UNDERSTANDING HOUSEHOLD WASTE PREVENTION BEHAVIOUR

Technical Report No. 4

WASTE PREVENTION MODELLING SCENARIOS

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EXECUTIVE SUMMARY

This report is the fourth technical report on the research investigation “Understanding Household Waste Prevention Behaviour”, funded by DEFRA’s Waste and Resources R&D Programme. The aim of the research is to establish a reference framework for understanding household waste prevention behaviours. The research is scheduled to deliver:

(i) A primary review of relevant academic research and other documented case studies;
(ii) New data on causal attitudes and demand side drivers, from a questionnaire survey;
(iii) Conceptual and predictive models of the impacts and outcome of alternative policies and management strategies.

The third technical report described the development of a conceptual model of waste prevention behaviour, and how it could be implemented in practice. That implementation and the initial results from the modelling study are discussed in this report.

Modelling Methodology

Our fundamental premise was that it is unlikely that we will ever identify all the factors affecting household waste reduction behaviours, and that a definitive, deterministic explanation (or model) will never be possible. We considered instead an alternative stochastic approach based on the concept of autonomous agents.

We present the basic model in the form of a mathematical inequality (see box).

The basic model

The moral (waste prevention) option will be chosen if its utility, $U_M$, satisfies the inequality:

$$U_M = \pm H \times h \pm P \times p \pm E \times e \pm C \times c \pm F \times f \pm S \times \chi_F \times s \pm A \times a \pm R \times r > \text{threshold}$$

Where individual attributes comprise: $H=$habit, $P=$preference/prejudice, $E=$self-efficacy, $C=$convenience/personal cost, $F=$real cost, $S=$social norm, $A=$moral attitude, $R=$random element, $\chi_F =$importance of cost to the individual, and $\chi_S =$the individual’s susceptibility to the social norm.

$h, p, e, c, f, s, a, r =$scaling and weighting factors (independent of the individual)

The threshold denotes the maximum utility of all the other options that could be taken to satisfy the basic need.

Notes:
1. Provided that the individual is aware of the option
2. If the individual is not aware that it is the moral option then the inequality loses its term in $A$

The model provides a normal ‘stable’ component based on the interplay of attitudes and contextual factors, but acknowledges that the stable component can be overridden by pressures and events that impact with an individual’s lifestyle. Those pressures could lead to behavioural excursions.

As well as the ‘background’ pressures the model can build in much more specific events including third party engineered interventions aimed at changing behaviours. The events are modelled as time dependent perturbations of the antecedent attributes.

Model Application

In the current research, we derived a working calibration for the model to provide a reasonable representation of the observed outcomes of the waste prevention attitude and behaviour survey (see second technical report, Tucker and Douglas, 2006b. The calibration was made for 18 individual waste prevention behaviours.
The calibration results clearly demonstrated that we were able to create a model society based on a combination of simple rules and randomness that could mimic some of the key behavioural features of the real society. This extended beyond a merely qualitative visualisation. It also provided reasonable quantitative matches to the performance indicators and performance statistics captured in the attitude/behaviour survey. Importantly, many different facets of the observed behaviours and attitudes could be matched simultaneously through a single model.

The matched behavioural characteristics included the average levels of engagement in each of 18 behaviours, the distributions of the individual levels of engagement in each of the behaviours, correlations between behaviours and their reduction to prime 'behavioural factors', and the strengths of the relationships between behaviours and underlying attitudes.

The fits were not perfect, but were deemed good enough to demonstrate proof of concept that a model society could be built to capture the main features of the waste prevention behaviours that are observed in a real society. The model reasons for the emergence of those features provides us with a useful analogue, or starting point, for hypothesising the reasons for the behaviours seen in the real society.

- The research strengthens the hypothesis that past experience is a very strong factor in determining current behaviours, and that past experience might be strongly coupled with attitudes.
- The research provides indications that the most important attitudes might be founded mainly at the behavioural class level (i.e. at the level of point of purchase decisions, buying long-life and durable goods, private reuse, valorisation of unwanted goods, or minimising the consumption of new resources).
- Household waste prevention activities have been modelled to increase 'naturally' by bolstering from a general increase in environmental concern, reinforcement through experience, habit formation and behavioural spillover. However, the kinetics of such changes are uncertain and probably quite slow, although some significant natural movement could occur within a four-year time frame.
- Interventions to stimulate behavioural change are shown to have very different impacts on different behaviours.

**Conclusions and Recommendations**

We have proposed and developed a new conceptual approach to looking at waste prevention (and other) behaviours based on distributed causal factors with inherent randomness.

Whilst the model is still in its early stages of development and needs further refinement and testing to improve our confidence in its predictions, we believe that we have clearly demonstrated the proof of concept of the technique and its aid to deepening understanding. We also believe that the model provides a new and broader perspective for visualising the impact of policy, and other, interventions on our heterogeneous and imperfect society. We strongly advocate:

- Further development of autonomous agent-based models of waste prevention behaviours to include:
  - Further development, refinement and validation of the model algorithms
  - Validation and comparison of model outcomes with independent data [e.g. from other research in DEFRA’s Waste and Resources R&D programme.
  - Continuing predictions (if possible with testable outcomes – through ongoing intervention studies).
1. INTRODUCTION

1.1 Context

1.1.1 The Project

This report is the fourth technical report for the research investigation “Understanding Household Waste Prevention Behaviour”, Project WRT109, funded by DEFRA’s Waste and Resources R&D Programme.

The research project WRT109 focuses primarily on the role that consumers might play in reducing and reusing their own waste. The overall aim of the research is to establish a reference framework for understanding those household waste prevention behaviours. The research comprises three strands:

(iii) Primary reviews of relevant academic research and other documented case studies;
(iv) Elicitation of new data on causal attitudes and demand side drivers;
(iii) The development of conceptual and predictive models that could inform policy and support policy development.

The first technical report on this project contained a review and critical analysis of the research literature (Tucker and Douglas, 2006a). A second report provided new evidence gained from a waste prevention attitude and behaviour survey (Tucker and Douglas, 2006b). A third report (Tucker, 2007) detailed the development of a new model of waste prevention behaviours. That model has now been implemented as a computer-based simulation. The current report discusses its implementation and presents some of the preliminary results obtained from the model.

1.1.2 Introduction to the Model

Methodology

The literature contains a wealth of conceptual models of behaviour and behavioural change, and many of those models can help us to conceptualise waste prevention behaviours. However, whilst those models serve as good aids to visualisation, the task of validating them (and operationalising them by filling them with survey data) remains expensive and subject to much uncertainty. Overall, their successes in explaining real world (target) behaviours have been modest. Normally, the models leave a significant part of the observed variations unexplained.

Everybody has different behaviours. Waste prevention behaviours can depend on many factors. Individuals have their own individual needs and priorities, hold different attitudes and values, and operate in different contexts. It is unlikely that all factors that influence an individual’s behaviour will ever be identified. Many of the factors can appear quite irrational. It is probable that we will never achieve a definitive, deterministic explanation (or model) of behaviour. There will always be some ‘randomness’ that we cannot account for. We believe that in order to understand waste prevention behaviours more fully, we must incorporate that ‘randomness’ (or irrationality) directly into our model.

To do that, we have adopted a stochastic modelling approach based on the methodology of autonomous agents. Autonomous agents are computer programs that represent the individual players in a system (in the current case, the individual households). Each agent is driven by its own individual goals (to satisfy its household living needs). The agents are programmed in the simulation to choose behavioural options to satisfy those needs. They each seek the maximum utility in meeting their needs based on their individual circumstances, attitudes and values. The agents are programmed to respond (individually) to external stimuli like policy interventions. They can also react according to their past experiences and, to a limited extent, react with each other through social interactions. The outcome is seen as the progressive emergence and evolution of individual behaviours.
Antecedents to Behaviour

Previous research has identified the following factors as potentially being important to determining behaviours, including pro-environmental behaviours and waste prevention behaviours:

- Attitudinal factors (attitudes and values, including the moral norm)
- Habit
- Convenience (set against personal cost)
- Self-efficacy (which includes knowledge and capabilities)
- Financial cost
- Social pressures
- Prejudice or preference (which could be through predisposition or gained as a result of experience)

We add one further factor “Randomness” which is considered to account for the myriad of unaccountable pressures and events that impact on our everyday lives.

Different researchers give different emphasis to each of the possible antecedents, and to how those antecedents might be connected. There is insufficient evidence to enable us to favour one representation over another. We therefore make the minimalist assumption that all the antecedents could be additive. In doing this we are assuming that we can find scaling or weighting factors that set the antecedents onto a common metric and allows us to adjust their relative importance. Those importances will differ amongst different behaviours (even amongst different waste prevention behaviours. They will also differ markedly amongst individuals, though their distribution across a community can be quite similar over different communities (Tucker and Douglas, 2006b).

Our proposed model is based soundly on the above two premises that:

- Each behaviour is the result of one or more antecedent or causal factors.
- Each antecedent factor can be represented as a distributed variable across the whole population.

To those, we add a third premise that:

- Behavioural change will ensue if perturbations of one or more causal factors produce a significant shift in the balance amongst those factors.

1.2 Model Outline

A full description of the model and its development is given in the third technical report on this project (Tucker, 2007). Only the main features are summarised here. It should be noted that the model has been based on many of the features of the Integrated Household Waste Management Model developed by Tucker and Smith (1999), Tucker (2001).

1.2.1 Quasi-stable Behaviours

The individual agents within the model are programmed to seek the maximum utility in meeting their needs based on their individual circumstances, attitudes and values. A pro-waste prevention behaviour will be adopted if it offers a relative utility $U_M$ above other behaviours. The utility $U_M$ is determined by the inequality expressed in box 1.

Note that the basic model predicts people’s normal behaviours with the probability of some behaviour excursions occurring when, or if, the random factor becomes dominant.

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1 Unaccountable can be taken to mean “not included in the model as an explicit event”. It can be thought of as bundling together all the short-term time-dependent perturbations in all the other identified factors.
Box 1. Mathematical Representation of the Basic Model

The basic model

The moral (waste prevention) option will be chosen if its utility, $U_M$, satisfies the inequality:

$$U_M = \pm H \times h \pm P \times p + E \times e \pm C \times c \pm F \times \chi_F \times f \pm S \times \chi_S \times s \pm A \times a \pm R \times r > \text{threshold}$$

Where individual attributes comprise: $H=$ habit, $P=$ preference/prejudice, $E=$ self-efficacy, $C=$ convenience/personal cost, $F=$ financial cost, $S=$ social norm, $A=$ moral attitude, $R=$ random element, $\chi_F =$ importance of cost to the individual, and $\chi_S =$ the individual’s susceptibility to the social norm.

$h, p, e, c, f, s, a, r =$ scaling and weighting factors (independent of the individual)

The threshold denotes the maximum utility of all the other options that could be taken to satisfy the basic need.

Notes:
1. Provided that the individual is aware of the option
2. If the individual is not aware that it is the moral option then the inequality loses its term in $A$

1.2.2 Model Mechanisms for Behavioural Change

The randomness factor, described above, can be thought of as providing short-term excursions in behaviours with no lasting effect. We must now look at the possible mechanisms that could lead to more durable longer-term changes.

‘Change’ events can be conceptualised as events that trigger irreversible changes in one or more of the antecedents to behaviour. Such events will include engineered interventions to change behaviour, significant identifiable external events, and internal reactions to experience. All those events can be modelled as causing a time-dependent perturbation of those targeted antecedents – see figure 1.1.

Figure 1.1. Representation of the Effects of Interventions and other Significant Events

The ‘shape’ of the response curve can be visualised as following a typical pattern: an initial boost, followed by a gradual drop-off in effect with time, which may or may not leave a ‘permanent’ residual effect. This shape is typical of the effects of recycling campaigns on recycling attitudes (see Tucker, 2001). Some events can, of course, introduce a permanent step change without any drop off (say the effect of the introduction of waste charging on the financial cost antecedent). Effects can be negative as well as positive and be multi-attributable (e.g. slimy compost could boost prejudices against home composting and damage one’s self-efficacy as well).
It is assumed that all experienced perturbations sum to produce an integrated time-dependent effect on the utility of the behaviour. If that utility then crosses the threshold, behavioural change will ensue. That change could be in either direction. It could be the initiation of a [new] moral waste prevention behaviour, or it could be the dropout from it.

It is very important to note here that many waste prevention behaviours are more to do with preventing drop-out than they are to do with instilling new behaviours, for example buying a new mobile phone when the old one is still functional is a dropout from the minimum waste option of sticking with one’s old phone. Such behaviours, effectively the premature replacement of goods before the end of their functional life span, need to be modelled differently.

We started out with the premise that a behaviour is the chosen option for an action that had the greatest utility in satisfying an identified need. The model assumes that behaviours are reset at each time of need. The timing and frequency of those needs vary for individual activities, from writing on paper almost every day, to shopping weekly, to hiring specialist tools (maybe annually). However, the premature replacement of goods can be construed as taking place without a real (at least functional) need. It could be conceptualised that the replacement behaviour was the response to an “exceptional” need that was triggered when the current behaviour and current attitudes went into dissonance (i.e. the utility function, U, crossed the change threshold).

1.2.3 Feedback and Longer-term Attitude Change

The model also accounts for another category of changes relating to attitude changes through experience (figure 1.2). Some of the changes, like the quantification of personal costs, take place rapidly on initial experience, whilst others, say negative perceptions, can develop in response to adverse experiences. Other changes such as habit formation can take a much longer time.

![Figure 1.2 Feedback from Experience to Attitudes](image)

These changes can be modelled as making step changes in the relevant attitudes according to the ‘strength’ of the experience and ones susceptibility to it. A catastrophic event will cause a large change whilst habit formation is modelled as a continuing series of small reinforcements.

1.2.4 Distributed Antecedent Variables

On our conceptual model, every individual will be subject to their own individual strength of driving force for each one of the behavioural drivers: H, P, E, C, F, S, A, R, and each of the susceptibilities, \( \chi \). Those individual household attributes are normally not known individually; however, we usually have a reasonable notion of the average value of each attribute across the overall population and how this might be distributed. In the model, individual attributes are allocated randomly, through a random sampling of the community-wide attribute distributions.

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Note the indirect evidence from the attitude / behaviour survey (Tucker and Douglas, 2006b) which showed that the more different the stimuli received, the higher the level of behavioural engagement resulting.

It is often forgotten that persistence is just as important as initiation in the sustainability of behaviours.
2. MODEL IMPLEMENTATION

2.1 Design and Structure

The model has been implemented as a weekly simulation. An initial calibration of the model sets up the distribution functions for each of the antecedent variables. Needs are set to occur randomly around a given frequency, depending on the specific behaviour. Background events are also set to occur around a given frequency, at a random strength up to a preset maximum. Three types of background events are included:

(i) Reversible weekly fluctuations
(ii) Irreversible small events (e.g. occasional media coverage of environmental issues)
(iii) Significant events (normally adverse experiences, for example fly infestations of the compost heap).

Major, or planned interventions, are constructed according to the time dependent profile shown in figure 1.1. All the interventions are compounded onto an intervention time line which sums with the individual antecedents.

If there is a need for a given activity that week and the individual is aware of the low waste (waste prevention) option for meeting the need, the main model computes whether that behaviour will occur (according to the inequality shown in box 1). If the behaviour occurs then sub-models are invoked that determine the degree of re-rationalisation of each of the antecedent variables. For example a run of repeated behaviours will augment habit.

The model is then repeated at regular time horizons to provide a time series of behaviours (figure 2.1).
2.2 Model Calibration

2.2.1 Methodology

The key to using the model in forecasting the outcome of future scenarios is to achieve a good initial calibration that can replicate current observations as comprehensively as possible. The more aspects of observation that can be matched simultaneously, the greater the confidence that can be placed on the model and its calibration. Conventional model calibration techniques, based on the inductive methodology of collecting data and then regressing the model onto those data, are not appropriate for our proposed model. The model contains a multiplicity of calibration parameters that remain grossly underdetermined, with little hard real-world data to enable their definitive specification. It is also a stochastic model based to a substantial extent on randomness. As such, it is highly unlikely that there would be any unique set of parameters that could provide a definitive calibration. Similar model outcomes might be achieved with very different parameter sets. To achieve a ‘unique’ calibration would also be prohibitively data hungry. As we are working in an area that is relatively data lean, we need to adopt a more deductive perspective towards making the calibration. At this initial exploratory stage, the model calibration can only be effected through making empirical adjustments to all the model parameters, consistent with what data is available, to achieve as close as possible matches to all available observational features. If we can achieve a model calibration “that provides a good predictive fit to the data that arise from naturalistic observation, then we tentatively accept the theory - as implemented in the model - as a pragmatically useful tool for making predictions, until a more accurate or simpler tool can be found” (Hanneman and Patrick, 1997).

In the current research, we have simply derived an initial working calibration for our behavioural model such that it provides a reasonable representation of the result of the waste prevention attitude and behaviour survey undertaken within our research programme (Tucker and Douglas, 2006). It does not necessarily represent the best calibration that could be achieved.

The calibration was undertaken for each of the 18 individual waste prevention behaviours tested in the survey. In the survey, the levels of engagement in those behaviours were tested on a four-point scale “whenever possible”, “usually”, “on occasions” and “never”. In order to provide model results that were on a consistent scale with the observations, the model behaviours (computed weekly) were reduced to the four frequency factions through aggregation over a 26-week period. If all [individual] model responses to a ‘need’ event opted for the waste prevention option then model behaviours were classified a “whenever possible”. If the majority of responses took the waste prevention option then the overall behaviour was classified as “usually”. If only a minority of responses took that option the model classification was “on occasions”. If no responses took the option the model classification was taken to be “never”.

2.2.2 Procedure

In order to understand the effectiveness of the calibration, and to understand how the calibration process can generate research information in its own right, we need to examine some of the finer details of the calibration process itself. Basically, the calibration involves adjusting the coefficients of the main model equation (box 1) until the model gives acceptable [simultaneous] fits to as many features of the real population as possible. The criteria we used for the fits were the average popularity scores of the individual behaviours, the distributions of behavioural intensities for each behaviour, the correlation and factor analysis across individual behaviours and the regression of the behaviours onto general [waste prevention] attitudes.

Because of the ‘thinness’ of the available calibration data, and for expediency, we have collapsed the first three terms of the model equation, ‘habit’, ‘preference/prejudice’ and ‘self-efficacy’ into a single term ‘Propensity to change behaviour’. The calibration then reduces to establishing just five scaling/weighting coefficients {q, c, f, s, a} for each of the 18 behaviours. Those scaling/weighting coefficients determine the respective probability distributions for propensity, convenience, financial cost, social norm and [waste prevention] attitudes respectively. It follows that the components will not be single valued. To be fully comprehensive, they must each comprise 4 sub-parameters, relating to the maximum and minimum values of the distribution, and its skewness and kurtosis (peakedness).
In the model ‘attitudes’ are treated as operating at three main levels (see Tucker, 2007): at the individual behavioural level, at the level of the parent behavioural class (e.g. reuse, point of purchase, buying long-life goods etc.), together with a general base attitude towards waste minimisation (or resource conservation) as a whole. Effectively, that means there are three distinct attitudinal variables to calibrate.

We have little \textit{a-priori} information on what relative values to expect for each of the calibration coefficients, though those values are essential to the whole thesis of our model, our theoretical concepts and our understanding. However, through actually making the calibration we can establish the ‘good fit’ values for each of the coefficients. Those values can then provide new research information (\textit{a-posteriori}) on the relative importances of the different antecedent factors to each of the behaviours (like regression coefficients in statistical models). However, as our model is designed to provide simultaneous estimates of multiple aspects of behaviour, the model coefficients potentially have a far more powerful role to play than simple regression coefficients. By predicting more and more features and facets of reality, the model calibration provides more and more insights into the possible relationships that might be occurring in the real world.

\subsection{Initial Insights}

In the initial attempts at calibration, we assumed that all coefficients [except the attitude coefficients] were mutually independent. The attitude coefficients were assumed to be coupled such that attitudes to individual behaviours are built upon the attitudes to class behaviours that, in turn, are built on the attitudes to waste minimisation more broadly.

\begin{equation}
A_3 = A_2 \times y_2; \quad A_2 = A_1 \times y_1
\end{equation}

where \(A_3\) = attitude to an individual behaviour, \(A_2\) = attitude to behavioural class, \(A_1\) = general attitude. In this formulation, the scaling coefficients controlled the values of \(A_1, y_1 \) and \(y_2\) respectively.

Whilst the above assumptions were able to provide reasonably close fits to both the overall behavioural scores and their distributions, it proved impossible [using the above assumptions alone] to reconcile all the inconsistencies between the inter-behavioural correlations, the strengths of attitudes towards explaining the behaviours and the [high] degree of randomness needed within the model.

\textbf{Interdependence of Antecedents}

The root problem for the inconsistencies lay in the initial assumption that all the antecedents were mutually independent. In actuality there could be a high degree of correlation between propensity and attitudes, for example. That linkage could reflect aspects pertaining to all three of the propensity factors, ‘habit’, ‘preference/prejudice’ and ‘self-efficacy’. We might think of such a linkage arising [to a large part] as an outcome of past experience.

In order to reconcile all the inconsistencies amongst the model calibration criteria, we needed to add ‘past experience’ to the model with that past experience being heavily loaded onto behavioural class attitudes.

\textbf{Comments on Randomness}

In order to replicate the observed distributions in the levels of engagement across the individual behaviours, a relatively high random factor needed to be included within the model. That factor ‘felt higher’ than would be intuitively expected as a result of the random pressures of everyday events. The randomness factor needs further justification.

In the model, random factor is applied at the level of the ‘individual’ behavioural components, like ‘buy recycled’, or ‘donate to charity’, or ‘hire instead of buy’. It must be recognised that those behavioural components are not, in themselves, homogeneous entities. Each behavioural component is actually a collection of more elemental (product-specific) behaviours. Individual levels of engagement are not necessarily uniform across all of those elements. One may buy recycled toilet rolls but not recycled writing paper. One may donate something of some worth, but sell something else of greater value, and...
not bother valorising items of dubious value. One may use both sides of the paper when making personal notes but not when writing official letters.

Realistically, it would be almost impossible to deconvolute all the behavioural comments to this finer, elemental, level of detail. By applying the randomness at the behaviour component level, we are making an implicit assumption that the random element accounts not only for the irregularities in specific manifestations of the behaviours, but also for the disparity between all the different possible manifestations of the behaviours.

The high random element is now explainable and justifiable.

Inferences and Insights

The inferences and insights outlined above arose through the practical experience gained in building the model. By deducing what extras were needed to make the model fit the observations, and by questioning the parameter values needed to achieve the fits, we have been able to draw a number of inferences about the different antecedents and to how those antecedents need to come together to provide the coherent picture. This could provide some important insights into how we might intervene to enhance real world behaviours.

The key indications that have emerged so far are:

- The major dispersion of waste prevention attitudes amongst the population is at the behavioural class level. More general attitudes are more tightly clustered and discriminate poorly amongst behaviours. Individual behaviour-specific attitudes appear less strongly involved in supporting behaviours. The individual behaviours are more dominated by needs and other local factors.

- Past experience appears to be a very dominant factor in determining current behaviours. Attributes like ‘habit’, ‘knowledge and capability’, ‘preference and prejudice’ might singly or jointly have emerged preferentially alongside attitudes supporting ‘self-responsibility’.

- There are indications that the propensities towards or against given behaviours are strongly coupled with attitudes. Those attitudes appear to be founded more at the behavioural class level, than at the level of individual behavioural components.

- Individual components of behaviour, at the level normally described and tested, are subject to much variability amongst individuals and can also fluctuate significantly for a given individual. Part of the variability, perhaps a large part, could be product-line specific rather than implying irregularities in the adoption of specific products from specific product lines4.

It follows that the point for intervention to increase waste prevention attitudes may be best effected at the behavioural class level (i.e. ‘point of purchase decisions’, ‘long-life and durable goods’, ‘private reuse’, ‘valorisation of unwanted goods’, and ‘minimising the consumption of new resources’). There is some [indirect] evidence that even the behaviours that are now locked in or habitual may have been originally founded on those attitudes.

Interventions at the behavioural component level (e.g. ‘buy loose produce’, ‘buy in bulk and refills’, ‘buy recycled’) would appear to face more problems in design and implementation, as the uncertainties amongst individual needs, day to day pressures, and discrimination amongst products and product lines are very high at this level and could dominate some behaviour.

It would be expected that the uncertainties could be reduced through increasingly product-specific promotions and, indeed, as concluded by Tucker and Douglas (2006b), our level of understanding would benefit from research at this added level of specificity. However, action at the highly specific level is more in the province of the manufacturers and retailers than issues for national campaigns.

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4 It is noted (see figure 2.2) that the more specifically worded behavioural components (e.g. “using rechargeable batteries”) do tend to be more polarised towards ‘always’ and ‘never’ than do the broader components (like “buying loose produce”). However there still remains a large component of intermediate behaviours in even the most specifically-worded components.
2.2.4 Calibration results

The results of the calibration of the model society against the survey results of Tucker and Douglas (2006b) are shown in tables 2.1 to 2.4 and figures 2.2 to 2.4.

Table 2.1 Average Activity Scores (Range 1 to 4)

<table>
<thead>
<tr>
<th>Activity</th>
<th>Survey</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n</td>
<td></td>
</tr>
<tr>
<td>Donate Donate to charity</td>
<td>3.22</td>
<td>3.22</td>
</tr>
<tr>
<td>Sell Sell unwanted items</td>
<td>2.99</td>
<td>3.02</td>
</tr>
<tr>
<td>Lights Use long life light bulbs</td>
<td>2.89</td>
<td>2.91</td>
</tr>
<tr>
<td>Repair Repair rather than replace</td>
<td>2.89</td>
<td>2.97</td>
</tr>
<tr>
<td>Leftovers Reuse leftover food</td>
<td>2.76</td>
<td>2.76</td>
</tr>
<tr>
<td>Loose Buy loose produce</td>
<td>2.74</td>
<td>2.70</td>
</tr>
<tr>
<td>R Glass Reuse jars and bottles</td>
<td>2.71</td>
<td>2.72</td>
</tr>
<tr>
<td>R Clothes Reuse clothes as rags</td>
<td>2.71</td>
<td>2.64</td>
</tr>
<tr>
<td>Buy rec Buy Recycled</td>
<td>2.67</td>
<td>2.60</td>
</tr>
<tr>
<td>Own bag Use own shopping bag</td>
<td>2.53</td>
<td>2.59</td>
</tr>
<tr>
<td>Bulk Buy in bulk or refills</td>
<td>2.47</td>
<td>2.41</td>
</tr>
<tr>
<td>R Paper Reuse paper</td>
<td>2.47</td>
<td>2.48</td>
</tr>
<tr>
<td>Batteries Use rechargeable batteries</td>
<td>2.40</td>
<td>2.38</td>
</tr>
<tr>
<td>Share Share appliances</td>
<td>2.34</td>
<td>2.36</td>
</tr>
<tr>
<td>R News Reuse newspapers</td>
<td>2.32</td>
<td>2.26</td>
</tr>
<tr>
<td>B2hand Buy second hand goods</td>
<td>2.19</td>
<td>2.18</td>
</tr>
<tr>
<td>Hire Hire rather than buy</td>
<td>1.96</td>
<td>1.97</td>
</tr>
<tr>
<td>O pack Reject over-packaged goods</td>
<td>1.83</td>
<td>1.76</td>
</tr>
</tbody>
</table>

Table 2.2a Factor Analysis (Survey)

<table>
<thead>
<tr>
<th>Factor</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>O pack</td>
<td>0.068</td>
<td>0.053</td>
<td>0.714</td>
<td>0.096</td>
</tr>
<tr>
<td>Bulk</td>
<td>0.12</td>
<td>0.243</td>
<td>0.657</td>
<td>0.123</td>
</tr>
<tr>
<td>Loose</td>
<td>0.153</td>
<td>0.147</td>
<td>0.724</td>
<td>0.02</td>
</tr>
<tr>
<td>Own bag</td>
<td>0.292</td>
<td>-0.048</td>
<td>0.518</td>
<td>0.146</td>
</tr>
<tr>
<td>Batteries</td>
<td>0.091</td>
<td>0.189</td>
<td>0.079</td>
<td>0.743</td>
</tr>
<tr>
<td>Lights</td>
<td>0.181</td>
<td>0.017</td>
<td>0.237</td>
<td>0.634</td>
</tr>
<tr>
<td>R glass</td>
<td>0.651</td>
<td>0.075</td>
<td>0.267</td>
<td>0.183</td>
</tr>
<tr>
<td>R paper</td>
<td>0.724</td>
<td>0.099</td>
<td>0.186</td>
<td>0.101</td>
</tr>
<tr>
<td>R news</td>
<td>0.711</td>
<td>0.08</td>
<td>0.131</td>
<td>0.031</td>
</tr>
<tr>
<td>R clothes</td>
<td>0.67</td>
<td>0.105</td>
<td>0.028</td>
<td>0.137</td>
</tr>
<tr>
<td>Leftovers</td>
<td>0.56</td>
<td>0.326</td>
<td>0.159</td>
<td>-0.093</td>
</tr>
<tr>
<td>Buy rec</td>
<td>0.375</td>
<td>0.354</td>
<td>0.367</td>
<td>0.061</td>
</tr>
<tr>
<td>Donate</td>
<td>0.24</td>
<td>0.461</td>
<td>0.292</td>
<td>-0.226</td>
</tr>
<tr>
<td>B2hand</td>
<td>0.412</td>
<td>0.387</td>
<td>0.138</td>
<td>0.046</td>
</tr>
<tr>
<td>Repair</td>
<td>0.389</td>
<td>0.549</td>
<td>0.027</td>
<td>0.201</td>
</tr>
<tr>
<td>Hire</td>
<td>0.067</td>
<td>0.643</td>
<td>-0.013</td>
<td>0.26</td>
</tr>
<tr>
<td>Share</td>
<td>-0.031</td>
<td>0.697</td>
<td>0.079</td>
<td>0.108</td>
</tr>
<tr>
<td>Sell</td>
<td>0.211</td>
<td>0.824</td>
<td>0.189</td>
<td>-0.097</td>
</tr>
</tbody>
</table>

% variance explained 16.47 12.99 12.35 6.98
### Table 2.2b Factor Analysis (Model)

<table>
<thead>
<tr>
<th>Factor</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>O pack</td>
<td>0.055</td>
<td>0.668</td>
<td>0.114</td>
<td>0.005</td>
<td>0.049</td>
</tr>
<tr>
<td>Bulk</td>
<td>0.005</td>
<td>0.626</td>
<td>0.126</td>
<td>0.000</td>
<td>0.012</td>
</tr>
<tr>
<td>Loose</td>
<td>0.091</td>
<td>0.602</td>
<td>-0.164</td>
<td>0.064</td>
<td>0.076</td>
</tr>
<tr>
<td>Own bag</td>
<td>0.125</td>
<td>0.168</td>
<td>-0.094</td>
<td>0.719</td>
<td>0.077</td>
</tr>
<tr>
<td>Batteries</td>
<td>-0.037</td>
<td>0.036</td>
<td>0.153</td>
<td>0.649</td>
<td>0.042</td>
</tr>
<tr>
<td>Lights</td>
<td>0.124</td>
<td>-0.057</td>
<td>0.048</td>
<td>0.616</td>
<td>-0.035</td>
</tr>
<tr>
<td>R glass</td>
<td>0.623</td>
<td>0.003</td>
<td>0.016</td>
<td>-0.080</td>
<td>0.061</td>
</tr>
<tr>
<td>R paper</td>
<td>0.655</td>
<td>0.105</td>
<td>0.065</td>
<td>0.086</td>
<td>-0.038</td>
</tr>
<tr>
<td>R news</td>
<td>0.636</td>
<td>0.039</td>
<td>0.060</td>
<td>0.057</td>
<td>0.066</td>
</tr>
<tr>
<td>R clothes</td>
<td>0.551</td>
<td>0.031</td>
<td>0.118</td>
<td>0.156</td>
<td>0.016</td>
</tr>
<tr>
<td>Leftovers</td>
<td>0.639</td>
<td>0.054</td>
<td>-0.038</td>
<td>0.024</td>
<td>-0.016</td>
</tr>
<tr>
<td>Buy rec</td>
<td>0.069</td>
<td>0.762</td>
<td>-0.016</td>
<td>0.060</td>
<td>0.026</td>
</tr>
<tr>
<td>Donate</td>
<td>0.083</td>
<td>0.028</td>
<td>-0.076</td>
<td>-0.082</td>
<td>0.662</td>
</tr>
<tr>
<td>B2hand</td>
<td>0.052</td>
<td>0.088</td>
<td>0.706</td>
<td>0.006</td>
<td>0.004</td>
</tr>
<tr>
<td>Repair</td>
<td>0.077</td>
<td>0.108</td>
<td>0.061</td>
<td>-0.021</td>
<td>0.708</td>
</tr>
<tr>
<td>Hire</td>
<td>0.090</td>
<td>-0.013</td>
<td>0.704</td>
<td>0.103</td>
<td>-0.003</td>
</tr>
<tr>
<td>Share</td>
<td>0.046</td>
<td>0.000</td>
<td>0.658</td>
<td>0.023</td>
<td>0.062</td>
</tr>
<tr>
<td>Sell</td>
<td>-0.074</td>
<td>0.009</td>
<td>0.077</td>
<td>0.176</td>
<td>0.479</td>
</tr>
</tbody>
</table>

% variance explained: 11.19, 10.28, 8.65, 7.88, 6.67

### Table 2.3 Significant Differences amongst Demographic Groups by Individual Area

× = significant difference (p < 0.5) amongst groups of the given demographic class

S = Survey; M = Model

<table>
<thead>
<tr>
<th>Activity</th>
<th>House type</th>
<th>Household size</th>
<th>Family life stage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>S</td>
<td>M</td>
<td>S</td>
</tr>
<tr>
<td>Donate</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Sell</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lights</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Repair</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leftovers</td>
<td></td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Loose</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R Glass</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>R Clothes</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Buy rec</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Own bag</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Bulk</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>R Paper</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Batteries</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Share</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>R News</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>B2hand</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Hire</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>O pack</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

X = significant difference, p < 0.05

### Table 2.4 Regression Model Fit of Average Behaviour Scores against Attitudes

<table>
<thead>
<tr>
<th>Behaviour</th>
<th>Survey</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>All 18</td>
<td>0.26</td>
<td>0.395</td>
</tr>
<tr>
<td>Leftovers</td>
<td>0.18</td>
<td>0.069</td>
</tr>
<tr>
<td>Buy recycled</td>
<td>0.13</td>
<td>0.130</td>
</tr>
<tr>
<td>Donate</td>
<td>0.13</td>
<td>0.016</td>
</tr>
<tr>
<td>Reuse newspaper</td>
<td>0.10</td>
<td>0.076</td>
</tr>
<tr>
<td>Long life lights</td>
<td>0.05</td>
<td>0.023</td>
</tr>
</tbody>
</table>
Figure 2.2 Distribution of Responses from the Attitude/ Behaviour Survey (top diagram) compared with the Model Community (bottom diagram)
1=’never’; 2=’on odd occasions’; 3=’quite often’; 4=’whenever possible’
<table>
<thead>
<tr>
<th>Activity</th>
<th>Bulk</th>
<th>Loose</th>
<th>Own bag</th>
<th>Batteries</th>
<th>Lights</th>
<th>R glass</th>
<th>R paper</th>
<th>R news</th>
<th>R clothes</th>
<th>Leftovers</th>
<th>Buy rec</th>
<th>Donate</th>
<th>B2hand</th>
<th>Repair</th>
<th>Hire</th>
<th>Share</th>
<th>Sell</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P &gt; 0.01</td>
<td>p &lt; 0.2</td>
<td>p &lt; 0.3</td>
<td>p &lt; 0.4</td>
<td>p &lt; 0.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Figure 2.3a** Correlations amongst Pairs of Activities (Survey Results)

<table>
<thead>
<tr>
<th>Activity</th>
<th>Bulk</th>
<th>Loose</th>
<th>Own bag</th>
<th>Batteries</th>
<th>Lights</th>
<th>R glass</th>
<th>R paper</th>
<th>R news</th>
<th>R clothes</th>
<th>Leftovers</th>
<th>Buy rec</th>
<th>Donate</th>
<th>B2hand</th>
<th>Repair</th>
<th>Hire</th>
<th>Share</th>
<th>Sell</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P &gt; 0.01</td>
<td>p &lt; 0.2</td>
<td>p &lt; 0.3</td>
<td>p &lt; 0.4</td>
<td>p &lt; 0.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Figure 2.3b** Correlations amongst Pairs of Activities (Model Community)
Figure 2.4 Scatter Plot of Attitudes against behaviours

Table 2.1 shows the average behaviour score in the range 1 (never) to 4 (whenever possible) for the 18 individual behaviours tested in the survey. The distributions of responses for each individual behavioural component are shown in figure 2.2a-b. The pair-wise correlations between individual behaviours are shown in figure 2.3 (based on Spearman’s rank correlation coefficient, r, plotted where the relationship is highly significant, P<0.01). Table 2.2 shows the results of principal components factor analyses with varimax rotations. Table 2.3 records significant differences in behaviours (based on the chi-squared statistic) amongst different demographic groups. Table 2.4 provides regression analyses of behaviours against attitudes, aggregated over all 18 behaviours and for selected individual behaviours. The model attitudes were taken to be the general waste minimisation attitudes. The survey attitudes were based on a linear combination of individual attitudes that proved statistically significant to explaining the behaviours.

It should be noted that all the reported data emanated from a single model run, chosen without bias. It should also be noted that because of the stochastic nature of the model, each model run gives slightly different results. However, there were no gross disparities amongst any of the runs. As such the reported results can be taken as being indicative. The key point to note is that all the results reported below were generated simultaneously.

Many sets of model parameters could be found to provide good fits to the individual behaviour scores and their distributions. There can be no unique solution as the model is underdetermined with respect the available ‘hard’ calibration data. The calibration used should simply be viewed as being a ‘working’ calibration that was consistent with the available data. The demographic significances, for example, were set up in the empirical calibration according to the survey results. Here, the rankings of behaviours with individual demographic factors (not shown) were calibrated to match the survey results as closely as possible. Although those rankings were broadly preserved with subsequent model runs, some details in the rankings and significances of effects varied each time the model was run (because of the stochastic nature of the model). The discrepancies shown below between the survey and the individual model run are not untoward. A similar scale of differences was found amongst the four areas that made up the composite survey (Tucker and Douglas, 2006b), and has been witnessed in other surveys as well (e.g. Tucker, 2003). The sensitivity of the demographic dependencies amongst model runs is a feature that appears to represent reality.

The pair-wise correlations amongst behaviours were under-predicted in the model implementation shown here, and the explanatory power of attitudes towards determining behaviours was over predicted (figure 2.3 and table 2.4). This shows that that the working model still suffers from some of the deficiencies discussed in section 2.2.3. In particular it reflects that the ‘past experience’ antecedent and its strong coupling with attitudes is still being under-estimated. With further work, loading more of
the model variation onto the propensity attribute, there is every expectation that the fits could be improved without causing any significant detriment elsewhere. In the current implementation the random and attitude-coupled contributions to propensity are approximately in balance. The need for further loading strengthens our hypothesis about how important attitudinal factors might have been in shaping the habit and preferences we observe today.

The factor analyses of behaviours of the model society have clearly loaded the individual behavioural components onto the five main behaviour classes: ‘point of purchase decisions’, ‘buying long-life goods’, ‘reuse’, ‘valorisation’ and ‘minimising new-buy’. It should be noted that the final two classes were not separately distinguished in the composite survey results shown here, though were clearly distinguished amongst the individual survey areas that were composited. However, although the individual factors were clearly identified in the model, less of the variance of those behaviours was explained for the model society than for the real society.

Overall, whilst the model captures many features of the household waste prevention behaviours seen amongst the real society, some of those features appear less prevalent and less well explained in the model society than in the real society. There are also some features that we are not yet able to replicate in the model. For example, the survey results of Tucker and Douglas (2006b) showed the emergence of [three] distinct behavioural clusters amongst the survey group. We have not yet been able to replicate that clustering in the model society. In the model, only one major behavioural cluster emerges alongside many minor clusters.

2.2.5 Conclusion

The model results are clearly showing that we are able to create a model society based on a combination of simple rules and randomness that can be calibrated to mimic some of the key behavioural features seen amongst the real society. This extends beyond a merely qualitative visualisation and is starting to provide reasonable quantitative matches to the performance indicators and performance statistics that we can capture in a practical attitude/behaviour survey. Perhaps, most importantly, we have been able to match many different aspects of behaviours and attitudes simultaneously with a single model.

There is still a long way to go. There are some observed features that, with more work, might be matched more closely. The model development reported here is still at an early stage. Unfortunately time, resources and reporting deadlines preclude further basic development work on this contract. Nevertheless, we believe that the research has clearly demonstrated the proof of concept that we can create a model society that captures enough real world detail to render it pragmatically useful.

We believe that the initial experience of calibrating and using the model has considerably deepened our knowledge and understanding of the factors that are not only important to modelling society, but which might also be important to shaping the behaviours of the real society itself. Of course, “any correspondence between what one sees emerging from the model and what one sees in the real world is only a necessary, but not a sufficient, condition for concluding that the model is correct. All one can do is to gradually increase one’s confidence in a model by testing it against observation in more and more ways” (Gilbert, 1995).

And then ….

“If the model produces results that provide a good predictive fit to the data that arise from naturalistic observation, then we tentatively accept the theory - as implemented in the model - as a pragmatically useful tool for making predictions, until a more accurate or simpler tool can be found” (Hanneman and Patrick, 1997).

The results of some pilot predictions are given in the next section.
3. MODEL PREDICTIONS

3.1 Caveat

This section reports some initial predictions made using the model, running it forward in time under different sets of assumptions and environmental conditions. The aim is to establish some of the possible responses of the model society to external stimuli and interventions imposed on their current (calibrated) behaviours. The model calibration has set the sensitivities of the model to the variations in the respective strengths of its main behavioural drivers, i.e. ‘awareness’, ‘attitudes’, ‘convenience’, ‘propensity’, ‘social pressures’ and ‘financial costs’. The model also contains feedback loops whereby the strengths of the drivers can be reinforced or weakened depending on the behavioural experiences of the model agents. At this point we are looking at behavioural change. It must be strongly borne in mind throughout this section that although the model algorithms and model mechanisms for simulating behavioural change are in place, they still need to be verified and corroborated and calibrated against independent [real world] data. To put it another way, the model will compute the behavioural change resulting from changes of $\Delta X$ or $\Delta Y$ in attitudes; we do not yet know what actual attitude changes real world interventions might bring. Until that is known, we need to revert to semi-quantitative reasoning: a strong intervention may produce the change $\Delta X$ whilst a weaker intervention may only produce a change of $\Delta Y$.

Like the model calibration, experience in running the behavioural change simulation can enhance and clarify our understanding of where the key determinants and sensitivities might lie. At this early stage in the model development, and with the ‘thinness’ of appropriate scientific test data, we can only test the model against broad experiential evidence and intuition.

3.2 Results

Internal Processes and Background Stimuli

Illustrative results from the simulation have been developed here, concentrating on two points of purchase activities: ‘buying loose produce’ and ‘rejecting over-packaged goods’ respectively. The first simulation (figure 3.1a-d) considers the forward evolution of the two behaviours in the absence of any permanently lasting effects from any external stimuli. The model mechanisms for change are a weak reinforcement of the behaviour-specific attitudes upon experience (post-rationalisation) and an increase in the propensities to participate or not participate (e.g. habit-formation) through experience.

The plots are shown as 4-year-long weekly time series of participations (e.g. buying loose produce), non-participations (buying packaged produce) and non-involvement (no need to buy produce that week). The results are then summarised through aggregating the model behaviours over six-month periods across the four years.

The results demonstrate that, as expected, there are weak increases over all participation levels with time, together with a move towards more polarised behaviour (‘always’ or ‘never’) rather than ‘sometimes’ or ‘always’. It is also noticeable that the rates of changes of participation are relatively slow over the first three years but then start to accelerate slightly.

Figure 3.2 a-d then adds in some permanent (weak) durable changes for background effects. These comprise a small random incremental increase in general environmental attitudes and a small random adjustment of preferences away from habitual choices.

The two behaviours now become affected differently. The rate of participation increase is enhanced in the rejection of packaging with a noticeable convergence of the levels of engagement. However, for buying loose produce, there is a continuing polarisation of behaviours (‘always’ and ‘never’ both increasing) with a slight weakening of participation over the first two years before it then picks up again.

5 The reversible random elements of behaviour are still included.
Figure 3.1 a-d. Simulation of Possible Effects of the Internal Evolution of Attitudes
Figure 3.2 a-d. As per Fig. 3.1 but also including Durable Effects of Small Background Stimuli
The model mechanisms (and model explanations) for the longer-term pick up in participation and acceleration in participation lie in the gradual emergence of strong attitudes towards the activity, with those attitudes developing with increasing experience and reinforced from below by the pervasive slow upward shift in general environmental concern. As the strength of the activity-specific attitudes becomes comparable with, then begins to dominate the effects of the other behavioural drivers, we can envisage some kind of diffuse breakthrough point at which the rate of behavioural change is maximised. This is seen more clearly in figure 3.3 which ‘accelerates the process’ by increasing the ambient background pro-environmental stimuli together with an increase of attitudinal feedback on experience. It could be hypothesised that such an environmental breakthrough might eventually happen in the real world if the day-to-day messages of environmental concern continue, though the kinetics would probably be much slower than depicted in the scenario of figure 3.3.

Figure 3.3 Increased Effects of Attitudinal Stimuli

**Spillover**

A second reason for the longer-term escalation of activity-specific attitudes is thought to lie in behavioural spillover. That is, experience in one type of behaviour is thought likely to lead to the take-up of other related behaviours (see Tucker and Douglas, 2006a) for a discussion. The current model mechanism for behavioural spillover lies in the hypothesis that individuals may only have a finite amount of environmental attitude (see Tucker, 2007a). Once a new behaviour becomes sufficiently supported to be sustainable (say through habit) then the pro-activity attitude can be diverted to support another activity. A simple analogy is a two-tank model. Once the ‘loose produce tank’ is full of attitudes any more will spill over into the ‘reject packaging tank’.

Figure 3.4 shows the model outcome of the spillover effect. It is the outcome of two simulations, firstly a control, effectively the scenario of figure 3.2. Then a strong intervention was applied to the attitudinal factor for buying loose produce. In the model, that intervention only provided a rather modest change (~5%) in participation in buying loose produce, and that change eroding slightly over the course of the four years. However, there was a model spillover from that intervention, with the attitudes being diverted across the other point of purchase activities, one of the beneficiaries being the rejection of packaging. At the end of the four-year period there was over 9% increase in participation in rejecting packaging compared to the control, even though no interventions were applied specifically to address packaging.

Again, the model has shown the functionality to capture real-world features. However, as there is a dearth of case study data of spillovers in the real world, we have little to judge on whether the scale and kinetics of the model effects are realistic or not. In the model shown here, spillover effects are
seen to be relatively small compared with the effects of other small background stimuli and self-
reinforcement of attitudes.

![Figure 3.4 Simulation of Behavioural Spillover](image)

**Engineered Interventions**

It was noted above that the intervention to increase the buying of loose produce, by stimulating the
environmental attitudes towards it, had very little effect on the overall participation in the activity. The
different effects of other types of stimuli can be compared in the simulations shown in figure 3.5a. Again they were applied as relatively strong interventions, this time to enhance the social norm, and to
increase the awareness that it was a moral behaviour to undertake. The interventions themselves
could be thought of as being one-off intensive campaigns (applied at week 13). As such, the implied
changes to the behavioural drivers took on the characteristic structure shown in figure 1.1, with the
behavioural response following that structure quite similarly. A third simulation looked at a step change
in convenience (say, provided by the retailer).

The model shows that similar strength campaigns all provided comparable initial boosts to the activity,
with the more permanent external change having the most durable effect on behaviours. This can be
compared with the identical interventions being applied to rejecting packaging. The moral awareness
campaign did very little for packaging (the model calibration for moral awareness was already
relatively high). However, the increased convenience provided by the retailers had a massive effect of
over 20% increase in weekly participation. (Convenience had a lesser effect for buying loose produce
as the base level of convenience for that activity was already quite high).

Further illustrative intervention experiments are shown in figures 3.6 a-b.

When interpreting the figures, it should be remembered that the weekly participations (as plotted)
exclude households who had ‘no need’ for a shopping bag of any description that particular week
(around 17% of the model population), and that the numerical forecasts should be viewed as being
illustrative rather than definitive predictions.

Figure 3.6a demonstrates the compounding effect of multiple interventions. Figure 3.6b applies very
strong interventions to promote the environmental and social aspects of private reuse in general. The
stronger effects on ‘paper’ than on ‘glass’ result to a large extent from the different frequencies of
need. Writing something down is a daily need for most people. The need that can be satisfied by the
reuse of glass\(^6\) is much more restricted, and the need may only be [say] once per 2 - 4 weeks. If the timing of the intervention does not match an individual’s need-cycle then the impact of the intervention can be strongly diluted (and possibly forgotten by the time the next need-vent arises).

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\(^6\) This should not be equated with the need to do something with glass arisings
Finally, it must be remembered that many waste prevention activities are more about not doing something rather than pro-actively engaging in a specific activity, for example, not replacing appliances, decorations, furniture etc. before the end of their functional (or technological) lifespans. Tucker (2007) has shown how such activities might be modelled as drop-out activities from the status quo. They can be modelled in a broadly similar way to the other activities. In the model, needs arise at the end of the functional life of the good. It is assumed a new good is purchased. A temporary social norm is set (at a relatively high value) and a new propensity is set randomly for the new good. Each week the social norm is shifted downwards by an increment, and the propensity decreased in response to random background events as per the other behaviours. A new scaling factor ‘susceptibility to new technology’ is introduced to magnify the effects of the background fluctuations on those who are most susceptible.

It should be noted that for this type of waste prevention behaviour, social norm refers to the normal behaviour towards not replacing an item at a given time before the end of the functional life.
Figure 3.7a illustrates the model outcomes for 3 appliances that are assumed in the model to have an average functional lifespan of 4 years. The model plots the percentage of the model community who replace those items before the end of their functional life. The chosen items are a toaster (low cost, low background stimuli for replacement, fairly neutral social norm), a mobile phone (medium to low cost, strong background stimuli for replacement, high spread in social norm), and a home computer (medium to high cost, moderately strong background stimuli, fairly high spread in social norm).

The model output shows early replacements increase with the age of the equipment for the computer and toaster, whilst a peak emerges at around 40% (~18 months after purchase) for the phone. The reasons why the model society made the very early replacements were largely because of initial low propensities towards the new phone (they didn’t like what they bought). Note the total percentages add up to > 100% in all cases (108% toasters, 160% phones and 128% computers) as several of the model society bought twice (or three of four) times during the 4 year accounting period.

As with other types of behaviour, interventions can be introduced. Figure 3.7b illustrates the effects of strong and regular 6 monthly campaigns to raise moral awareness, increase attitudes and raise the social norm. It was found in the model runs that weak or one-off campaigns had very little effect.

![Figure 3.7a-b. Modelling Premature Replacement of Goods, Appliances, Decorations, Furniture etc.](image-url)
4. SUMMARY AND CONCLUSIONS

4.1 Commentary on the Methodology

Research has shown that current household waste management behaviours depend on many different antecedents including attitudinal factors, knowledge and capabilities, situational factors and habits and inertia. Previous research has often highlighted the importance of habit or past experience as one of the most dominant determinants of behaviour. That is highlighted yet again in the current research. However, although current behaviours can depend strongly on past histories, those behaviours are not necessarily ‘locked in’ or unchangeable. Behaviours can change, not only through external intervention, but also from the myriad of day-to-day experiences that everybody passes through. Sometimes people’s responses can be considered irrational; there are many opportunities for short-term behavioural excursions. Significant triggering events can prompt rapid behavioural change whilst more gradual changes can emanate from changing social pressures or evolving self-modifications. Everybody is different, with different needs and priorities, operating in different contexts.

Traditional ways of conceptualising behaviours tend to be deterministic in nature and do not consider the diversities of those behaviours amongst individuals. Traditionally, we have hypothesised models to help visualise the cause/effect of behaviours, and have tested those models by regressing them onto survey data. Such data are expensive to collect and normally limited to a single snapshot in time over a rather limited population. Normally such models do not extrapolate well to new situations or evolving events. Also those models normally tend to be designed to look at just one feature (or performance indicator) of the behaviour rather than the whole raft of behavioural outcomes.

The alternative approach as adopted and developed here is to build a virtual society based on our conceptual models, and to analyse and test our virtual society against whatever real world data we can obtain from a real society. In that way we can test many more different facets of overall behaviours including their relationships. It is also possible to carry out experiments [interventions] on the model society and test the outcomes against real world case study data. Given the confidence from that validation and testing, we can then run experiments on our virtual society to explore outcomes and benefits and test and refine alternatives prior to committing those policies and strategies in the real world.

To develop our model society we have adopted a multi-agent [or autonomous agent] approach. The agents are programmed to react to their situations according to their individual attributes, each seeking their own goal – to meet their needs with behaviours that provide the maximum personal utility (which will be a combination of doing environmental good, incurring least cost, taking the easiest option and appearing respectable amongst one’s social peers).

The precise relationships amongst the antecedents and the corresponding utilities to the individual are not known in real life, though theories about them abound (as witnessed by the plethora of conceptual models in the literature). It is precisely those utilities and their relationships that we need to understand more about in order to design the most effective policies to help steer the behaviours more closely towards the desired outcomes. The role of modelling as applied here is not only to conceptualise viewpoints and test preconceived hypothetical relationships, it is an evolving process for progressively capturing more and more of the real world observations. The logic used in the model for matching those observations can then become a proxy, or hypothesis, for explaining the real world causes of the observed phenomena. Of course, “any correspondence between what one sees emerging from the model and what ones sees in the real world is only a necessary, but not a sufficient, condition for concluding that the model is correct. All one can do is to gradually increase one’s confidence in a model by testing it against observation in more and more ways” (Gilbert, 1995).

The model that we have developed is not a ‘black box’ model that provides a unique or precise solution. It is a tool for exploring relationships and sensitivities amongst different factors and for carrying out experiments that are impractical to do in the real world.

The main model itself is quite simple, just a linear inequality. There are also a small number of sub-models. The most important of these models is a [hypothesised] hierarchy of attitudes and mechanisms of spillover amongst those attitudes. There is a sub-model to describe a typical
intervention profile and just a few model rules taking the general form “On experience then ….”. As a model-developer, I never cease to be amazed by the amount of real world phenomena that can be reproduced from very simple model systems.

Some of the outcomes might seem intuitively obvious\(^8\), or the cynical might say the model has been configured to give the expected outcomes. It must reproduce the obvious and it must match all demonstrable outcomes, else the model is deficient. Yet, in running the model there are still surprises and, by analysing why the model turned up those unexpected outcomes, we learn more about the complexities and interactions of the system and can gain new perspectives, ideas and explanations of the processes that might be involved in our real world analogue. It is difficult for the human mind to visualise the whole picture. The model provides a framework that takes away some of the base load of that visualisation, allowing us to penetrate deeper beyond the immediately obvious and unexpected.

We can never prove that our model is correct. We can only prove that it is deficient, for example if it cannot be configured to reproduce a real world observation. Then the model must be developed on further through new algorithms and rules or rethinking the values of the model coefficients.

Whilst we have made a number of observations and drawn inferences that could be informative in the policy domain, without rigorous testing those observations and inferences must still be thought of as simply setting new hypotheses or as strengthening [or disputing] our prior hypotheses. The key points emanating from the development of the model are set out in the next section.

### 4.2 Key Points Arising

The key indications that have emerged so far are:

- The major dispersion of waste prevention attitudes amongst the population appears to be at the behavioural class level.
- Our research supports the hypothesis that past experience is a very dominant factor in determining current behaviours.
- There are indications that current propensities towards behaviours resulting from past experience are strongly coupled with [current] attitudes. Those attitudes also appear to be founded more at the behavioural class level, than at the level of individual behavioural components.
- Individual components of behaviour, at the level normally described and tested, are subject to much variability amongst individuals and can also fluctuate significantly for a given individual. Part of the variability could be product-line specific rather than implying irregularities in the adoption of specific products\(^9\).

It follows that the best point for intervention to increase waste prevention attitudes may be at the behavioural class level (i.e. to stimulate point-of-purchase decisions, long-life and durable goods, private reuse, valorisation of unwanted goods, or minimising the consumption of new resources).

The simulations of possible future scenarios and ‘what-ifs’ have provided the following observations and hypotheses:

- Without any engineered interventions, household waste prevention activities are considered likely to increase by bolstering from the background stimuli that increase the general levels of overall environmental concern.
- Reinforcement of attitudes through experience, habitualisation of experience and spillover of behaviours could also contribute to a ‘natural’ progressive enhancement of waste prevention behaviours.

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\(^8\) Retrospect, hindsight and post-rationalisation are excellent mechanisms for determining what is obvious.

\(^9\) It is noted (see figure 2.2) that the more specifically worded behavioural components (e.g. using rechargeable batteries) do tend to be more polarised towards ‘always’ and ‘never’ than do the broader components (like buying loose produce). However there still remains a large component of intermediate behaviours in even the most specifically-worded components.
However, the kinetics of such changes are uncertain and are probably quite slow, although some significant natural movement could easily occur within a four-year time frame.

Interventions to stimulate behavioural change can have very different impacts on different behaviours. To have most effect, interventions need to be focused on the most sensitive or most dominant behavioural driver of the behaviour in question (like ‘convenience’ for rejecting packaging).

Interventions can have significantly less effect on less frequent behaviours, especially where those behaviours are comprised of highly-specific, even less frequent sub-behaviours (like ‘hire instead of buy’).

The model has shown that massive repeat intervention may be needed to impact significantly on ‘premature’ replacement of goods and appliances for reasons of fashion rather than need.

Overall, the modelling scenarios have shown the importance of hitting the right target driver for the behaviour. It has demonstrated how multiple interventions can add to the levels of changes created. Interventions to hit single behavioural components might not provide the best value overall particularly where individual needs may be of low periodicity. Pointers are emerging that strengthen our hypothesis that best value overall might be achieved through intervening at the behavioural class level.

4.3 Recommendations for Further Work

We have developed a prototype operational model of waste prevention behaviours, based on the concepts of distributed antecedent factors and inherent randomness, implemented using the methodology of autonomous agents. It has been shown that the model can be calibrated to fit multiple aspects of observed behaviours and used to investigate the possible effects of different intervention strategies. However, it must be remembered that the model is a multi-parameter model, with many of the parameters being imprecisely known at this point in time.

Further research data and well-documented case study data is needed to reduce the uncertainties in the model parameters and increase the confidence in the model predictions.

In particular we need scientific case study data across engineered interventions aimed at promoting behavioural change to quantify the respective contributions of each of the behavioural drivers to the changes produced.

The model itself should not be looked on as a finished ‘black box’. It is a tool (or methodology) that can be progressively refined and improved as and when new evidence becomes available.

The model is still in its early stages of development and needs further refinement and testing. Some of the sub-models (e.g. for behavioural spillover, attitude hierarchy and past behaviour) are still not fully conceptualised. There is a growing pool of new and independent data that could be harnessed for model testing and improvement. We propose:

Further development of autonomous agent-based models of waste prevention behaviours to include:

- Development and refinement and validation of model algorithms
- Validation and comparison with independent data [e.g. from other research in DEFRA’s Waste and Resources R&D programme.
- Continuing predictions (if possible with testable outcomes – through subsequent intervention studies).

We do not prescribe that any of the sub-models developed for the simulation, or even the basic main model inequality itself, are necessarily adequate or correct. They could easily be exchanged for other models according to preference and evidence. What we do advocate is that the framework, into which we embed those models, provides us with a highly powerful tool and penetrating new perspective for
visualising the impacts of ‘natural processes’ and engineered or policy interventions on our heterogeneous and imperfect society.

- The tool could be broadened to encompass more aspects of behaviour.

The model has been developed primarily as a research model to help the contractors in this research develop a better understanding of household waste prevention behaviours. However, we believe that it could have much wider benefits, rather than simply to ourselves, as a hands-on visualisation tool.

- The model could be developed into a product for wider dissemination.