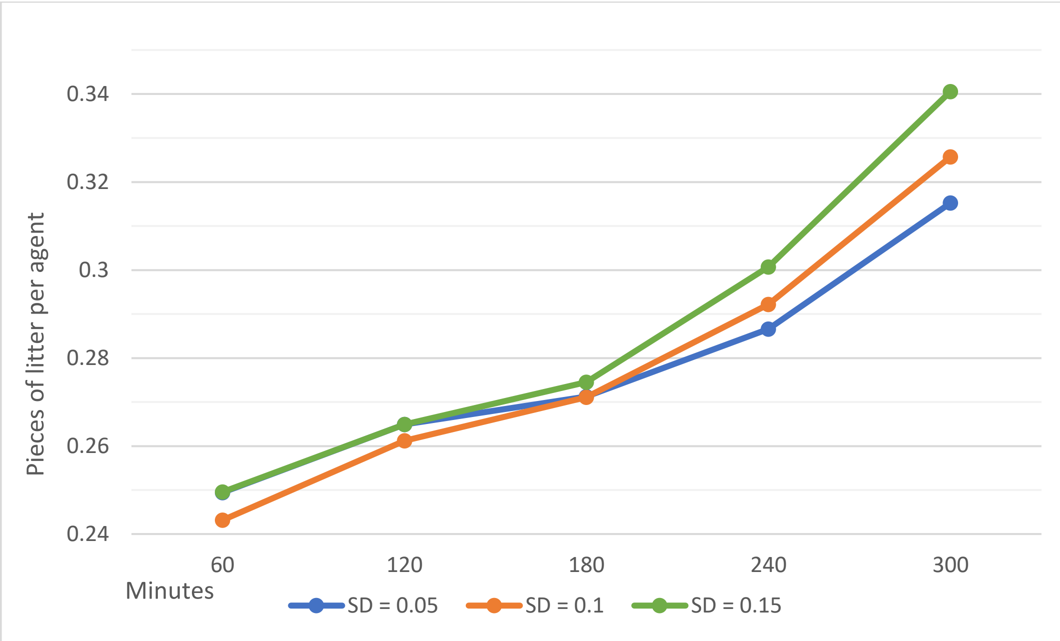


Figure 3.9: Average litter per pedestrian agent for different personal norm configurations.

Conversely, the littering rate in the original scenario is probably slightly lower than the others early in the model run because the difference between high and low personal norms is most balanced for that parameter value when the descriptive norm multiplier is generally low (due to a relatively small litter build-up early on). Though an explanation can be given for the different patterns, the possibility that such minor divergences have arisen from the probabilistic nature of the model should not be dismissed completely. Even though little difference in model output for different parameters indicates model stability and is therefore favourable, more research regarding real-world personal norm distribution is recommended. This is especially true because the model variable not only affects agents' chance to drop litter and perceptions of bin proximity, but it is also multiplied.

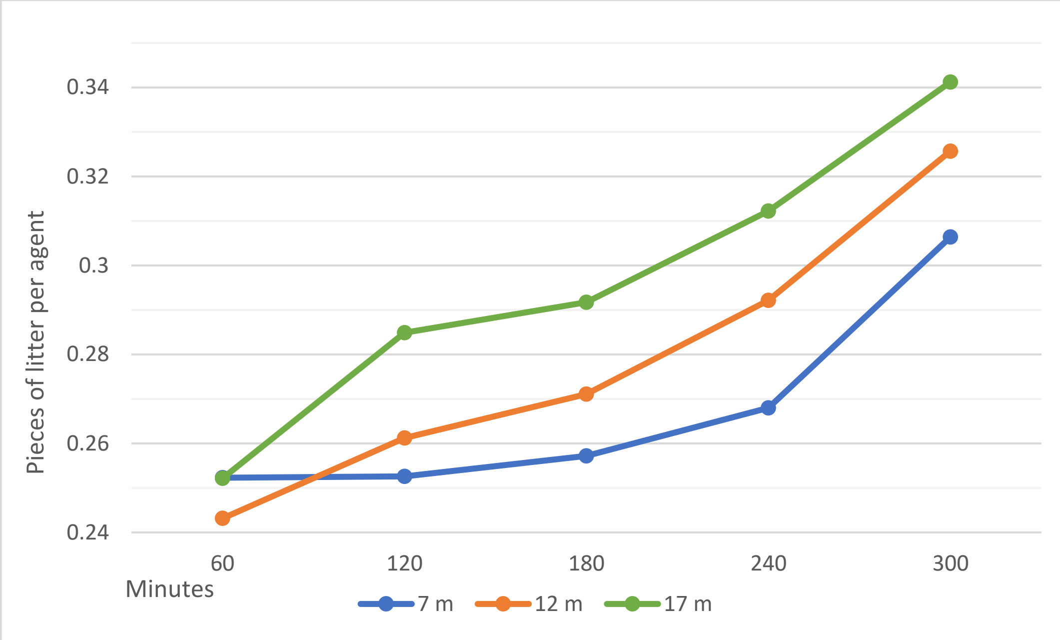


Figure 3.10: Average litter per pedestrian agent for different viewing distance configurations.

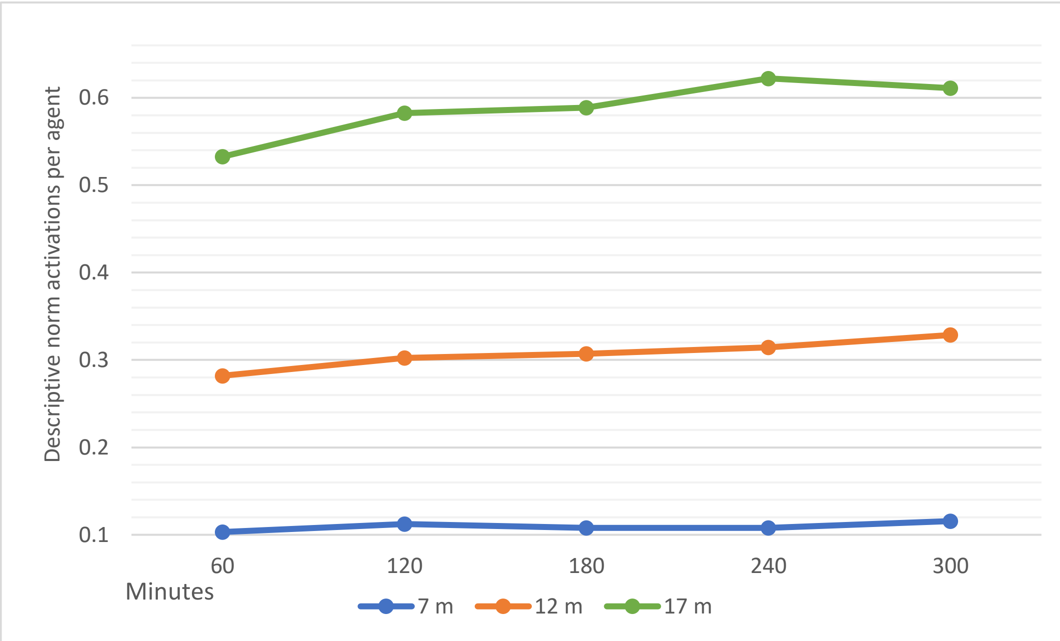


Figure 3.11: Average number of descriptive norm activations for different viewing distance configurations.

A similarly shaped litter-per-agent output is generated for the viewing distance alternatives, as depicted in figure 3.10. An area with a radius of 12 meters was considered a reasonable field of view for the agents, but radii of 7 and 17 meters were also considered in this analysis. Their influence is clearly displayed in the graphs: the larger the field of view, the more littered they consider their environment, and the more they litter themselves when the descriptive norm is active. Moreover, agents can observe each other disposing of litter more frequently when they can look farther, which leads to more descriptive norm activations and reinforces the littering pattern. The number of norm activations per agent confirm this explanation and is shown in figure 3.11. The mild trend upward in all three graphs is explained by a decrease in pocketing litter under conditions of activated descriptive norm and littered surroundings; which leads to increased litter disposal and therefore higher chances of communicating the descriptive norm to other agents.

Although the littering patterns for the alternative configurations of viewing distance diverge more than those for the personal norm standard deviation, their greatest difference is still only two percent. This value can be considered insignificant because real-world littering rates typically differ more among different empirical sources. Furthermore, a field of view spanning 12 meters in each direction seems realistic and certainly more so than 7 or 17 meters.

The chance of agents spawning with an activated descriptive norm was included to account for coincidental norm activation in the real world (i.e. when agents enter a street and are already focused on the amount of litter around them). The variable was set to 0.1 in the implementation of the model, a fraction that seems realistic. The test values that were applied in this sensitivity analysis are 0 and 1, or initially completely inactive norms and universally activated norms (as depicted in figure 3.12). The effect of the descriptive norm 'reinforcement' is clearly visible in the data; when all agents have an active norm, the littering rate is much lower in clean (early model run) settings, and much higher when the area is littered (late model run), as postulated by the focus theory of normative conduct.

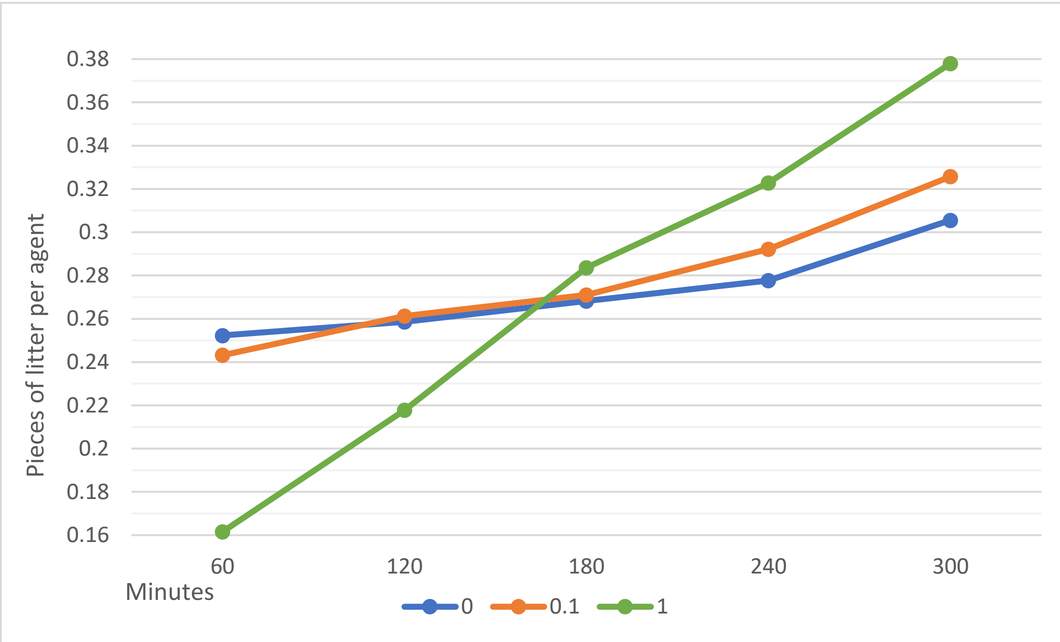


Figure 3.12: Average litter per pedestrian agent for different chances of agents entering the area with an active descriptive norm.

Although the impact of the variable is rather large (between the two extremes) and its value is not based on empirical findings, the inclusion of the initial activation variable seems justified. In the real world, being alone in a street does not mean the descriptive norm cannot play a role. Correspondingly, in model scenarios with few pedestrians (where inter-agent norm activation is low), the effect of the descriptive norm is still occasionally relevant. As long as there is no clarity as to the percentage of people with coincidentally activated descriptive norms in the real world, the value of the parameter should be kept small.

In order to analyse the effect of the suggested function of personal norm and bin proximity, two additional functions were used. Both describe a weaker reinforcement between the variables than the original function; alternative two even has a nearly linear shape between the relevant x-values. As with the original function, both alternatives were parameterised through trial and error with a graphical calculator. They are depicted in figure 3.13.

$$P_n(D) = \frac{66}{1 + 3.5e^{2D}}$$

and

$$P_n(D) = \frac{140}{1 + 10.97e^{1.1D}}$$

with personal norm P_n and distance to bin D.

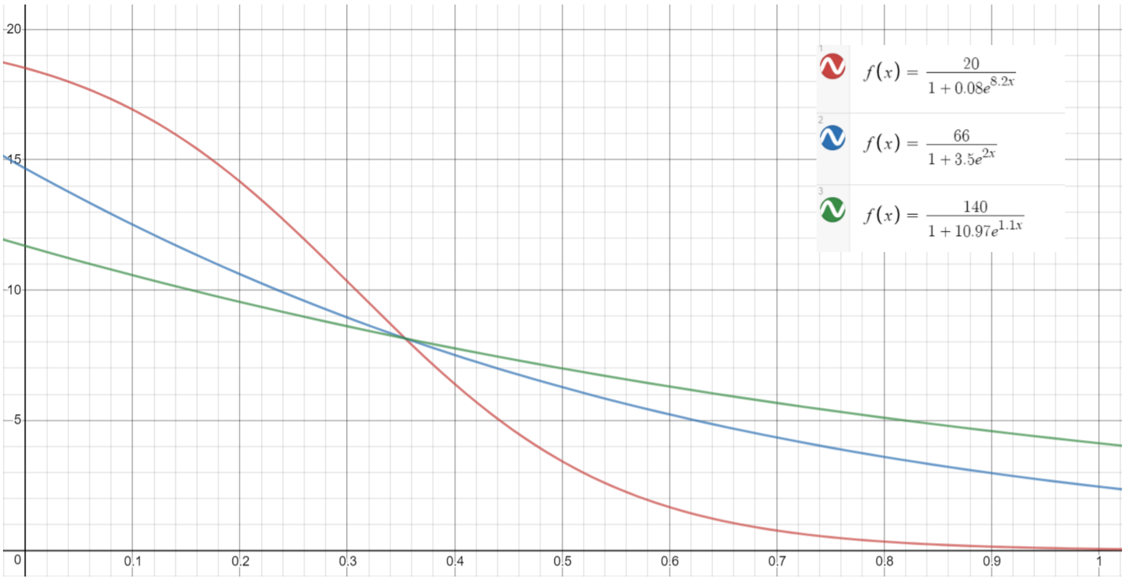


Figure 3.13: Alternative formulas for agents' willingness to travel to bins (y) under the influence of their personal norm (x).

The effects of the different functions on the average litter per pedestrian agent are shown in figure 3.14. Once more, the differences between the graphs are rather small. However, a markedly decreased littering rate can be observed for the alternative functions late in the model runs. This is a result of the much shorter distances agents are willing to travel (D) in the original function if their personal norm (P_n) has a high value, as is the case when the environment is heavily littered and personal norms are increased greatly by the activated norm multiplier. This shorter tolerated distance to bins leads to increased littering, as illustrated by the rising red graph in figure 3.14.

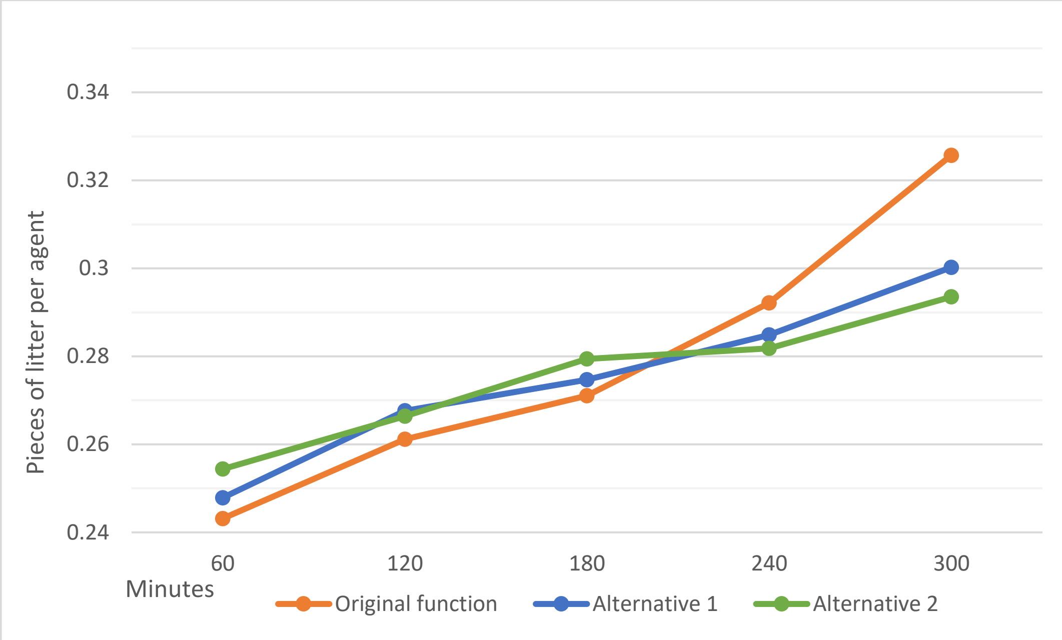


Figure 3.14: Average litter per pedestrian agent for different bin proximity functions.

The original tolerated distance function was shaped the way it is because people were found to occasionally litter at high rates even next to bins (Schultz et al., 2013), while it does not seem unrealistic that others are willing to walk relatively large distances to dispose of their litter in a bin. The logarithmic format seems reasonable because it dictates greater variation around the mean personal norm values, which reflects the large individual variation observed empirically. Since the relationship between personal norm and tolerated bin distance is not only under-studied but even merely assumed in this research project, it is highly recommended that the correlation is researched in order to be quantified. Regardless, the effect of the different functions still seems minor and therefore the original function will be judged as sufficiently reliable to be used in the model.

3.4: Summary

In this chapter, the previously compiled theory has been attempted to be implemented into an ABM. It was shown that though there is a good understanding of the mechanisms behind social norms as a whole and their general influence on littering, nuances in pedestrian and litterers' behaviour have not been reported on academically, let alone in a quantitative sense. Through iteration and sensitivity analysis, unknown variables such as agents' willingness to walk to a bin could be given a relatively reliable assumed value, while expert evaluation served as an additional step towards validity. The third sub-question, *how can littering behaviour plausibly be captured in an ABM*, has thusly been answered.

4: Results

In this chapter, the littering patterns in several scenarios with respect to crowdedness in the street, the age distribution of the population and bin positions will be researched. In the first part of this chapter, the scenarios are introduced. In the second, they are carried out on the ABM and the results are analysed.

4.1: Scenarios

Some littering mechanisms implied in the focus theory of normative conduct have been empirically researched; there is a relatively clear understanding of how descriptive norms activate, what their effect is relative to inactive conditions, in what settings they remain active and how their effect relates to those of injunctive norms. As described early in this study, other research topics regarding norms in realistic settings are hindered by practical limitations. With the finished ABM (that seems to follow the logic of real-world littering and the assumptions made in theory), a greater freedom of adjusting conditions that are difficult to study in the real world is potentially granted.

An important first subject of experimentation is the influence of the features of the built environment on littering behaviour. The effect of visibility (as a result of the street layout) on inter-agent norm activation, agents' capacity to find bins and their perception of the cleanliness of the environment are critical variables in this context. It could be expected that with high visibility resulting from little visual obstruction, more activations occur, bins are perceived as more nearby, and more litter can be seen. These factors likely affect littering rates mixedly, though reinforcement of increased norm activation is expected. Simulations of the model set in the Dam and Kalverstraat should provide sufficiently different contexts to analyse the dependent variables owing to their vastly different potential visibility.

The effect of crowdedness in an area on norm activation and littering behaviour is possibly even more difficult to study in the real world. Following the assumption of descriptive norms activation through observing litter disposals, it stands to reason that higher exposure to other pedestrians leads to increased norm activation rates, thereby increasing the reinforcement factor. Therefore, the chance of agents spawning will be increased by factor two for both settings.

A related scenario that is of research interest is the effect of a population composition on littering patterns. Although most demographic variables have been shown to be unimportant to littering behaviour, a negative correlation between age and littering rates was found in multiple studies. Since the recently increased littering rates in Amsterdam have also been linked to the relatively large share of younger adults in the city's tourist body, a different age distribution in the ABM will also be researched. On average, 33% of the agents are assigned to the 'below 32' age group (who were found to litter at 1.5 times above average as opposed to the other age groups that littered 0.8 times the average). This percentage will be increased to 66%, reflecting the hypothetical age composition of pedestrians in Amsterdam on a 'night out'.

Finally, based on the spatial patterns of litter in the research areas, alternative, more effective locations of bins will be attempted to be identified. The current bin positions are informed by aesthetics as well as pragmatism in terms of pedestrian flow obstruction and maintenance, which will not be taken into account in the scenario. Agent movement is also not highly realistic in the ABM (pedestrians often wander around the real-world Dam, rather than simply traverse it) so this scenario will be mostly aimed at exploring the potential uses of the model.

4.2: Experimentation

As in the sensitivity analysis, simulations for the varying parameter settings are run 100 times and averaged in the presented data. Upon reviewing the results of the first scenario, a wrong assumption seems to have been made with regard to the chance agents can generate litter in the different settings. While this chance was intended to be (1 / average number of steps to pass through the street), no more than 75% of agents in the Kalverstraat model generated litter, and only 46% did in the Dam model. As a simple transformation of the dependent variables using these factors would bypass the stochasticity and path dependency that make the models realistic, the results were rather used to calibrate the 'chance to generate litter' variable (by multiplying the original with 1 / 0.75 and 1 / 0.46, respectively), and the batch experiments were restarted.

4.2.1: Street layouts

Although it was expected that norm activations would occur more frequently in the Dam setting compared to the Kalverstraat, the opposite was found to be true (see figure 4.1). The openness of the square was reasoned to cause greater visibility of agents disposing of litter and by extension to more activations. Instead, it seems that the restrictive layout of the Kalverstraat forces the agents together, who are then more often within each other's visible range. This is especially true for bin disposals because bins are placed more strategically in the Kalverstraat (i.e. almost on agents' walking courses). The increase in the fraction of active norms over time that can be seen in figure 4.1 is a result of higher littering rates late in the model run (resulting from the increasingly littered environment) since littering leads to inter-agent norm activation.

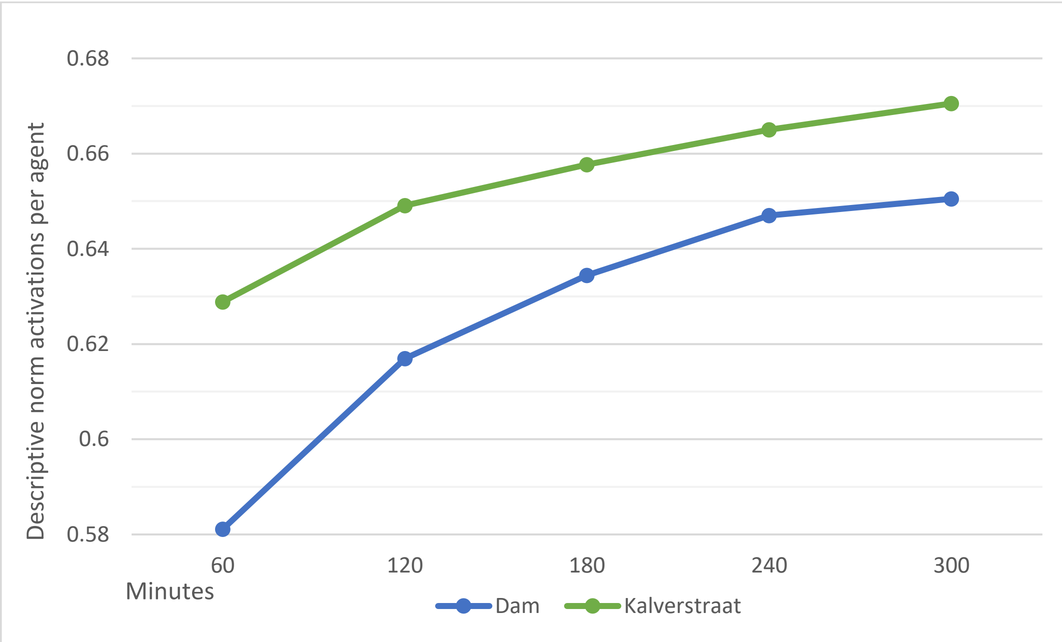


Figure 4.1: Average descriptive norm activations per agent for different street layouts.

Early during the model run, the littering rates for the two streets are as low as in the rectangular test area (compare figures 3.9 and 4.2), but they reach much higher rates later in the simulation. This is most likely also an effect of the more frequent descriptive norm activations in the real street scenarios (compare figures 3.11 and 4.1), which decrease the littering rate very early in the simulation, but greatly increase it later. Because the number of agents entering the street is modelled as a function of the environment's surface area, there are more agents present in the street scenarios at all times, increasing the chances of inter-agent norm activation. This effect will also be researched in section 4.2.2.

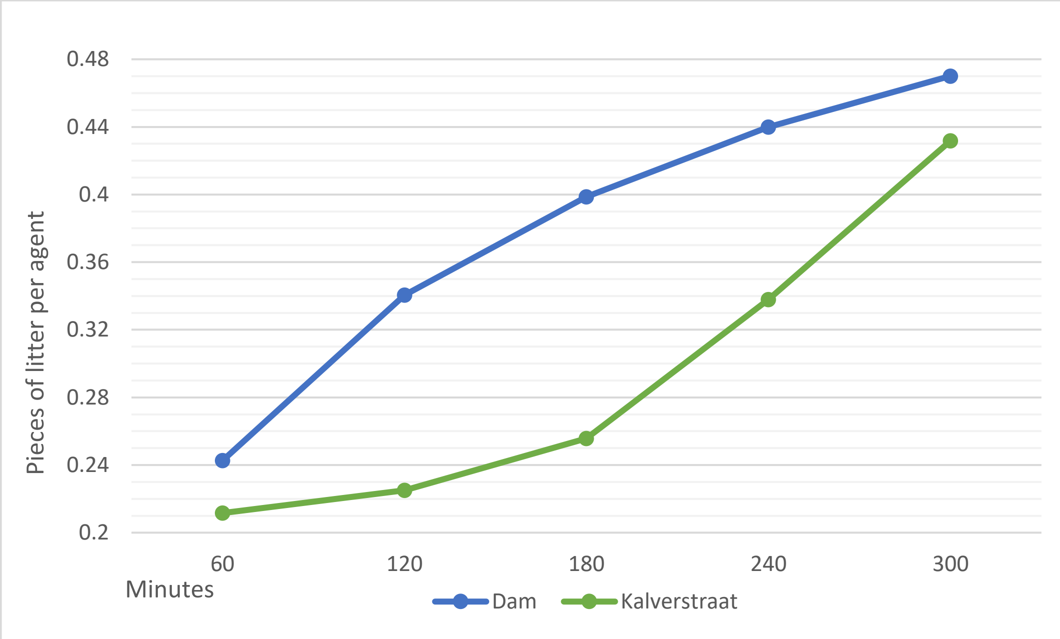


Figure 4.2: Average litter per pedestrian agent in different street layouts.

The descriptive norm activations led to the characteristically shaped 'reinforced' graph in the Kalverstraat area (figure 4.2). This shape is absent for the Dam graph, which can be explained by the temporal scale at which the data was gathered. Because of the large amount of litter in absolute terms, the environment shifted from clean to littered state (around 10 pieces of litter within agent viewing distance; see section 3.2.2.1) more quickly. The threshold was reached not after around three hours like in the Kalverstraat setting, but probably somewhere between one and two. If the simulation is run beyond 300 in-model minutes, the Kalverstraat graph will likely exhibit the same pattern as the Dam in this time scale, while that street will in turn approach a horizontal asymptote when the model is run much longer.

4.2.2: Crowdedness

When twice as many agents enter the street, both the global and the individual littering patterns are sped up. The more agents enter the area, the more litter is generated, filling up the bins and environment more quickly and activating more agents' descriptive norms. Moreover, the activated norm multiplier reaches high values sooner because of the relatively large amount of environmental litter, increasing agents' chances to drop litter and decreasing the distance they are willing to move to the nearest bin. The threshold of whether an environmental is clean or littered is thusly reached sooner when an area is crowded. Through the earlier occurrence of the inversion of the activated norm, crowdedness therefore greatly increases overall littering rates.

The sped-up pattern shows clearly for the Dam graph (figure 4.3), which describes an almost identical curve for both configurations of crowdedness, but with significantly higher values at every timestep for increased crowdedness. The graphs of the Kalverstraat layout have different shapes but both versions, too, seem to fit the hypothesis of sped up littering rates. As explained in the previous section, the shift between a clean and littered state of the environment is reached before the 120-minute mark in the first Dam scenario, and the graph has started flattening as it approaches the asymptote. While the shift between environmental states was already visible in the first Kalverstraat scenario, the flattening was not yet. In the second, both points are visible: the shift somewhere before 180 in-model minutes, the flattening from that point onwards.

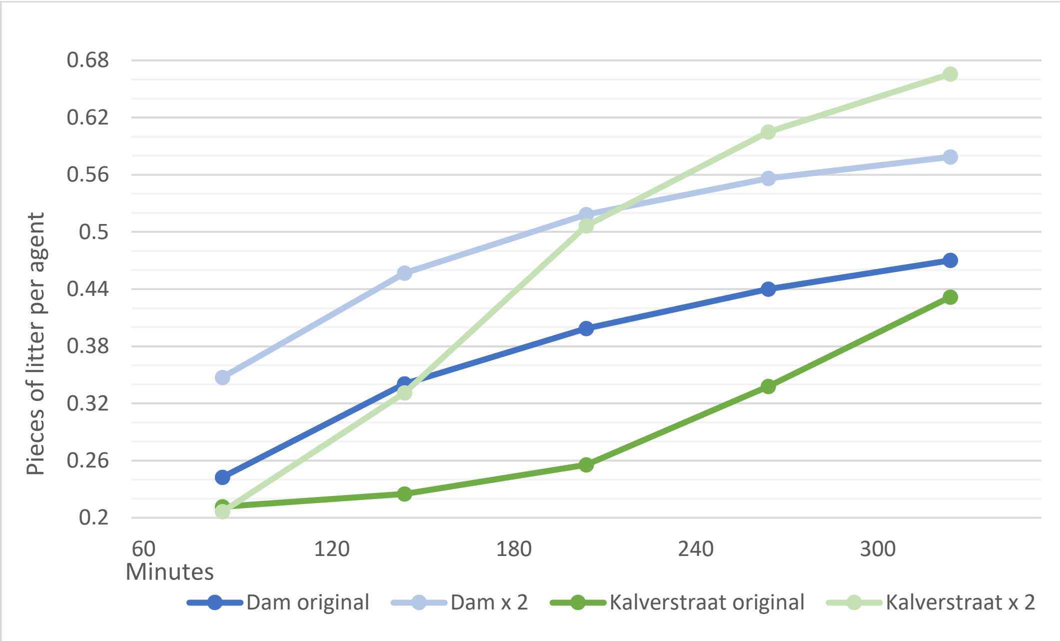


Figure 4.3: Average litter per pedestrian agent for different settings of crowdedness in different street layouts.

As mentioned before, crowdedness leads to more frequent descriptive norm activations, besides the increased absolute number of littered items in the environment. This number of activations is well above 1, meaning that on average all agents have an activated descriptive norm from early on in their traversal (figure 4.4). As shown in the sensitivity analysis, permanently activated norms have a large effect on littering rates, particularly when the environment is littered (figure 3.14). The influence of this factor outweighs the increased absolute littering rate, but is all the more influential in conjunction with it.

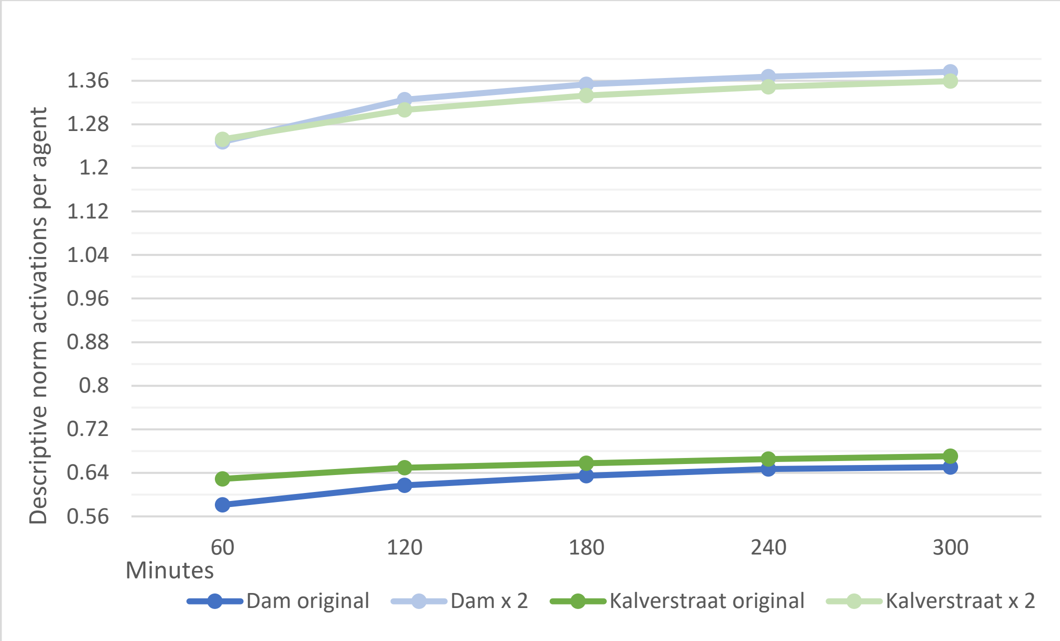


Figure 4.4: Average descriptive norm activations per pedestrian for different settings of crowdedness in different street layouts.

4.2.3: Age distribution

In the scenario of 'a night out' where the streets are populated with a younger demographic, littering rates are somewhat higher than in the original situation (figure 4.5). The change to the model parameters is effectively an increased mean personal norm. The younger demographic originally comprised 33% of the population and littered 1.5 times the average. The older demographic correspondingly comprised 67% and littered 0.8 times the average. Doubling the chance that younger agents enter the area leads shifts the average personal norm from 0.35 to roughly 0.44.

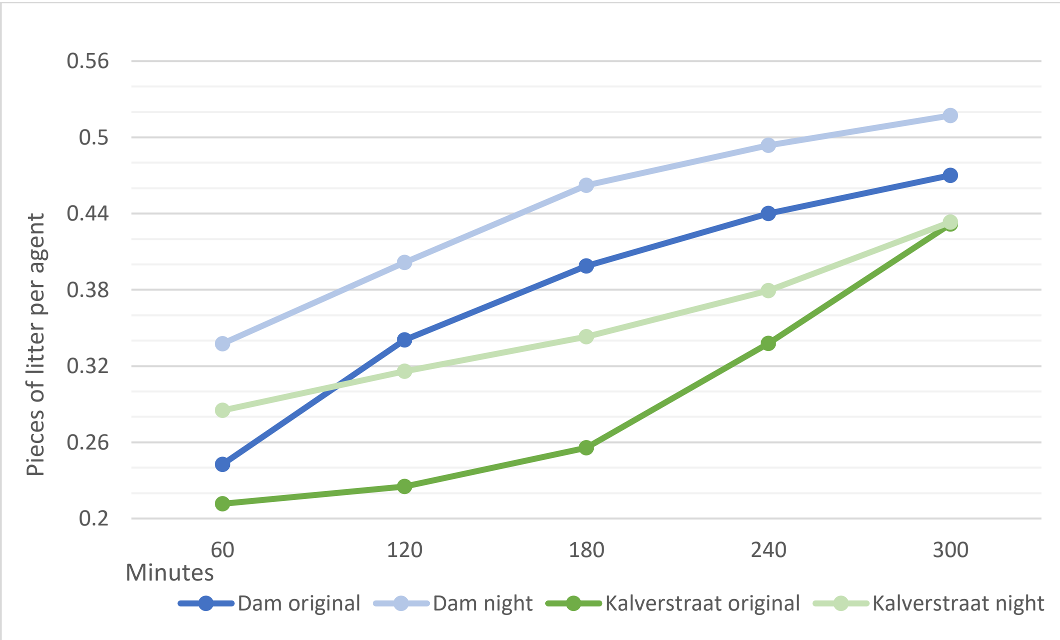


Figure 4.5: Average litter per pedestrian agent for different age distributions in different street layouts.

Surprisingly, the number of activations per agent is lower for the shifted age distribution (figure 4.6). While the explanation of socialising, possibly inebriated tourists who do not pay attention to their surroundings could be plausible for real-world littering patterns at night, the clarification of the model output has a different focus. Relative littering rates are higher, so the lower share of norm activations is a result of less frequent bin disposals. In this scenario, bin disposals not only decrease because less pedestrians hold on to litter as a result of a higher average personal norm, but also because the average distance agents are willing to move to the closest bin is lower. This decrease in bin disposals is also the reason for the markedly lower norm activation rate for the Kalverstraat.

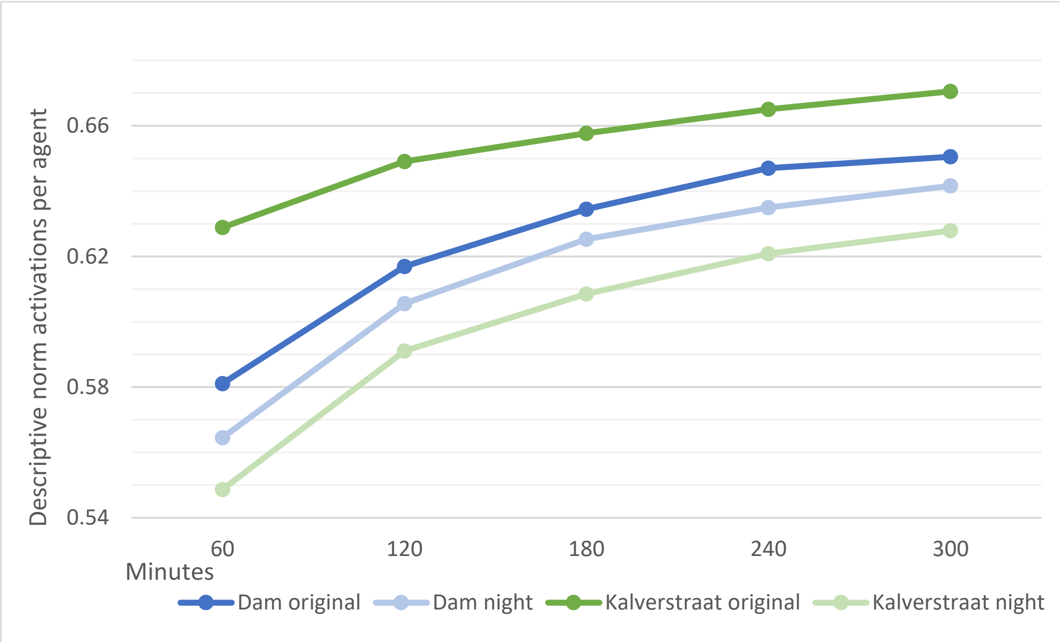


Figure 4.6: Average descriptive norm activations per pedestrian for different age distributions in different street layouts.

4.2.4: Bin positions

As part of the final experiment, the influence of the locations of bins is researched. The model is run for the Dam setting without bins with the intention of finding the locations in the area that are most highly pressured by littering. A heat map of the results is shown in figure 4.7. The spatial pattern of litter is strongly affected by the agents' simple rules for movement in the model. Agents spawn on a random pixel on the entrances/exits layer and have another random pixel on that layer set as their destination. Because the top-left and bottom-middle entrance/exit are the largest (i.e. have the most pixels), the largest pedestrian flow moves between these two locations (resulting in the most litter there). Coincidentally, the real-world busiest streets leading to the Dam are the same (Damrak and Kalverstraat, respectively). Since no quantitative pedestrian flow numbers are available to this author, this pattern is unintended and should not be taken as realistic. Still, the pattern is usable in the context of experimenting with the possibilities of the model.

Figure 4.7: Heatmap of litter in the Dam setting without bins.

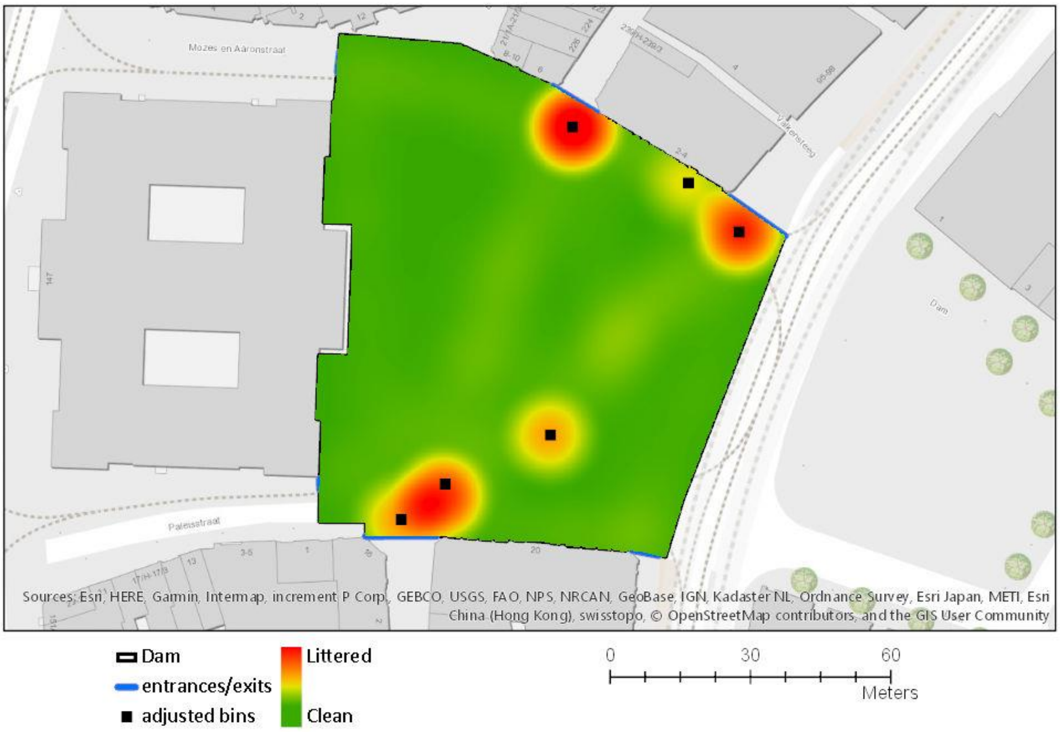


Figure 4.8: Heatmap of litter in the Dam setting with adjusted bin positions.

The six original bins in the Dam area are moved to the centres of the exposed litter hotspots. Their locations and the newly emerged spatial littering pattern are shown in figure 4.8. The littering pattern is strikingly concentrated around the new bin locations, with only little litter visible in the previously exposed hotspots where no bins were moved to. This is explained by the fact that bins do not lose their attractiveness to agents when filled beyond capacity: agents still move to them and dispose of their litter in the bin, which then spills onto the surrounding area, reflecting real-world pedestrian littering behaviour. Furthermore, the environmental litter is calculated locally by every agent, which leads the areas around the bins to be perceived as more littered, increasing littering rates there. Areas farther from bins are therefore not only relatively but also absolutely considered cleaner by the agents, further reinforcing the decreased littering rates there. Although the pattern visible in figure 4.8 is exaggerated, the mechanisms behind it seem to match real-world patterns.

The relative littering rates are counterintuitive - the addition of bins is would not be expected to lead to increased littering (figure 4.9). However, the littering pattern is lower prior to and on the first timestamp, indicating that norm activation rates have increased, and that only the higher values of the reinforced shape are visible, that is, those after the environment has on average shifted from a clean to a littered state. The graph of 3.12 (which shows the littering rates in the test area for universally activated descriptive norms) again seems to have been reproduced in this experiment, but it is also sped up (shifted towards the early model run) as a result of higher crowdedness and absolute littering rates in the Dam area. The intended optimisation of bin positions is thusly shown to lead to a higher descriptive norm activation rate, which counter-intuitively leads to increased littering over time. The highly increased norm activation rates for the adjusted bin locations are also shown in figure 4.10.

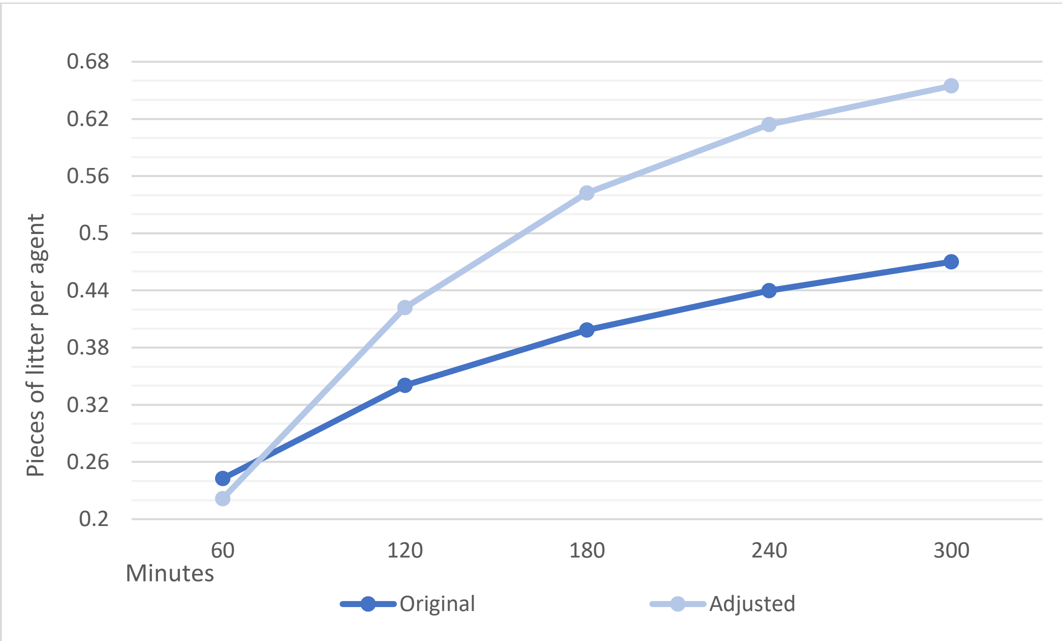


Figure 4.9: Average litter per pedestrian agent for the original and adjusted Dam bin positions.

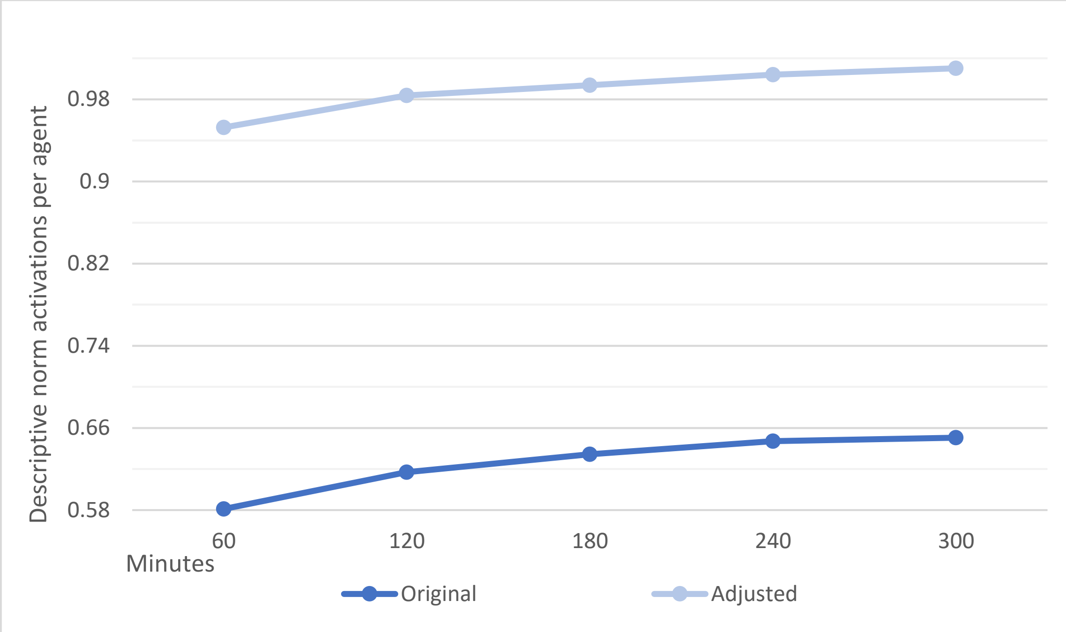


Figure 4.10: Average descriptive norm activations per pedestrian for the original and adjusted Dam bin positions.

4.3: Summary

The finalised agent-based model has been applied to scenarios that are difficult to study in real-world littering experiments. In experiments regarding street layouts, crowdedness, age composition and alternative bin locations, the activation of descriptive norms repeatedly emerged as a critical factor in littering rates. All subjects of experimentation but age distribution directly affected the norm activation rate through increased inter-agent exposure to litter disposals. Crowdedness and age distribution directly affect individual littering rates, but that does not have as much of an effect on global littering rates if not also reinforced by high norm activation. The fourth research sub-topics, *how does the physical environment affect littering rates*, *how do population size and composition affect littering rates*, have hereby been addressed.

5: Conclusion

5.1: Research aim

Agent-based modelling presented itself as a suitable method for capturing littering behaviour because of its capacity for simulating autonomous agent behaviour and its spatial explicitness. Complex models, which have the potential for generating predictive output, require extensive validation and availability of detailed input data. Because neither is available for this research topic, the model was kept relatively abstract and of limited validity. A remaining merit of agent-based modelling is that it enables the exploration of theoretical assumptions and that it could facilitate the exposal of gaps in theory. The research question *how can ABM be used to increase understanding about littering* is answered as such. During the modelling process and the accompanying literature study, vagueness in both qualitative and quantitative assumptions was found indeed.

The most influential and well-rounded explanation of littering behaviour, as described by the focus theory of normative conduct, was operationalised in this model. The theory details how the state of the local environment affects behaviour, as already observed in the well-known broken windows theory. However, it was found in the newer theory that increased littering occurs in dirty environments and decreased littering in clean environments only when the descriptive norm is activated in an individual, which occurs when they observe somebody else disposing of litter. This resolves the research question *what theory explains littering behaviour most effectively*. The extent of the influence of descriptive norm has been detailed in multiple studies and was approximated in the output of the model developed in this project. An important finding of this research is that the configuration of personal norms as stochastic variables and activated norms as corresponding multipliers is a valid interpretation of the theory through which it seems empirical data can be reproduced.

Throughout the modelling process and particularly in the final experiments, the importance of the activated descriptive norm was further emphasised. It was found to be more influential to overall littering rates than the traversing crowd's age composition or the accessibility of bins. Moreover, because people also activate each other's descriptive norm by disposing of their litter properly (in a bin), increased visibility of bins (due to placement or street layout) can counter-intuitively even lead to more littering in the long run. Although this finding is unforeseen, it is not inconsistent with the theory and is encouraged to be studied in practice. These conclusions were drawn during the project stages led by the research question regarding model development, *how can littering behaviour plausibly be captured in an ABM* and both questions about experimentation, *how does the physical environment affect littering rates* and *how do population size and composition affect littering rates*.

Several uncertainties also arose from the modelling process. The values and behaviours of numerous parameters of varying importance are not described in theory and were therefore given estimated definitions. Most were tested in sensitivity analysis or experiments and seemed to be represented reasonably, but the sheer number of uncertain variables suggests further research into specific aspects of littering behaviour is in order. Under-researched variables include:

- the distribution of personal norms,
- the conditions in which inter-personal norm activation occurs,

- the definitions of clean and littered areas,
- the distance people are willing to walk to bins and its correlation to personal norms.

The main objective of this research was *to gain insight into littering behaviour through agent-based modelling by simulating theoretical assumptions in settings that are otherwise difficult to examine in practice*. The agent-based model was successfully developed: its output is realistic, in line with theory and partially validated. By extension, this also means that the theory on which it was based has a logical foundation; even when its assumptions were simulated in unstudied scenarios, the results seemed reasonable. Moreover, several uncertainties with regard to underexposed assumptions were found in the modelling process. Agent-based modelling has therefore proved valuable in producing insights for littering research. A modest contribution to solving the societal and environmental problem of littering has thusly been attempted to be made.

5.2: Potential applications

The knowledge gained in this research and the model that sprouted from it are potentially usable in various practical applications. If certain parameters are defined more realistically, the spatiotemporal patterns of litter generated in simulation could be used for municipal research regarding the selection of areas that should have priority when public space is cleaned. Advanced versions of the model might even be used for making existing cleaning schedules more efficient, as illustrated by Rangoni and Jager (2017).

In city planning, an adaptation of the model might also be used in guiding bin placement, as shown in the experimentation phase of this research. Adjustments to the physical urban environment that could more indirectly affect littering behaviour could be explored in the model as well. The impact of far-fetched potential measures such as wind-sheltering structures around litter hotspots or see-through street corners could be cheaply examined.

The framework of the model could potentially also be used for research into different social psychological topics on which descriptive norms have been found to have an influence. Such topics could include smoking, alcohol consumption, jumping the queue, or situations prone to mass-panic such as evacuations. Particularly cases where the spatial component of norm activation is relevant may benefit from the general structure of the model developed here.

Realistically, the model would have to be refined to a significant extent before it is usable in practice to such ends. This refinement would principally have to be conducted with regards to research into the missing variables identified in the modelling process. The next chapter will provide an overview of the limitations of this research project.

6: Discussion

A first point of reflection concerns the central theory that was implemented in the model, the focus theory of normative conduct. That theory explicitly distinguishes between the effects of two types of norms; the descriptive and the injunctive. Injunctive norms, as explained in the conceptual framework section of this report, were omitted from the model because their activation occurs in complex, unpredictable ways. Although this choice has certainly contributed to the accuracy of the model, it has also abstracted the theory. The implementation of the complete focus theory of normative conduct should be considered a long-term goal for a future littering behaviour-related simulation.

The central research aim was finding the merit of ABM for research into littering behaviour and several gaps in theory and data were exposed, which is part of the constructive value of agent-based modelling. However, the model is built on multiple uncertain parameter values that could disproportionally impact the results. For instance, the study from which the average personal norm and age distribution and impact were derived, is an aggregation of surveys in variously urbanised North-American study areas (Schultz et al., 2013). While it appeared the most reliable dataset on which to base those values, it is likely a study in Amsterdam or in an urban tourist destination would represent the study area in this research more properly.

Similarly, several qualitative assumptions that were used to model real-world processes remained uncertain. The model eventually produced reasonable output that was evaluated in multiple ways and stages. but it must be noted that this dynamic sufficiency is not the same as mechanistic adequacy (Gräbner, 2018). The patterns produced in the model could have resulted from an implementation of mechanisms similar to those of the target model, but which differs on a structural level. Leombruni et al. (2006) similarly stated that even erroneous models can produce accurate output. Some caution with respect to the interpretation of the finished model is therefore advised.

Besides uncertainties regarding data input, several circumstances arose during the modelling process that led to sub-optimal research and model procedures. Critically, the quantitative model output was only generated for a limited number of timesteps. Continuous temporal output would be most appropriate for studying littering patterns, particularly when the descriptive norm is widely active, and the state of the environment shifts from relatively clean to relatively littered after little in-model time. No good solution for producing such detailed temporal output seemed available in the software, and it proved overly processor-intensive to include more time-steps. This was particularly true for the early model run because the output was extremely variable there, which would have demanded a greater number of permutations, which in turn is even more processor-intensive.

Also related to sub-optimal modelling is the agents' overly simplified visible range, as pointed out by Mr Goppel. The circular shape without regard for visible obstruction by other agents was selected partly because abstraction was deemed more appropriate than introducing additional assumptions. However, exploration of such assumptions about the visible range were not carried out because no method was available to the author to keep model processing efficient after such drastic behavioural changes. Realistic agent movement befell the same fate. An appropriately simple framework for how pedestrians move through the real-world streets was not available, let alone for the research areas. But moreover, the technique to simulate such behaviour efficiently was also lacking in this project.

Finally, several undiscussed model elements could contribute to the representational quality of a potential future agent-based model about littering behaviour:

- Realistic or actual pedestrian flows. Searching for optimal bin positions with a simulation is not meaningful unless agents' movement can represent real-world bottlenecks. Spatial patterns of litter will also become significantly more accurate.
- The amount of litter pedestrians generate. A stand-in value was used here to make all agents litter once on average during their traversal. If a realistic value is used, model time will also become usable in absolute terms with regard to the time it takes for the area to become littered.
- Differentiation between types of litter. Vastly different littering rates have been found for cigarettes specifically, and for food items during different times of day. Such a differentiation in the model could lead to applicability in a larger number of scenarios.

7. References

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8: Appendix

8.1: Model without street layout

```
model litteringNormsBins

global {
	geometry shape <- rectangle(70#m,25#m);
	float step <- 1 #s;
	int minutes <- round(time/60) update: round(time/60);

	int numberPedestriansInit <- 1 parameter:"Initial number of peds";
	int numberLitterInit <- 0 parameter:"Initial amount of litter";
	int numberLitter <- numberLitterInit update:length(litter);
	int numberPedestrians <- numberPedestriansInit update:length(totalPedestrians)+numberPedestriansInit;
	list totalPedestrians <- pedestrian;
	float litterPerPed <- numberLitter / numberPedestrians update:numberLitter / numberPedestrians;
	float pedSpawn <- 0.05 parameter:"Chance to spawn peds per tick";
	float initActiveNorm <- 0.1 parameter:"Chance to spawn peds with active descriptive norm";
	point bin1Pos <- {25,1};
	point bin2Pos <- {45,24};
	float allActivations <- 0.0;
	float relativeActivations <- allActivations update:allActivations / numberPedestrians;
	float persNormM <- 0.35;
	float persNormSD <- 0.05;
	float below32Littering <- 1.5;
	float above32Littering <- 0.8;
	float stepsToExit <- sqrt(70 ^ 2 + (25 / 2) ^ 2);
	float generateLitter <- 1 / stepsToExit;
	int totLitterGenerated <- 0;
	int viewingDistance <- 12;

	reflex spawnPed when:(flip(pedSpawn)) {
		create pedestrian {
			if flip(0.5) {
				set location <- left;
				myTarget <- right;
				add pedestrian to: totalPedestrians;
			}
			else {
				set location <- right;
				myTarget <- left;
				add pedestrian to: totalPedestrians;
			}
			if flip(initActiveNorm) {
				descriptiveNorm <- true;
			}
		}
	}

	init {
		create pedestrian number:numberPedestriansInit {
			if flip(0.5) {
				myTarget <- left;
			}
			else {
				myTarget <- right;
			}
			if flip(initActiveNorm) {
				descriptiveNorm <- true;
			}
		}
		create litter number:numberLitterInit;
		create bin1 {
			set location <- bin1Pos;
		}
		create bin2 {
			set location <- bin2Pos;
		}
	}
}

species pedestrian skills:[moving] {

	point myTarget;
	point left <- rnd({0.0,25.0});
	point right <- rnd({70,0},{70,25});
	point newTarget;
	float walkingSpeed <- rnd(0.85,1.35);

	bool below32 <- flip(0.33);
	bool litterer <- false;
	rgb pedColour;
```

```
float personalNorm <- gauss(persNormM,persNormSD) * (below32 ? below32Littering : above32Littering);
float activatedNorm <- 1.0;
bool descriptiveNorm <- false;
list surroundingLitterList;
int surroundingLitter <- length(surroundingLitterList) update:length(surroundingLitterList);
bool gotLitter <- false;
bool closeBin <- false;
float binTolerance <- (20 / (1 + 0.08 * #e ^ (8.2 * personalNorm * activatedNorm)));

reflex moving {
	do goto target:closeBin ? newTarget : myTarget speed:walkingSpeed #m/#s;
	if (self.location = myTarget) {
		do die;
	}
	else if (self.location = newTarget) {
		do throwInBin;
	}
}

action inactiveLittering {
	if flip(generateLitter) and (gotLitter = false) {
		write self.name + ":'oh-oh got litter'";
		totLitterGenerated <- totLitterGenerated + 1;
		do findBin;
	}
}

action findBin {
	if (self.location distance_to min(bin1Pos,bin2Pos) > binTolerance) {
		if flip(personalNorm * activatedNorm) {
			do dropLitter;
		}
		else {
			pedColour <- #plum;
			gotLitter <- true;
		}
	}
	else {
		do moveToBin;
	}
}

action dropLitter {
	create litter {
		set location <- myself.location;
	}
	litterer <- true;
	pedColour <- #orange;
	write self.name + ":'oopsie'";
	ask pedestrian at_distance(viewingDistance) {
		descriptiveNorm <- true;
		allActivations <- allActivations + 1;
	}
}

action moveToBin {
	pedColour <- #plum;
	closeBin <- true;
	if (self.location distance_to bin1Pos < self.location distance_to bin2Pos) {
		newTarget <- bin1Pos;
	}
	else {
		newTarget <- bin2Pos;
	}
}

action throwInBin {
	if (newTarget covers bin1Pos) {
		ask bin1 {
			containingLitter <- containingLitter + 1;
		}
	}
	else if (newTarget covers bin2Pos) {
		ask bin2 {
			containingLitter <- containingLitter + 1;
		}
	}
	closeBin <- false;
	gotLitter <- false;
	ask pedestrian at_distance(viewingDistance) {
		descriptiveNorm <- true;
		allActivations <- allActivations + 1;
	}
}
```

```
	action activeLittering {
		surroundingLitterList <- litter at_distance(viewingDistance);
		activatedNorm <- 1.7 / (1 + 2.4 * #e ^ (-0.13 * surroundingLitter));
		do inactiveLittering;
	}


	reflex littering {
		if (descriptiveNorm) {
			do activeLittering;
		}
		else {
			do inactiveLittering;
		}
	}

	reflex holdLitter when:gotLitter {
		if ((self.location distance_to bin1Pos) <= binTolerance or (self.location distance_to
bin2Pos) <= binTolerance) {
			do moveToBin;
		}
	}

	init {
		if (below32) {
			pedColour <- #green;
		}
		else {
			pedColour <- #purple;
		}
	}

	aspect defaultPed {
		draw circle (0.7) color:pedColour border:descriptiveNorm ? #lime : pedColour;
	}
}

species litter {
	aspect defaultLit {
		draw circle (0.15) color:#red;
	}
}

species bin {
	int binCapacity <- 100;
	int containingLitter <- 0;
	bool fullBin <- false;

	aspect defaultBin {
		draw square (0.5) color:#darkorange;
		draw "" + containingLitter + "/" + binCapacity color:#black;
	}

	reflex spillLitter {
		if (containingLitter > binCapacity) {
			create litter {
				set location <- myself.location + rnd({-1,-1},{1,1});
			}
			containingLitter <- containingLitter - 1;
		}
	}
}

species bin1 parent:bin {}
species bin2 parent:bin {}

experiment litteringSim type:gui {
	output {
		monitor "Minutes passed" value:minutes;
		monitor "Potential pieces of litter" value:totLitterGenerated;
		monitor "Pieces of litter dropped" value:numberLitter;
		monitor "Number of pedestrians passed" value:numberPedestrians;
		monitor "Pieces of litter per pedestrian" value:litterPerPed;
		monitor "Activated norm ratio" value:relativeActivations;
		display map {
			graphics "worldBackground" {
				draw world.shape color:#ghostwhite;
			}
			species litter aspect:defaultLit;
			species pedestrian aspect:defaultPed;
			species bin1 aspect:defaultBin;
			species bin2 aspect:defaultBin;
		}
		display chart {
```

```
				chart "Litter buildup" type:series {
					data "Pieces of litter per pedestrian" value:litterPerPed;
				}
			}
		}
}
```

8.2: Kalverstraat model

```
model litteringNormsStreet

global {
		file kalverShp <- file("../includes/kalverEdit.shp");
		geometry shape <- envelope(kalverShp);
		file inOutShp <- file("../includes/kalverInOuts.shp");
		geometry building <- simplification(shape,2.0);

		float step <- 1 #s;
		int minutes <- round(time/60) update: round(time/60);

		int numberPedestriansInit <- 1 parameter:"Initial number of peds";
		int numberLitterInit <- 0 parameter:"Initial amount of litter";
		int numberLitter <- numberLitterInit update:litter count(true);
		int numberPedestrians <- numberPedestriansInit update:totalPedestrians
count(true)+numberPedestriansInit;
		list totalPedestrians <- list(pedestrian);
		float litterPerPed <- numberLitter / numberPedestrians update:numberLitter / numberPedestrians;
		float pedSpawn <- 0.05*1.6 parameter:"Chance to spawn peds per tick";
		float initActiveNorm <- 0.1 parameter:"Chance to spawn peds with active descriptive norm";
		float percentBelow32 <- 0.33;
		float viewingDistance <- 12.0;

		point bin1Pos <- {110,105};
		point bin2Pos <- {71,132};
		point bin3Pos <- {175,171};
		point bin4Pos <- {88,71};
		point bin5Pos <- {18,161};
		point bin6Pos <- {75,24};
		point bin7Pos <- {133,140};

		float allActivations <- 0.0;
		float relativeActivations <- allActivations update:allActivations / numberPedestrians;

		float below32Littering <- 1.5;
		float above32Littering <- 0.8;
		float generateLitter <- (1 / (81.5 * 2)) * ( 1 / 0.75);
		int totLitterGenerated <- 0;
		float persNormM <- 0.35;
		float persNormSD <- 0.1;

		reflex spawnPed when:(flip(pedSpawn)) {
			create pedestrian {
				set location <- any_location_in(geometry(entrance));
				myTarget <- any_location_in(geometry(entrance));
				add pedestrian to: totalPedestrians;
				if flip(initActiveNorm) {
					descriptiveNorm <- true;
				}
			}
		}

		init {
			create street from:kalverShp{
				building <- building - geometry(street);
			}
			create entrance from:inOutShp {
				building <- building - (0.2 around geometry(entrance));
			}
			create pedestrian number:numberPedestriansInit {
				location <- any_location_in(geometry(street));
				myTarget <- any_location_in(geometry(entrance));
				if flip(initActiveNorm) {
					descriptiveNorm <- true;
				}
			}
			create litter number:numberLitterInit {
				location <- any_location_in(geometry(street));
			}
			create bin1 {
				set location <- bin1Pos;
			}
```

```
			create bin2 {
				set location <- bin2Pos;
			}
			create bin3 {
				set location <- bin3Pos;
			}
			create bin4 {
				set location <- bin4Pos;
			}
			create bin5 {
				set location <- bin5Pos;
			}
			create bin6 {
				set location <- bin6Pos;
			}
			create bin7 {
				set location <- bin7Pos;
			}
		}
}

species street schedules: [] {
		aspect defaultStreet {
			draw shape color:#ghostwhite border:#black;
		}
}

species entrance schedules: [] {
		aspect defaultEntrance {
			draw shape color:#green size:8.0;
		}
}

species pedestrian skills:[moving] {

		point myTarget;
		point newTarget;
		bool detour <- false;
		point altTarget <- {107,109};
		float walkingSpeed <- rnd(0.85,1.35);

		bool below32 <- flip(percentBelow32);
		bool litterer <- false;
		rgb pedColour;
		float personalNorm <- gauss(persNormM,persNormSD) * (below32 ? below32Littering : above32Littering);
		float activatedNorm <- 1.0;
		bool descriptiveNorm <- false;
		list surroundingLitterList;
		int surroundingLitter;
		bool gotLitter <- false;
		bool closeBin <- false;
		list visibleBins;
		float distToClosestBin;
		float binTolerance <- (20 / (1 + 0.08 * #e ^ (8.2 * personalNorm * activatedNorm)));


		action findBin {
			do lookForBin;
			if (distToClosestBin <= binTolerance) and (distToClosestBin > 0) {
				do moveToBin;
			}
			else {
				if flip(personalNorm * activatedNorm) {
					do dropLitter;
				}
				else {
					pedColour <- #plum;
					gotLitter <- true;
				}
			}
		}

		action lookForBin {
			visibleBins <- [];
			loop visbin over:[bin1,bin2,bin3,bin4,bin5,bin6,bin7] {
				if not (link(location,geometry(visbin)) intersects building) {
					add visbin to:visibleBins;
				}
			}
			distToClosestBin <- visibleBins min_of (self.location distance_to geometry(each));
		}

		action moveToBin {
			do lookForBin;
			pedColour <- #plum;
```

```
			closeBin <- true;
			newTarget <- visibleBins closest_to self.location;
		}

		action dropLitter {
			create litter {
				set location <- myself.location;
			}
			litterer <- true;
			pedColour <- #orange;
			write self.name + ":'oopsie'";

			loop witness over:(pedestrian at_distance(viewingDistance)) {
				if not (link(location,witness.location) intersects building) {
					ask witness {
						descriptiveNorm <- true;
						allActivations <- allActivations + 1;
					}
				}
			}
		}

		action throwInBin {
			if (newTarget covers bin1Pos) {
				ask bin1 {
					containingLitter <- containingLitter + 1;
				}
			}
			else if (newTarget covers bin2Pos) {
				ask bin2 {
					containingLitter <- containingLitter + 1;
				}
			}
			else if (newTarget covers bin3Pos) {
				ask bin3 {
					containingLitter <- containingLitter + 1;
				}
			}
			else if (newTarget covers bin4Pos) {
				ask bin4 {
					containingLitter <- containingLitter + 1;
				}
			}
			else if (newTarget covers bin5Pos) {
				ask bin5 {
					containingLitter <- containingLitter + 1;
				}
			}
			else if (newTarget covers bin6Pos) {
				ask bin6 {
					containingLitter <- containingLitter + 1;
				}
			}
			else if (newTarget covers bin7Pos) {
				ask bin7 {
					containingLitter <- containingLitter + 1;
				}
			}
			closeBin <- false;
			gotLitter <- false;
			loop witness over:(pedestrian at_distance(viewingDistance)) {
				if not (link(location,witness.location) intersects building) {
					ask witness {
						descriptiveNorm <- true;
						allActivations <- allActivations + 1;
					}
				}
			}
		}

		action activeLittering {
			surroundingLitterList <- [];
			loop vislit over:(litter at_distance(viewingDistance)) {
				if not (link(location,vislit.location) intersects building) {
					add vislit to:surroundingLitterList;
				}
			}
			surroundingLitter <- length(surroundingLitterList);
			activatedNorm <- 1.7 / (1 + 2.4 * #e ^ (-0.13 * surroundingLitter));
//			gecheckt met online logistische functierekenmachine op desmos.com
		}

		reflex moving {
			if (self.location = myTarget) {
				do die;
```

```
                }
                else if (self.location = newTarget) {
                        do throwInBin;
                }
                if (closeBin) {
                        if(link(self.location,newTarget) intersects building) {
                                detour <- true;
                                do goto target:altTarget speed:walkingSpeed #m/#s;
                        }
                        else if not (link(self.location,newTarget) intersects building) {
                                detour <- false;
                                do goto target:newTarget speed:walkingSpeed #m/#s;
                        }
                }
                else if not (closeBin) {
                        if (link(self.location,myTarget) intersects building) {
                                detour <- true;
                                do goto target:altTarget speed:walkingSpeed #m/#s;
                        }
                        else if not (link(self.location,myTarget) intersects building) {
                                detour <- false;
                                do goto target:myTarget speed:walkingSpeed #m/#s;

                        }
                }
        }

        reflex inactiveLittering {
                if flip(generateLitter) and (gotLitter = false) {
                        write self.name + ":'oh-oh got litter'";
                        totLitterGenerated <- totLitterGenerated + 1;
                        if (descriptiveNorm) {
                                do activeLittering;
                        }
                        do findBin;
                }
        }

        reflex holdLitter when:gotLitter {
                do lookForBin;
                if (distToClosestBin <= binTolerance) and !(empty(visibleBins)) {
                        do moveToBin;
                        gotLitter <- false;
                }
        }

        init {
                if (below32) {
                        pedColour <- #green;
                }
                else {
                        pedColour <- #purple;
                }
        }

        aspect defaultPed {
                draw circle (0.7) color:pedColour border:descriptiveNorm ? #lime : pedColour;
        }
}

species litter schedules: [] {
        aspect defaultLit {
                draw circle (0.15) color:#red;
        }
}

species bin {
        int binCapacity <- 100;
        int containingLitter <- 0;

        aspect defaultBin {
                draw square (0.5) color:#darkorange;
                draw "" + containingLitter + "/" + binCapacity color:#black;
        }

        reflex spillLitter {
                if (containingLitter > binCapacity) {
                        create litter {
                                set location <- myself.location + rnd({-1,-1},{1,1});
                        }
                        containingLitter <- containingLitter - 1;
                }
        }
}
```

```
species bin1 parent:bin {}
species bin2 parent:bin {}
species bin3 parent:bin {}
species bin4 parent:bin {}
species bin5 parent:bin {}
species bin6 parent:bin {}
species bin7 parent:bin {}

experiment litteringSim type:gui {
	output {
		monitor "Minutes passed" value:minutes;
		monitor "Potential pieces of litter" value:totLitterGenerated;
		monitor "Pieces of litter dropped" value:numberLitter;
		monitor "Number of pedestrians passed" value:numberPedestrians;
		monitor "Pieces of litter per pedestrian" value:litterPerPed;
		monitor "Activated norm ratio" value:relativeActivations;

		display map {
			species street aspect:defaultStreet refresh:false;
			species litter aspect:defaultLit;
			species pedestrian aspect:defaultPed;
			species bin1 aspect:defaultBin;
			species bin2 aspect:defaultBin;
			species bin3 aspect:defaultBin;
			species bin4 aspect:defaultBin;
			species bin5 aspect:defaultBin;
			species bin6 aspect:defaultBin;
			species bin7 aspect:defaultBin;

		}
		display chart {
			chart "Litter buildup" type:series {
				data "Pieces of litter per pedestrian" value:litterPerPed;
			}
		}
	}
}
```