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ORIGINAL ARTICLE

Using discrete event simulation to explore food wasted in the home

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ABSTRACT

Food waste is an issue of global importance. Households generate more food waste than any other source in high- and middle-income countries. There are many solutions to reduce household food waste, but measurement of the impact of each solution is costly, and therefore usually not undertaken. This is a major barrier to decision makers adopting the most effective solutions. Discrete event simulation (DES) modelling is ideally placed to overcome these problems. This paper presents the most developed application of DES to household food waste to date: The *Household Simulation Model* (HHSM). The HHSM has the flexibility to model several food items. It includes many household dynamics that can affect food waste (e.g., purchasing, storage, consumption). The HHSM simulates a range of household types to reflect the diversity of the population in question (for this paper, the United Kingdom). This paper demonstrates the innovation of the HHSM: it provides a framework allowing different types of evidence to be brought together to help understand how food waste is influenced by a range of factors. To illustrate its usefulness, we provide an analysis of six potential interventions to reduce milk waste, covering both product innovation and behaviour change.

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Food waste; household food waste; waste reduction; discrete event simulation

1. Introduction

The issue of food loss and waste has risen up the political and social agenda over the last decade. Approximately a third of all food produced on the planet is wasted or lost during its journey to consumption (FAO, 2011, 2019a). This leads to substantial negative impacts: the effective waste of the water and land required to produce this food, not to mention the energy and greenhouse gas emissions associated with processing, packaging, storing and transporting this food that is never eaten (FAO, 2011, 2019a). From 2010 to 2016, 8–10% of global greenhouse gas emissions were associated with food that was not consumed (Mbow et al., 2019). Indeed, if global food loss and waste were a country, it would be the third largest greenhouse-gas emitter, after the USA and China (Flanagan et al., 2019). There is also a financial impact: businesses and households that generate food loss and waste are buying food (or ingredients) that ultimately are not used: i.e. businesses and households' are spending money on food that is not sold or eaten (Drabik et al., 2019; Reynolds et al., 2019).

In light of this, reducing the amount of food loss and waste produced has become the subject of a number of high-profile programmes and targets. In particular, Sustainable Development Goal (SDG) 12.3 of the UN focuses on food loss and waste: "By 2030, halve per capita global food waste at the retail and consumer levels and reduce food losses along production and supply chains, including post-harvest losses" (FAO, 2019b). Many other targets have been aligned to SDG 12.3 (e.g., EU Circular Economy Package (European Commission, 2019), USA's 2030 food waste goal (US EPA, 2019), UK's Courtauld Commitment targets (WRAP, 2018a, 2019b)).

In high-income countries, households are usually the single-largest contributor to the total amount of food waste. For example, Stenmarck et al. (2016) estimate that approximately half of all food waste across the supply chain in Europe emanates from households. Therefore, to meet the ambitious goals of SDG 12.3 (and other targets relating to food waste), substantial reduction will be required in household food waste (HHFW), alongside other sectors.

However, reducing the amount of food waste from homes is not straightforward. The amount and types of HHFW are the result of many interactions within a household: how household members manage and consume food, alongside the types and amounts of food that they bring into the home (Quested et al.,

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2013). A range of activities can influence the amount of HHFW in a household, including meal planning, making shopping lists, impulse purchases, food storage, measuring amounts of food during cooking and managing leftovers (Schanes et al., 2018). These activities are, in turn, influenced by a wide range of attitudes, social norms, knowledge, intentions and lifestyle. Furthermore, attributes of the food itself can influence amounts of HHFW: e.g., the product life of food items, how they are packaged, the pricing and promotions in grocery stores (Quested et al., 2013).

Although there is a substantial body of research investigating the generation of food waste in the home and many potential solutions have been suggested to reduce HHFW (e.g., Hebrok & Boks, 2017; Schanes et al., 2018; Thyberg & Tonjes, 2016), many authors have noted the paucity of empirical studies measuring the effectiveness of different solutions in cutting HHFW (Porpino, 2016; Stöckli et al., 2018). Indeed, one recent review of food waste interventions (Reynolds et al., 2019) found only two studies in the academic literature empirically testing interventions aimed at reducing HHFW with a robust measurement method. In the context of this paper, an intervention is any change aimed at reducing the amount of food wasted in the home. This could include a change to a food product, how it is packaged or sold, or something designed to change decision-making or behaviour of a householder. Although there are a handful of other studies in the grey (non-academic) literature (Reynolds et al., 2019), this knowledge base is insufficient to answer key practical questions being asked by governments, businesses and other organisations: what are the most effective approaches to reducing the amount of HHFW in different circumstances? Although the number of studies that empirically test interventions is increasing, the rate of increase in food waste means that it will be many years (possibly decades) before this question can be confidently answered with empirical evidence.

The main reasons for this slow progress are related to the time and cost associated with existing methods of measuring food waste. Even within a single household, the amount of food waste varies substantially over time, and therefore relatively large sample sizes are required to detect any changes associated with the interventions being trialled against this background "noise".

Given this evidence gap, there is a place for modelling – and simulation in particular – to help decision makers. Preliminary simulation studies have been conducted by Quested (2013) and Stankiewicz et al. (2019), both of which used discrete event simulation (DES). In addition, agent-based modelling linked to Bayesian Networks has been applied to the issue of food waste in European households by Grainger et al. (2019). These and other modelling approaches have been summarised in Kandemir et al. (2020).

The Milk Model (Quested, 2013) was the first DES approach that addressed food waste in the home, tailoring the model to the UK. It demonstrated some of the advantages of applying system-based approaches to food waste prevention in the home: exploring the dynamics in the household and determining the approximate impact of potential changes (such as interventions). The Milk Model covers purchasing, storage, consumption and wastage of milk in the UK context. Its predictions are similar to results from empirical research.

Stankiewicz et al. (2019) applied the Milk Model framework to milk waste from US households. Improvements on the Milk Model included explicitly considering the consumption patterns of different household members. They analysed greenhouse gas emissions of increased packaging used for decreasing milk spoilage. This model used SimEvents discrete event simulation software (SimEvents, 2020).

Other models have been created that investigate food loss, waste, and packaging in the home and supply chain. However, due to the limited information in the public domain, no further comparison can be given at this stage (denkstatt, 2015; OVAM, 2015; Pack4Food, 2019).

These approaches show promise: the DES models were able to answer practical problems such as estimating the impact of different solutions aimed at reducing the amount of food waste in the home. However, both were confined to a single foodstuff (milk). They were also limited in the household dynamics that were included in the model: e.g. neither included the ability of a household to freeze food in order to increase its product life.

DES was favoured over system dynamics (SD) in this context due to the stochastic nature of the phenomena in question. For example, people do not undertake a shop on the same day of the week, nor do they eat the same amount of a certain food each day. These variations are important to include when estimating the amount of food waste in a home. Therefore, a probabilistic approach such as DES is required. DES was also favoured over agent-based modelling (ABM) as the study focussed on the interaction between human decisions and the journey of food into and through the home, rather than the interaction between humans or between households. SD and ABM both have a role to play in understanding other aspects of household food waste but were not as suited to meeting the particular needs of this study.

In this paper, we describe the newly developed household simulation model (HHSM) and compare the results to the existing Milk Model (Quested, 2013).

The HHSM presented in this paper is built upon the Milk Model framework. The advances of HHSM lies in the flexibility of using the model for a range of food items. To allow this, there is greater flexibility in the inputs and household dynamics relating to purchasing, storage and consumption dynamics. These features include (but are not limited to) freezing, defrosting by individual portion (instead of the whole pack), purchasing only through top-up shops, storing and consuming leftovers. Furthermore, changes to decision making or products have been assessed on a range of households ("household archetypes") to reflect the diversity of households in the UK (rather than simulating effects on a single household as found in previous models). Additional novelty of the HHSM is that the dynamics in the model are informed and validated with findings of existing social science and anthropological studies such as those by Evans (2014) and WRAP (2007).

The modelling was undertaken for the benefit of WRAP (the Waste & Resources Action Programme), a UK-based organisation, which, amongst other goals, aims to reduce the amount of food wasted by UK households. The research using the HHSM was designed to understand the relative effectiveness of different approaches designed to reduce food waste in the home.

2. Materials and methods

Reproducibility of research findings is at the centre of science in order to be able to extend the existing knowledge. In order to report the details of the HHSM, we have followed the STRESS guidelines developed by Monks et al. (2018). Model objectives are explained in the Introduction section. In the current section, the details on the logic of the model (dynamics of the modules and features) are explained with the data sources, input parameters and assumptions. Experimentation and implementation of the model can be found in Case Study section. Finally, the code of the model is shared on Figshare.[1]

2.1. Model overview

The HHSM presented in this paper was built and run using ARENA Simulation Software version 15.1 (Arena Simulation, 2020). The model consists of four main modules that replicate the stages and processes of home food purchase, storage, consumption and disposal as found through the research of Evans (2012, 2014)) and WRAP (2007) (Figure 1). These modules are named as *shopping, storage, consumption*, and *wastage*, respectively.

Each module and feature can be customised for different types of household, based on the number of occupants, their decision making, and the food type in question. The list of input parameters of the model can be found in Table 1. The ID number of the related input parameter is referred to in the description of the modules.

2.2. Module description

2.2.1. Shopping module

The shopping module determines when shopping events occur, how much is bought at each shopping trip and the product life of each product. Households can purchase food items from main shops and top-up shops.

There is much flexibility in determining when main shops occur. For most of the model runs in this paper, they are modelled to be weekly since most households in the UK do a main shop approximately weekly. The statistical evidence of shopping habits provided from various UK wide surveys (MRC Elsie Widdowson Laboratory & NatCen Social Research, 2019; Prior et al., 2014). To create a pattern of approximately weekly shops, they were modelled to occur on a Tuesday, Wednesday or Thursday, randomly determined at the beginning of the week. The occurrence of main shop and top-up shop visits can be turned on/off by the user (input variables 1 and 2, respectively).

A top-up shop is triggered if the household runs out of or is about to run out of the food item. This trigger level and the frequency of checking the fridge/cupboard and freezer can be defined by the user (variables 9, 10). If the amount of food items in the household falls below the trigger level, there is a chance that the top-up occurs on that day (variable 11) or on the following day, provided no main shop occurs. We set the trigger level for a top-up shop as the daily average consumption of the household for staple items. Top-up shop visits can be turned off if the food item under investigation is not a staple. Instant top-up shops can also occur if the household needs the product for immediate consumption such as cooking for a recipe, family dinner or a get together. The logic of this dynamic is explained under consumption module.

The size and number of packs that will be purchased from the main shop and top-up shop can be set by the user regarding the household archetype and food item (variables 3, 4, and 5). The amount of food item purchased at a main shop and top-up shop can be fixed (i.e. where households have set habits or the range of different sizes available is limited). However, these values can also be set as probabilistic distributions. Household purchases of food were informed by data from the Living Costs and Food Survey 2015–16 (DEFRA & Office for National Statistics, 2017). Information on the available pack sizes in retailers across the UK is sourced from WRAP's Retail Survey (WRAP, 2017b). The pack size and number of packs that are regularly purchased by the household are determined based on the weekly average purchases and consumption rate of the household.

If the household checks the fridge/cupboard and freezer before shopping, the amount purchased is adjusted accordingly by the model. For instance, if a household buys 4 pints of milk regularly on a main

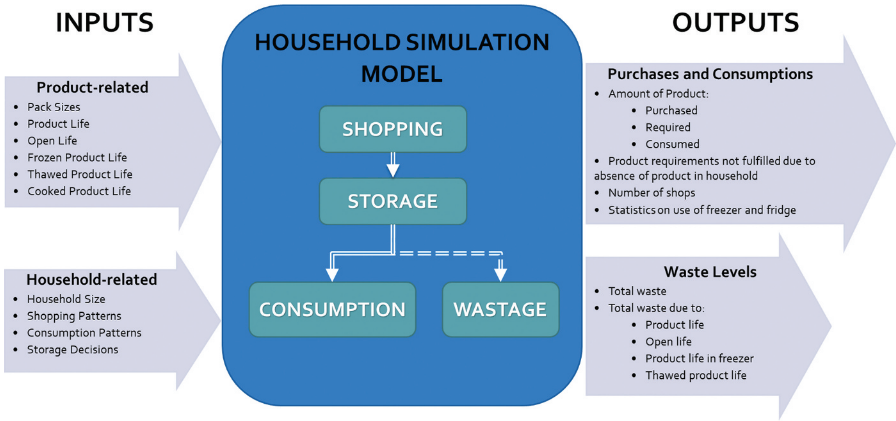

Figure 1. A visualisation of the household simulation model showing inputs, outputs and modules.

shop but they already have 2 pints in their fridge, they only buy 2 pints at the main shop visit. Different households commit on making a shopping list at different levels. As a result, the probability of checking the fridge and making a shopping list (variable 6) is defined as another variable that can be set by the user.

Once the packs are purchased from the main shop and top-up shop, a product life and open product life is assigned to each pack from statistical distributions defined by the user (WRAP, 2015). For the purposes of the model:

Product life is the time between the household *purchasing* a product and when they choose to throw it away, assuming that they have not frozen the product first (variable 7). In most simulation runs, this is related to either the use-by or best-before date of the product. Usually defined as a probabilistic distribution.

Open life is the time between the household *opening* a product and when they choose to throw it away, assuming that they have not frozen the product first (variable 8). This is often related to the open-life guidance on a pack ("once opened, use with x days") and usually set as a deterministic value (although probabilistic distributions are possible).

Data for product life and open life for a range of UK retailers was obtained from WRAP's Retail Survey (WRAP, 2010, 2012, 2017b, 2019a), which also contains pack-size information.

In order to fit a probabilistic distribution for product life, the least-squares-error method was used, seeking to minimise the difference between the modelled distribution and the empirical data. In the case of milk, the normal distribution was the best distribution to represent the product life. However, the normal distribution fitted occasionally generated values for product life that were negative (i.e. suggesting a product sold with a use-by date in the past). Given that it is illegal to sell food past the use-by date in the UK, distributions were truncated so that there are no products past the use-by or best-before date.

The values for product life and open life can be altered for different household archetypes to reflect the degree to which the household adheres to any date label of the pack. Previous research has shown that many households are prepared to eat food after the dates on the packaging (WRAP, 2011). This varies by the type of household modelled (see household archetype). As an example, for the product life of milk, the default model uses data on the use-by date found on bottles of milk in store from the 2011 Retail Survey (WRAP, 2012), which approximates to a normal distributed with mean 8.1 days and standard deviation 1.9 days. It is assumed that two of the seven household archetypes, this distribution is used unmodified to determine the product life. These two archetypes (Aspirational Discoverers and Spontaneous Creative Family) contain children and generally are composed of younger adults, both factors associated with more risk-averse behaviour relating to date labels. At the other extreme, the single-person Functional Fueller household (older with no children and therefore generally less risk averse) is modelled to consume milk for 3 days after the use-by date. The other three households fall within these two extremes.

If a product is frozen, two other types of product life need to be set:

Frozen product life is the time that an item can reside in the freezer before it is thrown away, usual set as the same length of time as the guidance on the pack (variable 50).

Thawed product life is the time between defrosting and when the item will be thrown away if not consumed (variable 51). This can have a significant effect on the household waste level.

These data are usually deterministic and usually are not varied for a given food item. These data are also obtained from WRAP's Retail Survey.

2.2.2. Storage module

The storage module simulates where food is stored in the home and changes product life accordingly. Food

Table 1. Input variables for the HHSM and sources of information used.

	ID #	Input Parameter	Sources of Information
Input for Shopping Decisions	1	Turn on/off main shop visits	When turned on, the main shop visits happen every once a week randomly (explained in "shopping module"). It is suggested to be turned off for rarely purchased/non-staple food items.
	2	Turn on/off top-up shop visits	This is suggested to be turned on for staple food items such as milk and bread and off for non-staple food items. When turned on, it needs to be triggered (see variable 9, 10 and 11).
	3	Pack size	The pack size (WRAP, 2017a) and the number of packages that are purchased from main and top-up shops are determined based on the weekly consumption rate (DEFRA & Office for National Statistics, 2017) of the household.
	4	Number of packs purchased at each main shop visit	
	5	Number of packs purchased at each top-up shop visit	
	6	Probability of shopping list making and adjusting consumption accordingly	This probability is calculated from WRAP's Consumer Segmentation Survey (WRAP, n.d.) for each household archetype under observation.
	7	Time from purchase of item until disposal (product life)	Data for product life and open product life probabilistic distributions are obtained from WRAP Retailer Survey (WRAP, 2010, WRAP, 2012, WRAP, 2017b, WRAP, 2019a). The interaction with the date labels (willingness to consume food items that pass best before and use by dates or open product life guidance) are obtained from consumer segmentation survey (WRAP, n.d.) and (Thompson et al., 2018).
	8	Time from opening of item until disposal (open product life)	
	9	Trigger level for top-up shop	It is suggested to be equal to household's average daily consumption for staple food items. For sources to calculate this value see sources on variable 12–20 and 32,34,38.
	10	Interval between checks to see if top-up trigger reached	It is suggested to be checked everyday by the households for staple food items.
	11	If top-up shop triggered, probability that it occurs today	These probabilities are obtained from WRAP's Consumer Segmentation Survey (WRAP, n.d.).

(*Continued*)

Table 1. (Continued).

	ID #	Input Parameter		Sources of Information
Input for People in the Household	12	Number of adults in the household		See "Household archetypes" section.
	13	Number of children aged 0–6 in the household		
	14	Number of children aged 7–17 in the household		
	15	Probability that the person actually consumes the item	Consumption probability children age 0–6	Data obtained from National Diet and Nutrition Survey Years 7–8 (2014 to 2015 and 2015 to 2016) (MRC Elsie Widdowson Laboratory & NatCen Social Research, 2019).
	16		Consumption probability children age 7–17	
	17		Consumption probability adult	
	18	Consumption amount per person per day	Consumption amount per adult	
	19		Consumption amount per children age 0–6	
	20		Consumption amount per children age 7–17	
	21	In case there isn't enough to consume	Probability of not consuming anything	For most food items, no empirical data is available. Expert judgement and sensitivity tests applied to see the influence of these variables on output. Highly depends on the nature and the price of the food item.
	22		Probability of only consuming what is available	
	23		Probability of purchasing the minimum possible amount from top-up shop	
	24	Increase probability for consumption if	Fridge is not empty	For most food items, no empirical data is available. Expert judgement and sensitivity tests applied to see the influence of these variables on output. These variables were introduced to be used with meat products that have short product life and open product life.
	25		There is unopened pack(s) in the fridge	
	26		The item pack is already open	
	27	Additional probability for consumption when	Fridge is not empty	
	28		There is/are unopened pack(s) in the fridge	
	29		There is/are already opened pack(s)	

(*Continued*)

Table 1. (Continued).

	ID #	Input Parameter		Sources of Information
Input for Cooking for the Household and Special Occasions	30	Turn on/off cooking		For food items that are purchased to cook for the family and used in recipes such as chicken, mince, pork, potato etc.
	31	Turn on/off cooking for a special occasion		No empirical data is available. Expert judgement and sensitivity analysis are applied.
	32	Demand interval per household	Cooking	Data obtained from National Diet and Nutrition Survey Years 7–8 (2014 to 2015 and 2015 to 2016) (MRC Elsie Widdowson Laboratory & NatCen Social Research, 2019).
	33		Special occasion	No empirical data is available. Expert judgement and sensitivity analysis are applied.
	34	Consumption amount per household	Cooking	Data obtained from National Diet and Nutrition Survey Years 7–8 (2014 to 2015 and 2015 to 2016) (MRC Elsie Widdowson Laboratory & NatCen Social Research, 2019)
	35	In case there isn't enough to cook	Probability of not cooking	For most food items, no empirical data is available. Expert judgement and sensitivity tests applied to see the influence of these variables on output. Highly depends on the nature and the price of the food item.
	36		Probability of cooking with what is available	
	37		Probability of purchasing the necessary amount from top-up shop	
	38	Probability that the household actually cooks with the item		Data obtained from National Diet and Nutrition Survey Years 7–8 (2014 to 2015 and 2015 to 2016) (MRC Elsie Widdowson Laboratory & NatCen Social Research, 2019)
	39	Increase Probability for Consumption if	Fridge is not empty	For most food items, no empirical data is available. Expert judgement and sensitivity tests applied to see influence of these variables on outputs.
	40		There is unopened pack(s) in the fridge	
	41		The pack is already open	
	42	Additional probability for consumption when	Fridge is not empty	
	43		There is/are unopened pack(s) in the fridge	
	44		There is/are already opened pack(s)	
	45	Consumption amount for Special Occasion		
	46	Probability that the special occasion cancels		
	47	In case special occasion cancels	Probability of freezing the item	No empirical data is available. Expert judgement and sensitivity tests applied to see influence of these variables on output.
Input for Freezing	48	Does the household freeze?		The preferences of the households on freezer usage is obtained from WRAP consumer segmentation survey (WRAP, 2013, n.d.).
	49	Probability that item purchased is frozen directly after shop		
	50	Frozen Product Life		Guidance on frozen and thawed product life obtained from WRAP Retail Survey, (WRAP, 2010, WRAP, 2012, WRAP, 2017b, WRAP, 2019a).
	51	Thawed Product Life		
	52	Does a household check items in the fridge/cupboard to freeze?		The preferences of the households on freezer usage is obtained from WRAP consumer segmentation survey, (WRAP, 2013, n.d.).
	53	Checking interval for the items in the fridge/cupboard to freeze		
	54	Probability of freezing these items that are about to expire		
	55	Minimum amount that can be frozen		This variable is introduced to make sure that reasonable amounts are put to freezer. For example, set the minimum amount of beef mince that can be frozen to one portion (i.e. 125 g. (British Nutrition Foundation, 2019).
	56	If cupboard/fridge is empty, probability of defrosting a frozen item		The preferences of the households on freezer usage is obtained from WRAP consumer segmentation survey, (WRAP, 2013, n.d.).
	57	Defrost by portion?		No empirical data is available. Expert judgement and sensitivity analysis applied to explore influence of this variable on outputs.

(*Continued*)

Table 1. (Continued).

	ID #	Input Parameter	Sources of Information
Input for Leftovers	58	Probability of cooking all items in a pack and storing any leftovers	This option is introduced for food items where the whole pack can be cooked such as chicken, potato.
	59	Product life for leftovers	Guidance on cooked product life obtained from (WRAP, 2013, WRAP, 2014b).
Input for behaviour on consumption increase for items approaching product life	60	Turn on/off behaviour change option	This variable and variables 61–65 is introduced to explore behaviour change on increased consumption for items approaching product life.
	61	Average daily consumption	See variables 15–20 for calculation of this value.
	62	Threshold	No empirical data is available.
	63	% Increase in consumption if 1 day remain	
	64	% Increase in consumption if 2 days remains	
	65	% Increase in consumption if 3 days remains	

items can be stored at ambient temperature (e.g., in a cupboard), in the fridge or in the freezer.

If freezer is going to be used, this option can be turned on (variable 48). Depending on the household behaviour, non-frozen food items can be frozen after purchase (likelihood entered as variable 49) or when they are about to expire (variables 52, 53, and 54). In the latter case, unopened and previously opened packs can each be put in the freezer. Once a pack is put in the freezer, the frozen product life and thawed product life are assigned to that pack (see above).

There are two options to defrost an item: everything in a pack (a whole pack or what is left in the pack if frozen partially consumed) or by the portion needed (variable 57). The minimum amount that can be frozen (variable 55) can be set to make sure that reasonable amounts are put to freezer. The probability of defrosting and consuming a frozen item when there is a requirement for the item but none in the cupboard/fridge can be set for the household (variable 56). This probability represents cases where a product is frozen but then forgotten about, or the household prefers not to consume the frozen item.

2.2.3. Consumption module

The consumption module determines when food is consumed, and in what quantities, and where leftovers might be stored after cooking. The household's requirements for the food item in question are determined in this module. In this context, "requirement" is how much of the food item in question the household would like to consume. There are a number of ways in which a household's requirement can be calculated.

Firstly, requirement can be determined for each member of the household and summed. This requires the number of household occupants, differentiating between adults, children aged between 0 and 6 years, and children between 7 and 17 years (variables 12, 13 and 14). For each group of people (e.g., adults), two bits of each information need to be specified: the probability that the person requires that food item on a given day (variables 15–17) and the distribution of how much is eaten on days when consumption occurs (variables 18–20). The values for these two bits of information are calculated using consumption data from the National Diet and Nutrition Survey for 2014/15 (n = 1363, 45% age 0–17) and 2015/16 (n = 1364, 45% age 0–17) (MRC Elsie Widdowson Laboratory & NatCen Social Research, 2019). This data is obtained from a diary of consumers' daily consumption for various food items covering 4 days. The distribution of amounts required each day was fitted to the consumption data using the least squares method.

The above method for calculating a household's requirements assumes that the requirements for each household member are independent of each other (which is more appropriate for staple items such as milk). The HHSM allows household requirements to be calculated assuming all household members eat the same food item as part of a single occasion (e.g., meat products as part of dinner). For the latter situation, the requirements are determined for the household as a whole, based on consumption amounts as previously described. This option, cooking for the whole household, can be turned on (variable 30) and the frequency (variable 32), consumption probability (variable 38) and the consumption amount (variable 34) can be entered.

A third way to enter requirement data is to use the "cooking for special occasion" option (variable 31). This option can be used for infrequent high-consumption events such as cooking for a family get-together or a celebration. The interval between special occasions (variable 33) and the amount consumed (variable 45) for the special occasions can be stated. The probability that the special occasion is cancelled can be entered (variable 46) and the household behaviour after the cancellation can be specified. As a default the household store the unused item after cancellation in the fridge/cupboard. However, they can store the item in the freezer (probability specified in variable 47), since the amount is large relative to their usual requirements.

Once the amount of the food item required by a household has been determined, the model works out how this compares to what is available within the household. If the household has a sufficient amount present at home, then the amount consumed is modelled to be equal to the requirement. Items are consumed from the fridge and cupboards first; if there are no packs in the fridge or cupboards, the freezer is checked for available packs.

If there is an insufficient amount present in the home, then there are three options for a household:

Consume what is available (a lower amount than the calculated requirement), Trigger an immediate top-up shop, and then consume the full amount required, or Forego any consumption of the product. The likelihood of these options is set by the user (variables 21–23 for individual consumption and variables 35–37 for cooking). As an example, for expensive food items the likelihood of consuming what is available can be higher than the option to forego any consumption of the product. Moreover, non-staple food items or treats are usually purchased based on need. By turning off main and top-up shops and only triggering an immediate top-up shop, the model can be used to investigate highly priced, rarely purchased food items. These items can be related to a special recipe, for instance. As a default, the likelihood of consuming what is available is set to 100%. These three options can be investigated further for various consumer behaviour analysis.

Households may tend to increase their consumption *frequency* based on the availability and condition of the food item, such as when the pack is opened or approaching the product life. For items with a short product life or open life, the household may increase the consumption frequency in order to finish the item before it expires. These options are controlled by variables 24–29 for individual consumption and variables 39–44 for cooking.

The model can also increase the consumption *amount* for items approaching their open or product life. In this option (switched on by variable 60), if there is a substantial amount of food that is about to go out of date, then the consumption amount is increased. This is modelled by measuring the amount of food that would be thrown away in the next few days. If there is more milk in the household than product (variable 62[2] x number of days until expiration x average daily consumption), then the consumption amount is increased by the percentage entered based on number of days remain until expiration date (variables 63–65). Expiration date is related to product life, open product life, and thawed product life.

Especially for meat products, households may prefer to cook the whole pack even though they are not going to consume it all immediately, and will therefore have leftovers to consume at a later time. In this case, the leftovers are assigned the "cooked product life" (the time available for consumption now that they have been cooked). Once there is a requirement for that food item, the leftovers are consumed first. Freezing the leftovers is also allowed in the model. The cooked product life of the item and the probability of storing and consuming leftovers can be defined by the user for the household (variables 58, 59). For the product life of cooked products, various UK food safety guidelines are used (Food Standards Agency, 2019; Ministry of Defence, 2019; ServSafe International, 2018).

2.2.4. Wastage module

The wastage module checks if the product is beyond its product life, open product life, frozen product life, thawed product life or cooked product life and, if it is, the food is thrown out. The "expired" items become waste. The total waste is recorded, alongside the reason for being discarded (e.g., open life exceeded).

2.3. Model inputs

As noted above, the HHSM requires a large range of input data. These are listed in Table 1, alongside the sources used to determine their values.

2.4. Model outputs

The model records various information from each run of the model. Of primary interest are the headline indicators:

Total amount purchased, required (i.e., amount "demanded" by the household) or consumed

Total amount wasted (also expressed as a percentage of total purchases)

- Split of total waste by why it was thrown away: due to product life, open life, frozen product life or thawed product life.

Total requirement not fulfilled due to no product in the home (expressed as a percentage of total requirements)

In addition, the HHSM tracks the number of shopping trips and the number of items stored in different locations (e.g., the freezer).

Each of these variables is recorded for the whole of the model run: 50 years of simulation time, with 30 replications. This allows a long-term average to be calculated, circumventing issues associated with the high temporal variation in levels of food waste.

2.5. Household archetypes

A challenge for the HHSM is that it only models a single household for a given simulation. However, to get the most out of the results, it is necessary to understand how an intervention affects the amount of food waste in a range of households (e.g. across the UK population). We have addressed this challenge by modelling several different "household archetypes" designed to be representative of the range of households within the UK. The use of household archetypes bridges the gap so that multiple simulation runs can be used to infer results for a whole population.

The seven household archetypes are based on WRAP's segmentation of the UK population (WRAP, n.d.). These archetypes provide a range of simulation households encompassing different numbers of occupants and a range of practices relating to food and food waste (Table 2). For each of the archetypes, the input variables were modified to reflect these differences. These include variables such as people in the household, which also influence other input parameters (e.g., the amount bought, and the amount consumed). Full input data for each household archetype for the following example (for milk) can be found in the supplementary material. Weighting factors were determined to ensure that the average number of occupants in the households reflects the UK average.

2.6. Model verification and validation

In order to verify the model, a daily log was created as an additional output to the model. This logged the amount of a specific food item purchased, consumed, stored and wasted for each day simulated in the model. These logs were scrutinised by the modellers to ensure that the HHSM was behaving consistently with the specification of the model. A section from this daily

Table 2. Household archetypes for the UK population, based on segmentation research by WRAP.

Household archetype	Brief description (changes to input conditions)	Weighting factor
Aspirational Discoverers (AD), Family	4-person household, younger children, not willing to take risks with food, confident, good planning, moderately likely to throw away leftovers.	7.8%
Functional Fuellers (FF), Single	1-person household, less willing to take risks, low confidence in the kitchen, poor planning, likely to throw leftovers.	14.3%
Functional Fuellers, Couple	2-person household, no children, less risk averse, low confidence in the kitchen, poor planning, likely to throw leftovers.	10.7%
Spontaneous Creatives (SC), Single	1-person household, less risk averse, moderately low confidence in the kitchen, poor planning, leftovers likely to be thrown away.	13.7%
Spontaneous Creatives, Couple with one child	3-person household, one child, more risk averse, moderately low confidence in the kitchen, poor planning, leftovers likely to be thrown away.	16.0%
Ideal Advocates (IA), Couple	2-person household, no children, less risk averse, high confidence in the kitchen, good planning, leftovers will be used.	24.3%
Pressured Providers (PP), Family	4-person household with (generally older) children, medium confidence in the kitchen, good planning, leftovers will be used.	13.2%

log can be found in Appendix 1. Moreover, extreme condition tests were applied in order to verify the turn on/off features.

Checks were run on the daily log, as well as other outputs, to ensure that the sum of the daily totals were consistent with the global totals for the whole model. Mass balance checks were conducted to ensure that all food entering the home was accounted for (either consumed, wasted or still being stored in the home).

To validate the model, various techniques were used as described by (Sargent, 2013). For face validity; purchasing, storage, consumption, and wastage events were animated to observe their behaviours. The daily log and other outputs were also scrutinised by subject matter experts (authors KF, EH and TQ) to ensure that it had face validity. This often led to refinement to the structure of the model or input data.

Even though verification and validation of the model was achieved, for any new food item the validation of the input-output transformations needs to be obtained. The results of the "default" models, averaged over the household archetypes, were compared to corresponding averages levels of food waste in the UK measured empirically (WRAP, 2014b). In some instances, simulated and measured levels of waste initially had a large discrepancy. In such instances, input values were scrutinised to see if they could be altered so that they were a) still within realistic bounds (e.g., consistent with the data they were based on) while also b) providing more realistic output values (i.e. for the amount wasted).

Unfortunately, there is not sufficient empirical data to validate input-output transformation for individual household archetypes or for scenarios away from the default (i.e. the current situation in the UK). This lack of data creates a paradox – it heightens the need for simulation, while starving the model of validation data. In the future, more empirical data may be available to perform further validation tests.

Given this limited validation, the modelling was assumed to only provide an approximate indication of the impact of changes to the input parameters, rather than a precise estimate. The implications for this are discussed in the *Limitations* section.

In the following section, an example can be found where the baseline scenario output is compared to the reported percentage of purchases that are wasted on milk.

3. Case study: interventions to reduce milk waste in the home

The HHSM presented in this paper had a run length of 50 years. No warm-up period and initial conditions were included. All point estimates are based on the average of 30 replications.

The HHSM can be used for various food items: currently it is set up to model milk, cheese, yoghurt, bread, potatoes, chicken breasts, ham, bacon and sausages. The current model has the potential to model a wider range of products as information on input data are available. In this paper we focus on milk, providing a comparison of results between the HHSM and its forerunner, the Milk Model (Quested, 2013) highlighting the depth and complexity of the HHSM. To illustrate this comparison, we present simulations relating to product-life extension and a change in consumption dynamics. (Many more interventions can be modelled with the HHSM, including changes in: pack size; food-labelling terms (e.g. use by date vs. best before date); storage location (e.g., use of the freezer; shopping frequency; and leftover storage and consumption).

A **default scenario** was constructed for each of the household archetypes to represent the dynamics associated with milk in a range of typical UK homes. The input data for these models can be found in Appendix 2. Approximately 3.8% of the milk purchased by UK homes is wasted because it was not used in time (WRAP, 2014b). The calculated percentage of the purchases that are wasted taking into consideration of the weighting factor for the household archetypes of percentage of purchases that are wasted is 3.3% (Table 3). Therefore, the simulated waste level is similar to the amount estimated from primary research. There is no empirical data for the amount

Table 3. Milk default scenario output: percentage of purchases that are wasted per household archetype and whole population.

HH archetype	Weighting factors of hh archetypes	Percentage of purchases wasted
AD, family	7.8%	2.05%
FF, single	14.3%	7.13%
FF, couples	10.7%	12.34%
SC, single	13.7%	7.61%
SC, family	16.0%	2.12%
IA, couple	24.3%	1.11%
PP, family	13.2%	1.26%
UK Population		3.27%

of milk waste for individual household archetypes, so no comparisons are available for these.

The six intervention scenarios to reduce milk waste were modelled, the first four scenarios focusing on product-life extension:

Scenario1- An increase in product-life of 1 day (e.g. the milk moves through the supply chain more quickly, giving an extra day to citizens)

Scenario 2- An increase in product-life of 3 days (e.g. as above)

Scenario 3- A switch to long-life milk with an average product life of 21 days for all household archetypes and a standard deviation of 1.9 days. This also increases the open life from 3 to 6 days (for standard milk, length depending on household archetype) to 7–10 days.

Scenario 4- A switch to long-life milk accompanied by purchasing bigger packs. (If default purchase is 1 pint, household purchases 2 pints instead; similarly, 2 pints shifts to 4 pints; 4 pints shifts to 6 pints).

For the first two scenarios, product-life extension was modelled in the absence of any other change to the HHSM. It is assumed that, given the variability in product life, people won't notice these relatively small shifts in product life and therefore will continue to use the same rules when making decisions relating to milk purchases, consumption and wastage.

The third and fourth scenarios relate to long-life milk (e.g. Cravendale: "ultra-filtered" or "micro filtered" (Arla Cravendale, 2019)). In addition to a product-life extension, both scenarios also model an increase in open life; additional, the fourth scenario looks at switching to larger packs (which may be more convenient for households).

Another method of avoiding waste is to adjust consumption patterns (i.e. increase milk consumption) in response to milk that is close to expiry. Two scenarios are investigated:

Scenario 5- Increasing consumption of milk by 10% when there are 3 days or less left until expiration date.

Scenario 6- Increasing consumption of milk by 10% when there are 3 days until expiration date, 20% when there are 2 days until expiration date, and 30% when there is 1 day until expiration date. In these last two scenarios, closeness to expiry is checked regarding product life, open product life, and thawed product life. The additional consumption of scenarios 5 and 6 is triggered when there is more milk than the following product "average daily consumption amount" x "number of days until the expiration date" (i.e. the threshold value (variable 62) equals one).

3.1. Results

3.1.1. Variation between household archetypes for product life extensions

Overall, the HHSM estimates that the UK population wastes 3.3% of purchases due to the milk not being used in time. This compares with an estimate of 3.8% from measured values (WRAP, 2014c). As the product life is increased, the amount of milk waste decreases, both overall and for all households Figure 2. For the overall UK, this represents a reduction to 2.7% for a one-day product-life extension and to 2.3% for a three-day product-life extension.

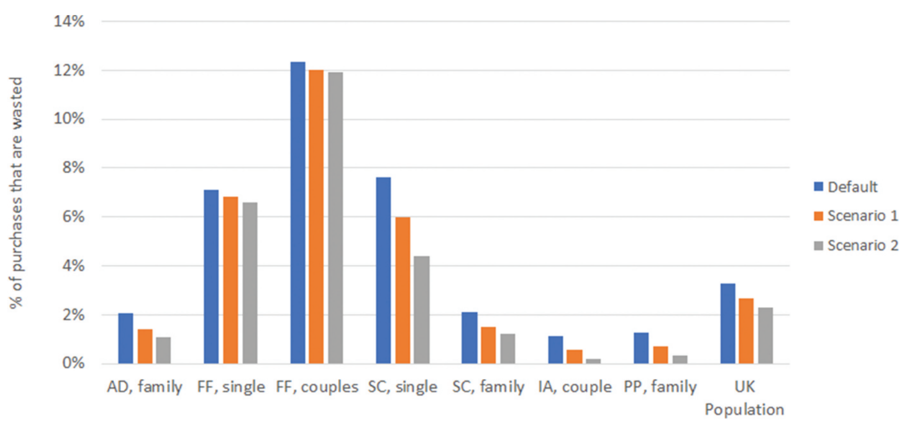

Figure 2. Estimates of milk waste, comparing the default scenario with extensions in product life (Scenario 1: +1 day; Scenario 2: +3 days).

The reduction in waste with increasing product life varies substantially by household archetype. For 3 additional days of product life (scenario 2), the percentage reduction ranges from 3% (for Functional Fuellers, couple) to 84% (Ideal Advocates, couple), compared to 30% for the overall UK population.

We found a strong correlation (R^2 = 0.9897) between the percentage change in wasted milk from a product-life extension and the proportion of milk wasted due to either the product life or thawed product life Figure 3. Therefore, and perhaps unsurprisingly, the impact of a product-life extension is larger in households where more milk is wasted due to the product life. Note that the default scenario in the Milk Model models a four-person household in which a high proportion of milk waste is due to the product life. Therefore, the use of only a 'standard' four-person household to make estimates for the UK population as a whole will give an unrepresentative result. This illustrates the benefit of using a range of household archetypes to model a diverse population.

By switching the purchases to only long product life milk (scenario 3), the population waste decreased from 3.3% to 0.01% Figure 4; the decrease was drastic for all defined household archetypes.

However, with long product life people may tend to purchase larger amounts. As a result, we have examined a further scenario where each household purchases the next larger pack size that is available from the store (scenario 4). In this case, the decrease in the population's waste level was more modest: from 3.3 to 1.8%. Furthermore, waste increased for some household archetypes (those with single occupants) and decreased for all others.

Variation between household archetypes for adjusting consumption patterns in response to close expiry date

As the consumption rate increased for the milk approaching expiry date, the amount of milk waste decreased as expected, both overall and for all households Figure 5. For the overall UK, this represents a reduction to 2.3% for Scenario 5 and 1.9% for Scenario 6. While this pattern increases consumption (the milk that would have been thrown away is being consumed instead), it doesn't cause an undesirable increase in unfulfilled requirement of milk Figure 6. Note that for scenarios 5 and 6, the HHSM's

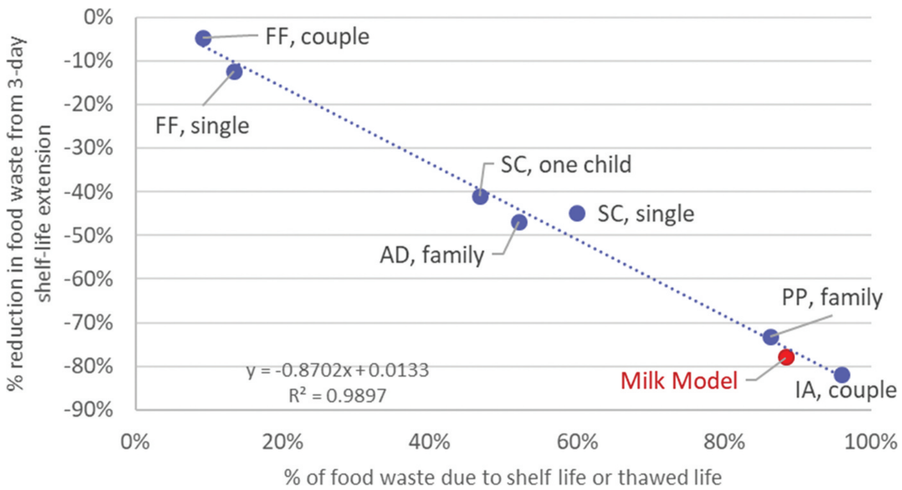

Figure 3. Correlation between the percentage reduction in milk waste for a three-day product life extension (vertical axis) and the percentage of milk wasted in the default scenario due to product life of thawed life. Results plotted for seven household archetypes from the HHSM and the 'standard scenario' from the Milk Model.

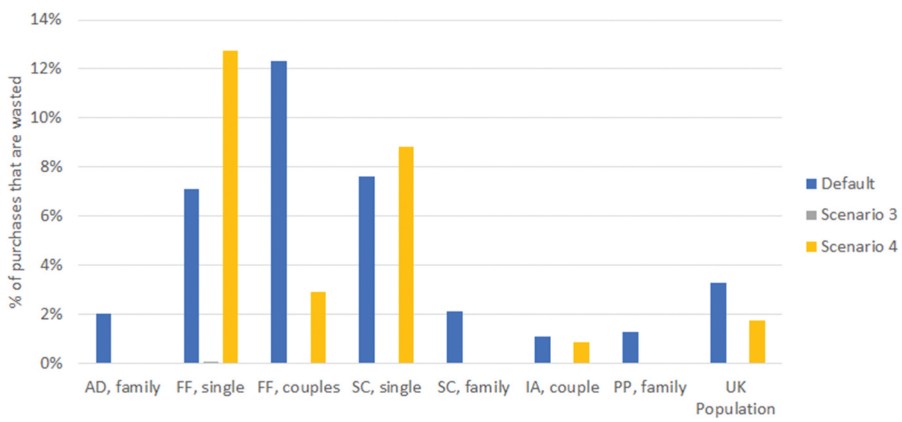

Figure 4. Estimates of milk waste, comparing the default scenario with a switch to long product life milk (Scenario 3) and purchasing larger pack sizes whilst also switching to long product life milk (Scenario 4).

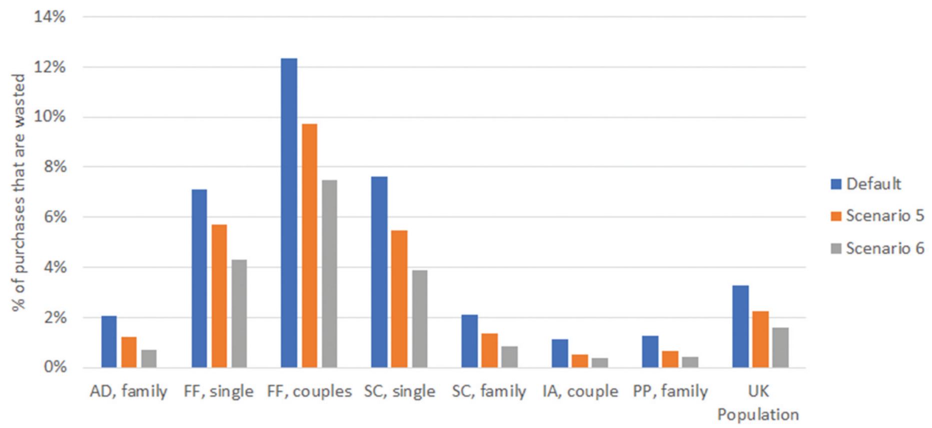

Figure 5. Percentage change in the volumes of milk wasted due to consuming up the milk that is about to expire.

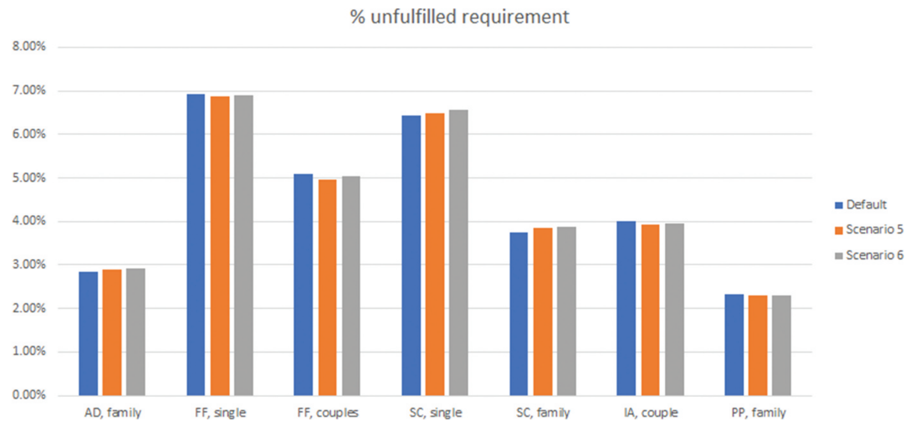

Figure 6. Percentage change in unfulfilled milk requirement due to consuming up the milk that is about to expire.

functionality was more advanced, so the equivalent runs weren't possible in the Milk Model.

The results indicate that milk waste in the UK could be reduced via strategies relating to the scenarios above – i.e. increasing shelf life and/or changing behaviour so that people use up milk that is about to expire. The modelling allows us to assess the approximate impact of these (discussed further below), which can be compared to the resources required to (and difficulty in) bringing about these changes.

3.1.2. Overall impact

The UK currently wastes 156,000 tonnes of milk because it is not used in time: it is thrown away because it has gone past its use-by date, the open life or because it looks, tastes or smells off (WRAP, 2018b). This information can be combined with the above results to estimate the approximate impact of the scenarios modelled:

Scenario 1 – 1-day product life extension: 19% reduction in "not used in time" milk waste, equating to c. 30,000 tonnes less waste within the UK.

Scenario 2 – 3-day product life extension: 30% reduction in "not used in time" milk waste, equating to c. 50,000 tonnes less waste within the UK.

Scenario 3 – A switch to long-life milk: 99% reduction in "not used in time" milk waste, equating to c. 150,000 tonnes less waste within the UK.

Scenario 4 – A switch to long-life milk with bigger size purchases: 46% reduction in "not used in time" milk waste, equating to c. 70,000 tonnes less waste within the UK.

Scenario 5 – Citizens increase the consumption as milk is about to expire (10% when there are 3 days or less left until expiration date): 30% reduction in 'not used in time milk waste, equating to c. 50,000 tonnes less waste within the UK.

Scenario 6 – Citizens increase the consumption as milk is about to expire (10% when there are 3 days until expiration date, 20% for 2 days until expiration date, 30% when 1 day): 51% reduction in 'not used in time milk waste, equating to c. 80,000 tonnes less waste within the UK.

4. Discussion

4.1. Application of the HHSM

In this paper, we have presented the household simulation model (HHSM) and use it to examine the approximate reduction in food waste from changes to a food product (product-life extension) or behavioural dynamics (responding to food about to expire). Alongside previous, small-scale deployment of discrete event simulation (DES) to the topic of household food waste (Quested, 2013; Stankiewicz et al., 2019), this paper demonstrates the benefits of the model for those working to reduce the amount of food waste. The HHSM can now provide simulated evidence on product innovation and behaviour change to policy makers, the food industry, and wider society. In so doing, it has led to a major step change in evaluating and prioritising solutions designed to tackle food waste in the home by providing an estimate of the impact of each solution for the population in question. For example, as a result of extensive use of the HHSM, WRAP presented the approximate impact on HHFW of a range of interventions and products (see Table 5 in WRAP, 2019a).

The model can provide results for a wider variety of foods than previously modelled: it is currently set up for a range of products covering vegetables, dairy, bakery, and meat (although this paper only focuses on milk to allow comparison with previous modelling). Furthermore, the HHSM can model a wider range of dynamics within the home (including freezing, purchasing food in a wider range of ways and modelling consumption and requirements with reference to individuals in the household).

The paper also illustrates how household archetypes can better represent a population than previous modelling. For example, we can observe that the impact of product-life extension varies for different households: for a 3-day product life extension, the change will be as little as 3% for a "Functional Fueller couple" and over 83% for an "Ideal Advocate couple". This level of analysis was not possible using the Milk Model and allows integration with food-waste prevention programmes that seek to influence different groups of the population in ways that are most effective for that group.

The results from the HHSM can be compared to earlier (and simpler) modelling within the Milk Model (Quested, 2013). For instance, the estimated reduction in food waste associated with a three-day increase in product life calculated by the HHSM was 30% (from 3.3 to 2.3%). In contrast, the result for the Milk Model was more than twice as high: 78% (from 4.9 to 1.1%). The more in-depth analysis in the HHSM – particularly the use of household archetypes – has determined why there is this difference. However, the absence of empirical data to compare these results doesn't allow us to say which result is closer to reality. However, the HHSM can help understand the dynamics in a household and therefore how the inputs influence the results. For instance, Figure 3 illustrates that the decrease in food waste due to product-life extension is related to the proportion of food waste caused by the product life being exceeded. Furthermore, we can use the model to explore what factors determine the amount of food waste from the product life and the open life. For instance, Figure 7 shows that, despite the complexities of household dynamics, the level of waste due to open life can largely be explained by three variables: the pack size purchased, the average daily requirements of that item and the effective open life for that household. Isolating the important factors and understanding their relationship can help narrow down the potential solutions to focus on to tackle food waste. Furthermore, it can help determine which inputs are important to accurate modelling (and which have less influence on the results).

4.2. Other benefits of the HHSM

In addition to the above benefits to people working to prevent food waste, the HHSM provides benefits to researchers or those gathering information about household food waste. It provides a framework in which "fragments" of evidence can be placed in context: for instance,

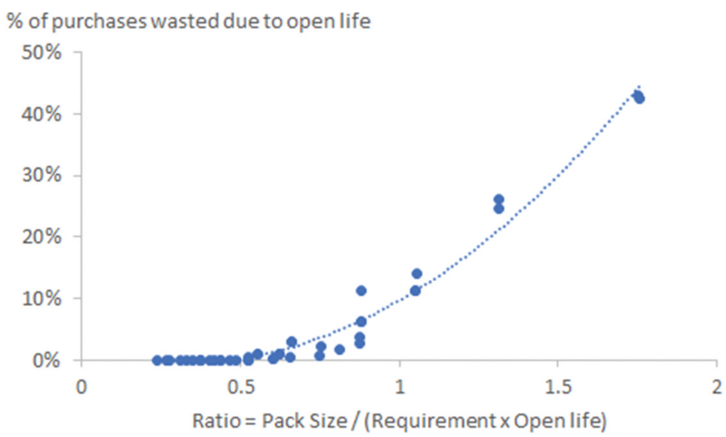

Figure 7. Scatter plot showing the percentage of purchases wasted due to open life plotted against the ratio of pack size divided by (daily requirement x open life) for 42 runs of the model for milk.

an anthropological study which helps understand how people use their freezer can inform the input parameters and construction of the dynamics within the HHSM relating to the freezer. Similarly, measured data on, say, an increase in the product life of a given food item can be used as input data to the HHSM. In both cases, the HHSM can assess the importance of these pieces of evidence for food waste.

Anthropological studies can also be used to qualitatively validate the study: comparing the range of outputs from the model to observations of researchers working in this field can (and, for this study, did) provide a crucial sense-check of the model. Therefore, closer working between the seemingly disparate disciplines of simulation and social sciences within the context of the HHSM can be mutually beneficial for both.

The stochastic nature of the simulation runs helps the user investigate the wide variability in behaviour of households, and therefore helps make the results more robust. Dynamic temporal modifications to household behaviour could be another avenue for future investigation and research.

4.3. Limitations of the HHSM

There are limitations to the HHSM. Firstly, it only models food wasted in the home that has not been used in time. There are other reasons for food being wasted, the main contributors to UK household food waste being too much cooked or preparing, too much served or personal preference (WRAP 2018b). The practical implication of this is that, when comparing solutions to reduce the amount of food wasted, those pertaining to these other reasons cannot be explored with the HHSM; other methods need to be used.

Secondly, HHSM can only consider one household archetype and one type of food item at a time. The interactions between different food items (such as consuming more milk if there is muesli available) and their wastages are not explicitly modelled, although they may be implicitly modelled via the variability of consumption.

Thirdly, as discussed in *Model verification and validation*, the model only provides an approximate estimate of the impact of a change to a product or people's behaviour. To ensure the results were not over-interpreted, they were reported to one significant figure. Even though this is a limitation, this still provides valuable information, as different options for preventing food waste will have impacts that are different orders of magnitude.

Fourth, the household food consumption and purchase data used as inputs for the HHSM is based on surveys. Although the sample sizes for these surveys are more than sufficient for our purposes, the surveys suffer from their own biases. For instance, estimating the amount of food consumed by asking research participants to record it in a diary (as happens for the National Diet and Nutrition Survey) usual leads to an underestimate of the actual level of consumption. (e.g., food consumption) often leads to an underestimation. Expanding and improving the underlying datasets used will help to will reduce uncertainty into the estimates produced by the HHSM.

While the model can explore the impact on food waste of a household changing its decision-making process, it cannot assess whether different methods will influence that decision-making process. For example, the HHSM can estimate the impact on food waste of a household starting to use the freezer effectively to store bread, but cannot determine the extent to which this change could be triggered by, say, a campaign, changes to the labelling on loaves of bread with regard to freezing, or any other intervention that has the aim of promoting freezing of bread. Therefore, to fully assess changes aimed at households' decision making, the model requires additional information relating to how successful an intervention is in influencing a household's decisions.

The results presented in this paper are for the UK population. It is likely that the results will be similar in other countries with comparable patterns of purchasing and consumption (although it would be good practice to review and adjust input parameters). In contrast, for countries with dissimilar patterns, substantial changes to the model's inputs or even its structure would be required.

For product-life extension, our results would apply in situations where the product and the label both reflect a longer life product: i.e. customers receive milk that can last 1 or 3 days longer, and the date label reflects this (e.g., the milk has been moved through the supply chain more quickly so that there is more time to consume it in the home). There will be situations where only one of the date labels and the product life will change (e.g., date labels being set less conservatively by dairies and grocery retailers). In such cases, assumptions have to be made about the proportion of the population who will be affected by a change to date labels in the absence of a product-life extension.

There may be a small number of households who throw away milk based on the time since it was purchase irrespective of the date: e.g., they throw away milk after 1 week, perhaps triggered by their next shop, irrespective of the date label or the state of the milk. Previous research from Evans (Evans, 2014, 2012) and WRAP (WRAP, 2007, 2014a) suggests that this is likely to be a small part of the UK population.

5. Conclusions and recommendations

The Household Simulation Model (HHSM) has been able to incorporate a large number of household dynamics into a single model designed to explore food wasted in the home, using discrete event simulation (DES). Although DES is not a new technique, its application to food waste in the home is novel and provides many useful insights. For example, we assess the impact of six different changes to a food product (milk) entering the home and/or the behavioural dynamics with the home. The model, however, can be applied to a wider range of food products, potentially in a wide range of countries.

The HHSM can support (and, since 2019, has been supporting) organisations wanting to focus on the most cost-effect approaches to reducing the amount of food wasted in the home. Therefore, the HHSM is an innovative application of DES to rapidly test many food waste reduction interventions and provides an evidence base with which policy makers, industry and governments can act upon. Thus, the HHSM is stimulating a step change in organisations' ability to evaluate and prioritise interventions.

There are a number of directions that future research in this area could take, including: apply the HHSM to a wider range of food products and to countries outside the UK; continue to refine the representation of human behaviour within the simulation; and testing the results of the model against emerging empirical data. Any further extension to the HHSM can be performed using the reproduced models to help address one of the most important issues of our time.

Notes

1. 10.15131/shef.data.12794528
2. Variable 62 is a "threshold value" comparing the amount of milk left against the number of days left to consume multiplied by the average daily consumption. A value of 1 would mean that there is an increase in consumption if the amount of milk left is larger than this product; a value of 2 would mean that increased consumption would only be triggered if there was twice as much milk left as would normally be consumed.

Contributions

The HHSM was conceived by TQ and programmed in Arena by CK. Expert advice relating to the structure of the model and input data were provided by CR, TQ, KF, EH, DE, and LK. The simulation runs were undertaken by CK and RD, with verification undertaken by CK, TQ, and CR. Validation was provided by TQ, KF and EH. The manuscript was drafted by CK, CR, and TQ with contributions and review from all authors.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix 1. Extract from daily log (output) of HHSM for milk

	Events at the beginning of the day		Events during the day									Total amounts at the end of the day			
Day	Total Waste	Total Frozen	Total Purchase	Number of packages purchased from Main shop	Number of packages purchased from Top-up Shop	Number of packages purchased from Top-up Shop for missing amount	Total Amount Opened	Total Amount Defrosted	Total Requirement	Total Consumption	Requirement Not fulfilled	Total Amount in Home	In Open Pack	In Fridge Unopened	In Freezer
...															
105	298	0	4546	0	2	0	2273	0	720	720	0	3826	1553	2273	0
106	0	0	0	0	0	0	0	0	1251	1251	0	2575	302	2273	0
107	0	0	2273	1	0	0	2273	0	855	855	0	3993	1720	2273	0
108	0	0	0	0	0	0	0	0	1381	1381	0	2612	339	2273	0
109	0	0	0	0	0	0	2273	0	1045	1045	0	1567	1567	0	0
110	0	0	0	0	0	0	0	0	1197	1197	0	370	370	0	0
111	0	0	4546	0	2	0	2273	0	1067	1067	0	3849	1576	2273	0
112	0	0	0	0	0	0	0	0	724	724	0	3125	852	2273	0
113	0	0	0	0	0	0	2273	0	872	872	0	2253	2253	0	0
114	0	0	2273	1	0	0	0	0	1336	1336	0	3190	917	2273	0
115	0	0	0	0	0	0	0	0	477	477	0	2713	440	2273	0
….															

Commentary:

The first day of the extract (day 105) sees milk being thrown away, leaving the household with no milk until a top-up shop is triggered. By the end of the day, 3,826 ml of the purchased 4,564 ml is left.

On day 107, a main shop was undertaken. As the household already had 2,575 ml of milk the home (see Total Amount in the Home on day 106), the amount purchased was not the usual 8 pints (4,546 ml), but only 4 pints (2,273 ml).

Day 111, sees a top-up shop, where 8 pints are purchased

Appendix 2. Input List of HHSM Default Scenario for Milk

Input Variables				Household Archetype						
				AD-Family	FF-Single	FF-Couple	SC-Single	SC-Couple with 1 child	IA-Couple	PP-Family
Input for Shopping Decisions	1		Turn on/off main shop visits	On	On	On	On	On	On	On
	2		Turn on/off top-up shop visits	On	On	On	On	On	On	On
	3		Package size	2273 ml	1137 ml	2273 ml	568 ml	1137 ml	1137 ml	2273 ml
	4		Number of packages purchased at each main shop visit	2	1	1	2	2	2	2
	5		Number of packages purchased at each top-up shop visit	2	1	1	2	2	2	2
	6		Probability of shopping list making and adjusting consumption accordingly	67%	51%	51%	41%	41%	73%	77%
	7		Time from purchase of item until disposal (Product life)	Normal(8.1,1.9) days	Normal (11.1,1.9) days	Normal (10.1,1.9) days	Normal(9.1,1.9) days	Normal(8.1,1.9) days	Normal (10.1,1.9) days	Normal(9.1,1.9) days
	8		Time from opening of item until disposal (Open Life)	3 days	6 days	5 days	4 days	3 days	5 days	4 days
	9		Trigger level for top-up shop	1210 ml	215 ml	433 ml	216 ml	685 ml	432 ml	935 ml
	10		Interval between checks to see if top-up trigger reached	1 day	2 day	3 day	4 day	5 day	6 day	7 day
	11		If top-up shop triggered, probability that it occurs today	75%	25%	50%	25%	75%	50%	75%
Input for People in the Household	12		Number of adults in the household	2	1	2	1	2	2	2
	13		Number of children between age 0–6 in the household	2	0	0	0	0	0	0
	14		Number of children between age 7–18 in the household	0	0	0	0	1	0	2
	15	Probability that the person actually consumes the item	Consumption probability children age 0–6	95%	95%	95%	95%	95%	95%	95%
	16		Consumption probability children age 7–18	83%	83%	83%	83%	83%	83%	83%
	17		Consumption probability adult	95%	95%	95%	95%	95%	95%	95%
	18	Consumption amount per person per day[a]	Consumption amount per adult	(5+ weibull (176,1.63)) a1.4 ml	(5+ weibull (176,1.63)) a1.4 ml	(5+ weibull (176,1.63)) a1.4 ml	(5+ weibull (176,1.63)) a1.4 ml	(5+ weibull (176,1.63)) a1.4 ml	(5+ weibull (176,1.63)) a1.4 ml	(5+ weibull (176,1.63)) a1.4 ml
	19		Consumption amount per children age 0–6	(27+ weibull (301,1.99)) a1.4 ml	(27+ weibull (301,1.99)) a1.4 ml	(27+ weibull (301,1.99)) a1.4 ml	(27+ weibull (301,1.99)) a1.4 ml	(27+ weibull (301,1.99)) a1.4 ml	(27+ weibull (301,1.99)) a1.4 ml	(27+ weibull (301,1.99)) a1.4 ml
	20		Consumption amount per children age 7–18	(2+ weibull (241,1.77)) a1.4 ml	(2+ weibull (241,1.77)) a1.4 ml	(2+ weibull (241,1.77)) a1.4 ml	(2+ weibull (241,1.77)) a1.4 ml	(2+ weibull (241,1.77)) a1.4 ml	(2+ weibull (241,1.77)) a1.4 ml	(2+ weibull (241,1.77)) a1.4 ml
	21	In case there isn't enough to consume	Probability of not consuming anything	0%	0%	0%	0%	0%	0%	0%
	22		Probability of only consuming what is available	100%	100%	100%	100%	100%	100%	100%
	23		Probability of purchasing the minimum possible amount from top-up shop	0%	0%	0%	0%	0%	0%	0%
	24	Increase probability for consumption if	Fridge is not empty	Off	Off	Off	Off	Off	Off	Off
	25		There is unopened package/packages in the fridge	Off	Off	Off	Off	Off	Off	Off
	26		The item package is already opened	Off	Off	Off	Off	Off	Off	Off
	27	Additional probability for consumption when	Fridge is not empty	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	28		There is/are unopened package/ packages in the fridge	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	29		There is/are already opened package/ packages	N/A	N/A	N/A	N/A	N/A	N/A	N/A

(*Continued*)

(Continued).

Input Variables				AD-Family	FF-Single	FF-Couple	SC-Single	SC-Couple with 1 child	IA-Couple	PP-Family
				Household Archetype						
Input for Cooking for the Household and Special Occasions	30	Turn on/off cooking		Off	Off	Off	Off	Off	Off	Off
	31	Turn on/off cooking for a special occasion		Off	Off	Off	Off	Off	Off	Off
	32	Demand interval per household	Cooking	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	33		Special occasion	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	34	Consumption amount per household	Cooking	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	35	In case there isn't enough to cook	Probability of not cooking	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	36		Probability of cooking with what is available	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	37		Probability of purchasing the necessary amount from top-up shop	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	38	Probability that the household actually cooks with the item		N/A	N/A	N/A	N/A	N/A	N/A	N/A
	39	Increase Probability for Consumption if	Fridge is not empty	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	40		There is unopened package/packages in the fridge	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	41		The item package is already opened	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	42	Additional probability for consumption when	Fridge is not empty	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	43		There is/are unopened package/packages in the fridge	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	44		There is/are already opened package/packages	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	45	Consumption amount for Special Occasion		N/A	N/A	N/A	N/A	N/A	N/A	N/A
	46	Probability that the special occasions cancel		N/A	N/A	N/A	N/A	N/A	N/A	N/A
	47	In case special occasion cancels	Probability of freezing the item	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Input for Freezing	48	Does the household freeze?		Off	Off	Off	Off	Off	On	On
	49	Probability that item purchased is frozen directly after shop		N/A	N/A	N/A	N/A	N/A	Off	Off
	50	Frozen product life		N/A	N/A	N/A	N/A	N/A	90 days	90 days
	51	Thawed product life		N/A	N/A	N/A	N/A	N/A	1 day	1 day
	52	Does a household check items in the fridge/cupboard to freeze?		N/A	N/A	N/A	N/A	N/A	On	On
	53	Checking interval for the items in the fridge/cupboard to freeze		N/A	N/A	N/A	N/A	N/A	1 day (everyday)	1 day (everyday)
	54	Probability of freezing these items that are about to expire		N/A	N/A	N/A	N/A	N/A	75%	75%
	55	Minimum amount that can be frozen		N/A	N/A	N/A	N/A	N/A	284 ml	568 ml
	56	If cupboard/fridge is empty, probability of defrosting a frozen item		N/A	N/A	N/A	N/A	N/A	75%	75%
	57	Defrost by portion?		N/A	N/A	N/A	N/A	N/A	Off	Off
Input for Leftovers	58	Probability of cooking all items in a pack and storing any leftovers		Off	Off	Off	Off	Off	Off	Off
	59	Cooked product life		N/A	N/A	N/A	N/A	N/A	N/A	N/A
Input for behaviour on consumption increase for items approaching product life	60	Turn on/off behaviour change option		Off	Off	Off	Off	Off	Off	Off
	61	Average daily consumption		N/A	N/A	N/A	N/A	N/A	N/A	N/A
	62	Threshold		N/A	N/A	N/A	N/A	N/A	N/A	N/A
	63	% Increase in consumption if 1 day remain		N/A	N/A	N/A	N/A	N/A	N/A	N/A
	64	% Increase in consumption if 2 days remains		N/A	N/A	N/A	N/A	N/A	N/A	N/A
	65	% Increase in consumption if 3 days remains		N/A	N/A	N/A	N/A	N/A	N/A	N/A

aThe consumption amounts obtained from National Diet and Nutrition Survey Years 7–8 (2014 to 2015 and 2015 to 2016) (Lennox et al., 2012; Office for National Statistics, 2017) suffer from under reporting. As a result, the consumption amounts (variables 18,19, and 20) are increased by 40% based on the discussions on Lennox et al. (2012).