A Data Driven Approach to Reducing Household Food Waste

Sustainable Production and Consumption 29 (2022) 600–613

Contents lists available at ScienceDirect

Sustainable Production and Consumption

journal homepage: www.elsevier.com/locate/spc

A data driven approach to reducing household food waste

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A R T I C L E I N F O

Article history:
Received 11 August 2021
Revised 20 October 2021
Accepted 5 November 2021
Available online 12 November 2021

Editor: Dr. Gonzalo Guillen Gosalbez

Keywords:
Waste minimisation
Food industry
Sustainable consumption
Inventory management
Optimisation
Consumer behaviour

A B S T R A C T

Of all food wastes, that which is produced from the household is the most damaging in terms of environmental and economic impact. Many efforts have been made to quantify and analyse the reasons for and problems associated with household food waste generation which has led to the development of both technical solutions and behavioural interventions (including education and awareness) to try and reduce its generation. In this work a novel solution is proposed and developed which connects food providers and consumers, enabling more intelligent food planning, purchasing and consumption. A data driven Recipe Suggestion tool, supported by a Particle Swarm Optimisation (PSO) engine, is described for the first time. Recipes and associated ingredients are suggested for users which consider their preferences, remaining food items already held at home, expiry dates and minimum pack sizes. The tool is applied to a simulated case study to demonstrate its applicability and potential to generate a range of useful waste metrics. Results of the application of the tool, in terms of optimization capabilities and computation time, show encouraging potential for platform integration. The suitability of the tool to be incorporated into modern e-commerce systems is discussed.

1. Introduction

About one third of food produced globally never enters anybody's mouth (FAO, 2011; IMechE, 2013); this 1.3 billion tonnes of food ends up as either food loss or food waste somewhere between the farm and the consumer. The associated economic, social and environmental implications of food waste have led to initiatives to reduce food waste being on many national agendas. The challenge of reducing global food waste has been further highlighted in the UN Sustainable Development Goal (SDG) Target 12.3 aiming to half the global per capita food waste by 2030 (FAO, 2018).

It has been reported that the composition of food waste varies across the world with household food waste (HFW) dominating the proportion of food waste generated in developed economies (IMechE, 2013) however confidence of estimates across different regions varies somewhat (UNEP, 2021). Indeed it has been indicated that per-capita food waste generated from the household increases with an increase of per-capita GDP (Xue et al., 2017) although this has since been disputed (UNEP, 2021). In any case, by way of example, in the United Kingdom about two-thirds of post-farm food waste is generated at the household level (Jeswani et al., 2021), and indeed 70% of this HFW is reported to be avoidable or possibly avoidable (WRAP, 2020). The UNEP Food Waste Index Report, 2021, has highlighted many difficulties with measuring HFW, especially in lower income countries, and has indicated that the problem could be much more severe than is currently understood.

Clearly as food progresses through the supply chain, the invested cost, time and environmental impact increases (WBCSD, 2008). Despite an increase in the implementation of separate food waste collection streams and the application of anaerobic digestion and composting technologies, food waste generated at the household level, as opposed to that generated elsewhere in the supply chain, is regarded as the most damaging and most expensive and most difficult to deal with due to it often being mixed with other waste types and of highly variable composition. For this reason, it could be argued that preventing HFW has more benefits than reducing food waste upstream of the supply chain. In addition to supporting sustainability objectives, reducing food waste has been regarded as highly important to ensure a sustainable food security (Foley et al., 2011; Godfray et al., 2010).

The challenge however is not straightforward. Unlike the actors in all other parts of the supply chain (e.g. farmers, manufactur-

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https://doi.org/10.1016/j.spc.2021.11.004

Nomenclature

C	recipe category
D	food item description
DB	database
ED	food item expiry date (mm/dd/yyyy)
EDT	food item expiry date type
FI	food item instance
I	ingredients matrix
N	recipe name
P	number of permutations
PSO	particle Swarm Optimisation
Q	food item quantity
RI	recipe instance
S	recipe source
SL	stock List
U	food item unit
d	food item desirability after the expiry date
g^*	global best
m	number of available recipes
n	number of particles in the optimisation algorithm
p	number of dimensions
t	pseudo-time (iterations)
v	particle velocity
x	position vector
α, β, c_1, c_2	learning parameters
w	inertia weight
ε_1, ε_2	random vectors

ers, retailers) consumers are not as well organised, exhibit variable and unpredictable behavior and are notoriously difficult to model (Stancu et al., 2016). Therefore in order to encourage consumers to consume food in a less wasteful manner, it is perhaps appropriate to enable them to be more organised and predictable in their approach to purchasing and consumption (Jellil et al., 2018). Clearly there is an opportunity for manufacturers and retailers to utilize their strong capabilities in stock flow control and data management to support consumers to better manage their food. Hence, as is the case for industry, data driven models may be able to provide bespoke solutions for reducing waste within the household (Woolley et al., 2016, 2021).

This article initially reviews the reasons for the generation of HFW in developed economies, identifies a number of actions and proposed solutions from the literature, before highlighting the potential opportunity for better integration of consumers and providers (manufacturers and retailers). A data driven approach is proposed and described to support consumers in managing their domestic food inventory and planning food purchases. The developed tools are implemented in a simulated case study to demonstrate the benefits of the system with the results discussed in the context of real-world applicability.

2. Literature review

Despite the significant importance of the challenge in reducing HFW and the scale of the problem very high-quality data about food wasted by consumers remains sparse (Xue et al., 2017; UNEP 2021). Whilst attempts have been made to improve data collection (e.g. Roe et al., 2020), the variety of reasons for HFW is quite complex (Evans 2011; Evans and Welch 2015; Stancu et al., 2016) and therefore solutions to reduce these wastes may only ever be partially effective and relevant only to certain global demographics. Some of the factors for the generation of HFW have been reported (for example: Jeswani et al., 2021; Quested et al., 2013; Stancu et al., 2016; Cicatiello et al., 2016; Stefan et al., 2013; WRAP, 2007) and are shown in Fig. 1.

With many reasons for HFW generation, there are clearly many opportunities to try and reduce the generation of HFW. However, it has been noticed that the majority of published academic articles regarding food waste provide an analysis of the issue rather than proposing solutions (Aschemann-Witzel et al., 2015). Studying consumer behavior seems like an obvious starting point to better understand HFW generation and the potential solutions (PWC, 2010), but it should not be regarded as the only cause for food wastage (Evans and Welch, 2015; Evans, 2011), given that the generation of HFW is also a consequence of how food is provisioned (Stancu et al., 2016; Evans, 2011).

Regarding actions that can be taken by providers, proposals have been made for a range of both strategic and operational solutions. Strategic examples include those identified by the World Business Council for Sustainable Development (WBCSD, 2008): innovation, choice editing and choice influencing; DEFRAs 4 E's framework, Institute of Grocery Distribution (IGD)'s Working on Waste (WoW) programme, and a UNEP-WRAP-FAO collaboration reminiscent of and environmental management system specifically targeting food waste. Operational solutions are easier to comprehend in terms of how they might immediately lead to a reduction in HFW: abolition of best before dates (Adam 2015); smart labelling to determine packed food quality (Zhang et al., 2013), improved packaging technologies (Kirtil and Oztop, 2016; Sand, 2015; Smithers, 2012) and resealable packaging (Sand, 2015). Improved information delivery has been proposed to help consumers better store food (WRAP, 2014) and to better utilise it (Woolley et al., 2016) and to support more sustainable food provisioning (Samsioe and Fuentes, 2021).

Instigating actions by consumers is more difficult to achieve and more difficult to measure in terms of effectiveness. In the UK one of the most prominent consumer engagement and communication programmes is Love Food Hate Waste which raises consumers' awareness specifically around planning, portioning, storing and understanding date labels (WRAP, 2015). This programme strongly promotes the idea of carefully planning shopping to better use items already within the home and to pay attention to expiry dates in relation to when food will be consumed.

In this work it is hypothesised that using a data driven approach to better enable consumers to plan food purchases would lead to a reduction in HFW. The data driven approach is intended to better enable the integration of consumers within the predictable and manageable food supply chain. Specifically in this research, a cloud-based inventory management system with a Recipe Suggestion tool and purchasing support is described to enable users to better align their existing food, meal requirements and purchases. The Recipe Suggestion tool utilises Particle Swarm Optimisation to suggest the most suitable recipes based on user requirements and waste minimisation. The system has not yet been implemented in a real scenario since there are many technological, legislative, commercial and social barriers to this, but is presented as part of a potential solution to reduce HFW.

3. Methods

The approach taken in this research regards the consumer as an actor in the supply chain of food production and consumption that interacts with the providers via one of four mechanisms as shown in Fig. 2:(1) as physical in-store shoppers, (2) as 'click and collect' shoppers, (3) as online shoppers who receive food by delivery or (4) as subscribers to food provision services, who also then receive food deliveries. In reality domestic food purchasers are likely to utilise more than one of these purchasing mechanisms. Of in-

Fig. 1. Reasons for household food waste.

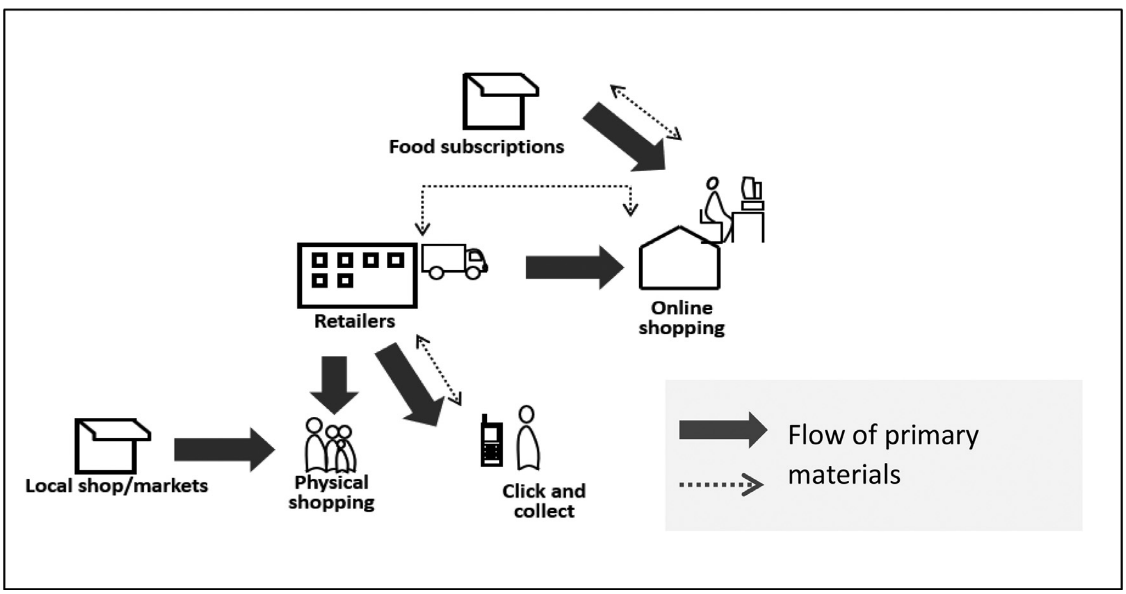

Fig. 2. Consumers interactions with retailers, local shops/markets, and food subscriptions.

terest in this research are those mechanisms that enable easy bi-directional data transfer between retailer and consumer (2–4) as it is this link that can be used to influence better consumer choices and also provide retailers with data about individual consumption habits.

It is assumed that before purchasing, shoppers have some idea about what they may wish to buy (variety and quantity) based on their preferences and needs. It is also assumed that each shopper will have at least some food available already at home which could be utilised for future meals. By extension, it is therefore also assumed that for some shoppers at least, their purchase intentions are influenced by their preferences and needs and their available inventory. In this case it is possible to define three 'databases' which are a consumer's Stock List (i.e. their available inventory), their Preferences (encompassing both needs and desires) and their Shopping List (in an ideal world, this would be their Preferences minus their Stock List). These are the fundamental 'databases' that this research seeks to optimise in terms of their mutual relationships by creating a Recipe Suggestion tool that matches Preferences with Stock List to produce a Shopping List.

4. Framework

The Recipe Suggestion platform aims at providing the best solution for matching suitable recipes on a short timescale (e.g. weekly) with the available food items in a Stock List and the user Preferences, creating a Shopping List of the ingredients required to make the recipes, but which are not already held in the Stock List. The platform is designed to optimize the utilization of the remaining inventory, under the constraint of the expiry dates, and match purchase quantities to actual needs, thus reducing waste generated.

The proposed platform has a modular architecture. Three modules respectively dedicated to the Data Collection, Data Processing,

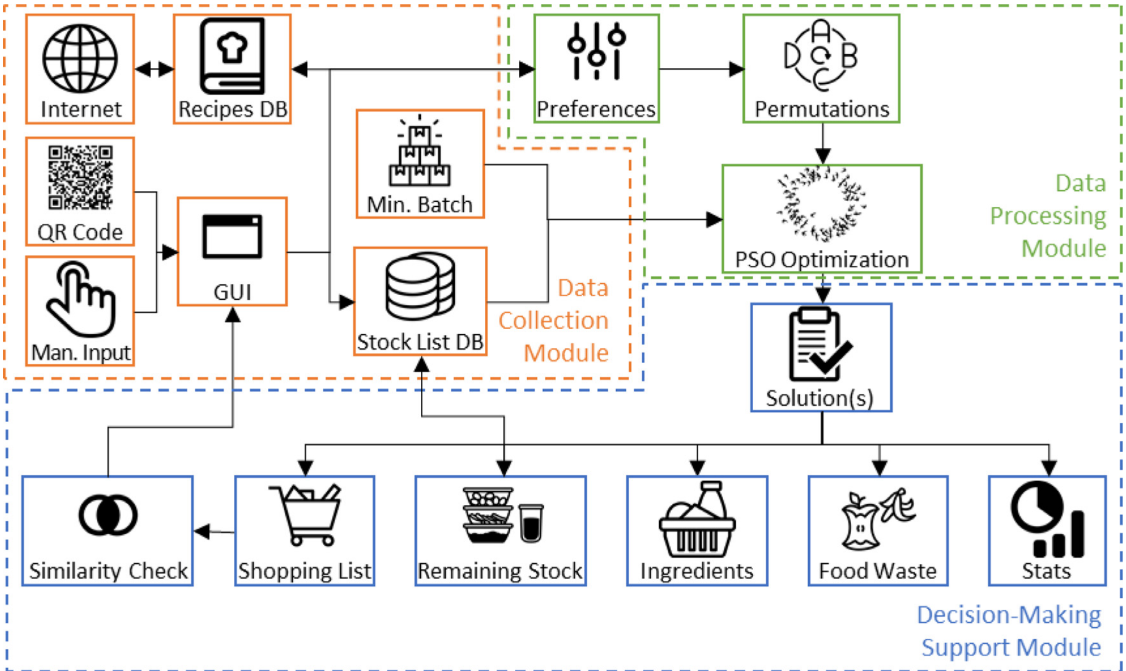

Fig. 3. Overall framework scheme.

and Decision-Making Support are defined in this section as depicted in Fig. 3. The diagram shows the flow of information within the platform. A detailed description of the three modules along with their computational engines is reported in the remainder of this section.

4.1. Data collection module

The Recipe Suggestion platform needs to access the details of the Stock List (including expiry dates) as well as the available recipes.

The Stock List data are collected through a number of mechanisms (e.g. Woolley et al., 2016) such as a graphical user interface which allows for a manual input of food items data, in the case fresh produce purchased without a printed expiry date for example, as well as for an automatic data import via QR code scanning. Since expiry dates are not currently tracked electronically in store, it is assumed in the current version of the system that all newly supplied food items have an expiry of at least seven days. If the expiry dates of items were known within the store, this could be incorporated into the optimisation system to ensure that sufficient life remains for the product to be utilised before becoming waste. The food items data are stored in a Stock List (SL) database (DB). A generic instance FI for a food item i appears as follows: $FI_i = \{D_i, Q_i, U_i, ED_i, EDT_i,\ d_i\}$ where D_i represent the food item description (i.e. name), Q_i is the quantity along with its related measurement unit U_i, ED_i is the expiry date (mm/dd/yyyy format) and EDT_i is the expiry date type, i.e. "use by" or "best before". In the latter case, d_i represents the duration, i.e. the number of days in which a certain food item can be consumed after it passes its expiry date. For "use by" expiry date, $d_i = 0$.

Regarding the recipes, these are retrieved from an online repository, (for example www.food.com), and stored in a Recipes DB. A generic recipe instance appears as follows: $R_i = \{N_i, I_i, C_i, S_i\}$, where N_i is the recipe name, I_i is a matrix containing the ingredients, quantities and units, C_i indicates the recipe category (e.g. Chinese, vegetarian, gluten-free etc.) and S_i is the recipe source, i.e. a link to the recipe website visualizing instructions etc.

4.2. Data processing module

This module is responsible for the generation of all the possible feasible recipes sequences. The recipe selections will be based on the user's Preferences, hence they may select how many times a week a certain recipe category is desired and in which quantities amongst other limiting factors such as their skill level, maximum cooking time and health-related dietary requirements. The Preferences feature is important for better matching a user's requirements to suggested solutions and enables the system to consider only the recipes which match the Preferences and hence reduce the number of permutations to be analysed. For example, if the user selects "Chinese food" x 2 AND "Italian food" x 3 AND "Vegetarian food" x 2 the data processing module will generate only those permutations that meet such proportions. Equally, a user with a low level of cooking skill, or who is time-poor, may require meals that have pre-prepared components or are complete ready-meals. The system is suitable to consider all food types.

The Data Processing Module will need to identify all possible recipe permutations for the recipes accessible from its database and which match the user Preferences, i.e. generating P permutations of seven recipes (in a case considering one recipe per day for a week) from the m recipes available in the database. A small number of recipes will yield to a very high number of possible permutations, as shown in Eq. (1). For example, selecting seven recipes from 10 options yields 604,800 possible permutations. Each permutation represents a sequence of recipes to be prepared during the week and needs to be considered with respect to how much of the Stock List could be utilised, how much new food would need purchasing and how much HFW is likely to be generated.

$$P = \frac{m!}{(m-7)!} \tag{1}$$

Checking every possible permutation, based on the users' preferences, to establish the amount of HFW which might be generated is computationally demanding, especially given that there could be hundreds of recipes to choose from and users may want to select more than one meal per day. In this case it is sensible to utilise a

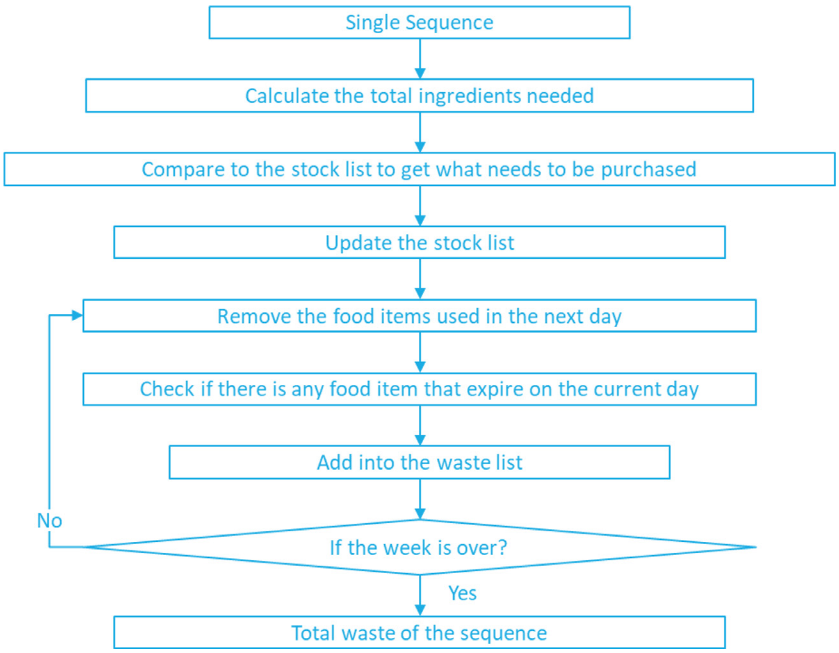

Fig. 4. Objective function construction flow-chart.

metaheuristic optimisation algorithm to reduce the number of permutations considered by honing in on solutions that provide the most desirable results. In this research a Particle Swarm Optimisation (PSO) approach is used as described in the following section. The Data Processing Module receives all the feasible permutations from the previous module and computes an intelligent optimization to select the recipe sequence that minimizes the amount of food waste generated.

The optimization is modelled as the minimization of the food waste whilst meeting the user preferences, taking into account the expiry dates of the food items. In principle, since the sequences list is previously filtered by removing the sequences that do not meet the user preferences, the optimisation search space is made of only feasible sequences, so the problem is configured as unconstrained optimisation.

Due to the problem formulation complexity, the multi-step objective function utilised in this paper is reported in Fig. 4 as a flow chart, as the representation in compact mathematical form would not be practical.

Given a sequence of recipes, the objective function first computes all the ingredients required to realize the seven meals over one week. Subsequently, the ingredients required are compared to the available Stock List to compute those items which need to be purchased. The items can be purchased according to the commercial minimum batch sizes, or multiples thereof, therefore the objective function updates the Stock List considering the amount that would be purchased. For every day of the week, the objective function computes the items used to cook the scheduled recipe and removes any expired food item (if any) adding it to the 'food waste' list. Note that users can avoid the generation of some food waste by adding any small amount remaining (e.g. 20 g of chicken) to their recipe and recording this on the Stock List. The same flexibility also allows, to some extent, personalisation of meals due to individual tastes. The objective function then sums up the wasted food items for each recipe sequence. Sequences with the least waste generated would be preferentially presented to the user and hopefully selected.

The objective function follows the material flow illustrated in Fig. 5.

4.2.1. Particle swarm optimisation engine

The high number of feasible sequences requires a more efficient solution search. In this respect, a PSO engine is designed to minimise the objective function of such modelled combinatorial problem. PSO, initially developed by Eberhart and Kennedy (1995) is based on the natural swarm behaviour such as fish and birds. PSO utilises the real-number randomness and the global communication among the swarm particles to explore a problem's search space with the aim of finding the global optimum configuration (Chopard and Tomassini, 2018). This algorithm searches the space of an objective function by adjusting the trajectories of individual agents, i.e. particles, as these trajectories form piecewise paths in a quasi-stochastic manner.

The PSO engine is initialised with a random sequence, characterised encoded with n particles, the position vector x_i and the velocity v_i. The algorithm computes the global best g^* as the $\min\{f(x_1),\dots,f(x_n)\}$ (at $t=0$). A stopping criterion is then set, e.g. a maximum number of iterations or a minimum improvement threshold. Subsequently, looped over all the n particles and the p dimensions, for a generic particle i, the new velocity vector is computed as per Eq. (2):

$$v_i^{t+1} = \omega \cdot v_i^t + \alpha\varepsilon_1 \cdot \left[g^* - x_i^t\right] + \beta\varepsilon_2 \cdot \left[x_i^* - x_i^t\right] \tag{2}$$

Where ω is the inertia weight, ε_1, ε_2 are random vectors with values ranging between 0 and 1, α and β are the learning parameters, typically $\approx$2.

The Initial velocity of a particle, $v_i^{t=0}$, is set to zero. The algorithm updates the new particles position x_i^{t+1} according to Eq. (3).

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{3}$$

At this point the algorithm evaluates the objective function in correspondence of the new locations x_i^{t+1} identifying the current best x_i^* for each particle.

In this way it is possible to compute the global best g^* for every iteration. Once the termination criterion is met, the algorithm will output the final result, consisting in the best position x_i^* (i.e. the best recipes sequence) and its corresponding overall global best g^*, i.e. the total amount of food waste.

A flow chart of the PSO engine algorithm is reported in Fig. 6.

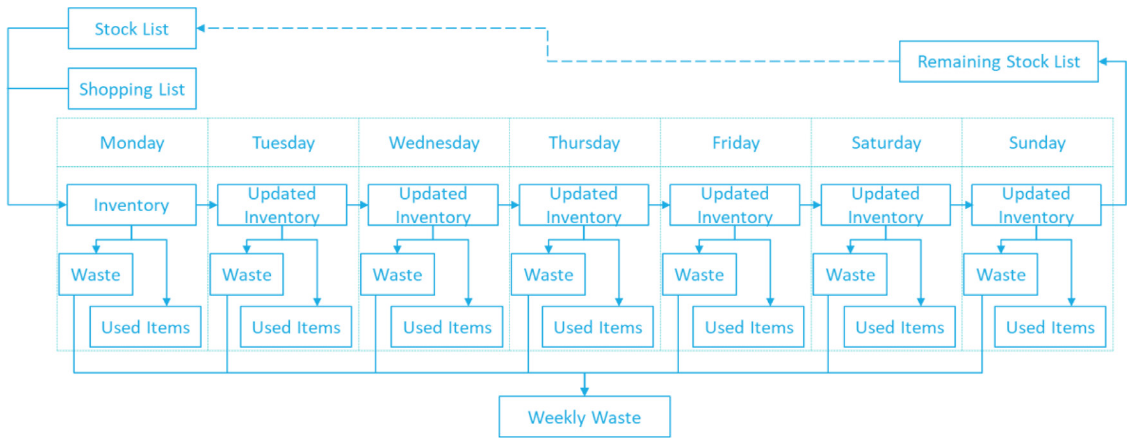

Fig. 5. Recipe Suggestion platform material flow.

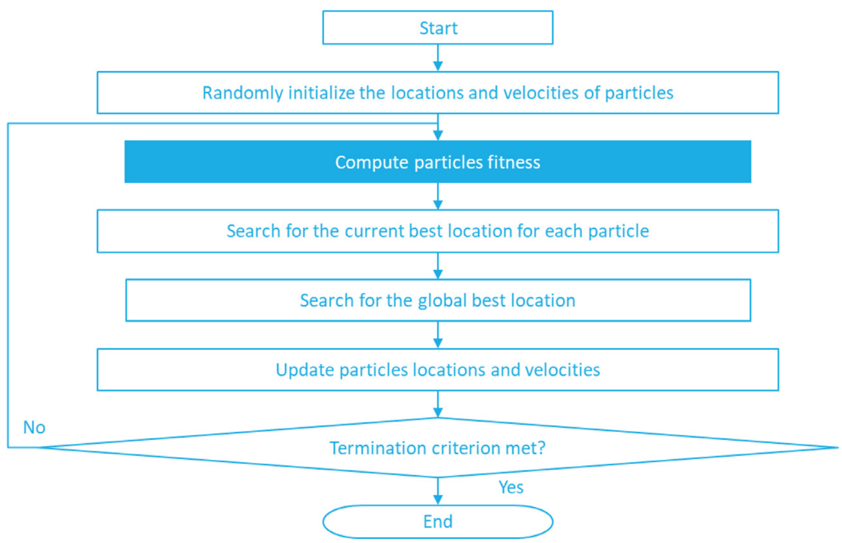

Fig. 6. PSO flowchart.

The implementation of the PSO engine will identify the solution, i.e. recipe sequence, that minimizes the amount of food waste over the week. Due to its simple structure and fast convergence, PSO have been utilised by many scholars to solve multi-objective optimization problems. However, compared with other well-developed metaheuristic algorithms, particle swarm algorithms are still relatively easy to fall into local optimality and lead to premature convergence.

In order to obtain optimal solutions with better diversity and improve the global search ability of the PSO algorithm (Ma et al., 2016) proposed sine-based acceleration coefficients of particle swarm optimization algorithm, which enables the learning factors to be dynamically adjusted as the iterations increase during the algorithm search. This strategy sets a larger and a smaller learning factors (Ma et al., 2016), c_1 and c_2, respectively, at the early stage of algorithm search, which makes the particles have a stronger sense of self-cognition and weakens the social cognitive ability of particles among populations to increase the population diversity. At the later stage of the algorithm search, a larger c_2 and a smaller c_1 is set to move the whole population toward the global optimal position and ensure that the algorithm can converge to an optimal result.

In this strategy, the learning factors of the PSO algorithm change dynamically based on a sinusoidal function. The dynamic nonlinear variation of the learning factors is given by Eq. (4) and (5).

$$c_1 = c_{1i} - \left(c_{1i} - c_{1f}\right) \sin\left(\frac{t}{2 \cdot t_{max}}\right) \tag{4}$$

$$c_2 = c_{2i} + \left(c_{2f} - c_{2i}\right) \sin\left(\frac{t}{2 \cdot t_{max}}\right) \tag{5}$$

where t is the number of current iterations, t_{max} is the preset number of termination iterations, c_{1i} and c_{2i} are the initial values of learning factors c_1 and c_2, and c_{1f} and c_{2f} are the final values of c_1 and c_2. The trend diagram of the learning factors c_1 and c_2 based on the dynamic nonlinear variation of the sine function is shown in Fig. 7. The learning factor c_1 tends to decrease sinusoidally as the number of iterations increases, and the learning factor c_2 increases nonlinearly with the number of iterations.

4.3. Decision-Making support module

The solution outputted by the PSO engine is then characterised in terms of food waste amount and source, required ingredients and remaining stock. In the current research, amount of waste is recorded and optimised for by mass as this is the most widely recorded, reported and understood metric, but providing sufficient information were available, the system could calculate optimisations based on carbon footprint, calorie content or economic cost,

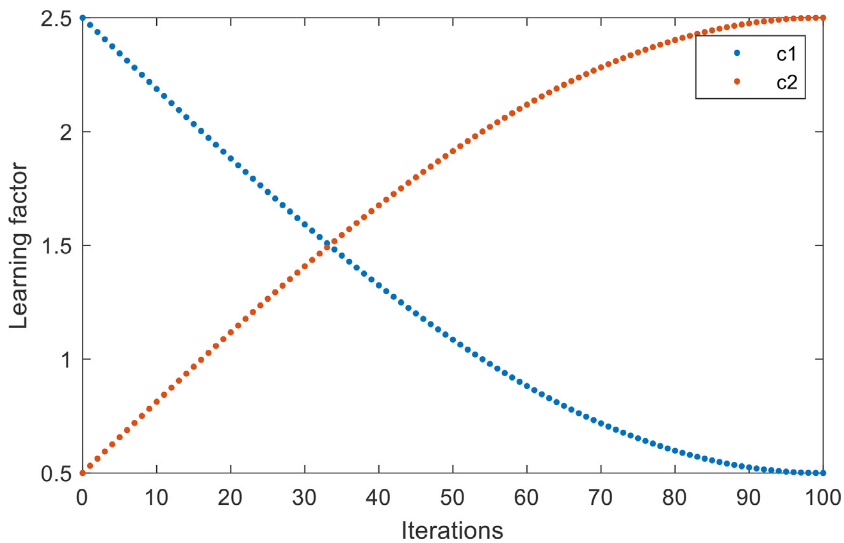

Fig. 7. Trend diagram of learning factors.

Table 1
Solution characterisation template.

Weekly meal plan			Shopping List		Waste			Remaining Stock	
Day	Recipe	Category	Item	Quantity (unit)	Item	Quantity	Source	Item	Quantity (unit)
Monday									
Tuesday									
…									
Sunday									

or a combination thereof. A number of efficiency indicators can be then derived (for example: potential consumption to waste ratio, likely mass of meat-based products wasted) which could be used to influence user choice. The solution appears as a table containing the sequence breakdown as shown in Table 1.

As regards the food waste amount, all the various units of waste food items are converted to 'grams' for direct comparison and convenient visualisation.

The food waste characterisation is considered methodically (see Fig. 8): For a generic food item in the Stock List, if the quantity available exceeds the quantity needed, the expiry date has to be considered, where in case the food item will expire, then the item will be classified as waste "from the Stock List". Alternatively, if the item will not expire and thus still be available, it will be part of the remaining stock. In the case where the quantity in the Stock List is less than the required quantity, a new batch has to be purchased. Any unused purchased items, if expired, will be classified as waste "from the shopping list", otherwise it will be still available in the remaining stock. This classification of waste allows for insight into the success of the recipe selection and inventory management system.

Users of the system can select a recipe permutation that suits their preferences, utilises items from their inventory and minimises the amount of food, or type of waste that will be generated. The selection of a solution will therefore automatically generate a 'Shopping List' which could be used for either in-store or on-line shopping. In the case of on-line shopping, the Stock List can be automatically updated within the framework.

5. Results and discussion

Full implementation of the presented framework would require significant infrastructure and participation by many supply chain actors and hence is infeasible at the current stage of research. Therefore, with the aim of demonstrating the feasibility of the proposed system, a simulated case study is conducted. The operational procedure summary of the case study presented in this paper is reported in Fig. 9.

The Recipe Suggestion tool is used to evaluate the HFW associated with a particular scenario of consumer demand. Although the described framework could be implemented over several weeks the following assumptions have been made to simplify the computation and the results display:

- One meal a day for two people for one week
- Preferences consideration is limited only to style of food
- Shopping carried out only once per week, in this case on Sunday
- All the products have an explicit expiry date reported on the packaging
- All food purchased has an expiry date of at least seven days

The initial Stock List contains 22 items partially displayed in Table 2 and entirely reported in Appendix A.

The tool could be implemented via a smartphone app interface (or web-based system) which could be used to support the recording of available inventory as well and input the consumers meal

Table 2
The available Stock List.

	D	Q	U	ED	EDT	d
1	Bacon rashers	250	g	Nov/25/2020	Use By	0
2	Black pepper	20	g	Jun/12/2021	Best Before	10
…	…	…	…	…	…	…
21	Soy sauce	500	ml	Apr/16/2022	Best Before	5
22	Tomato	40	g	Nov/23/2020	Use By	0

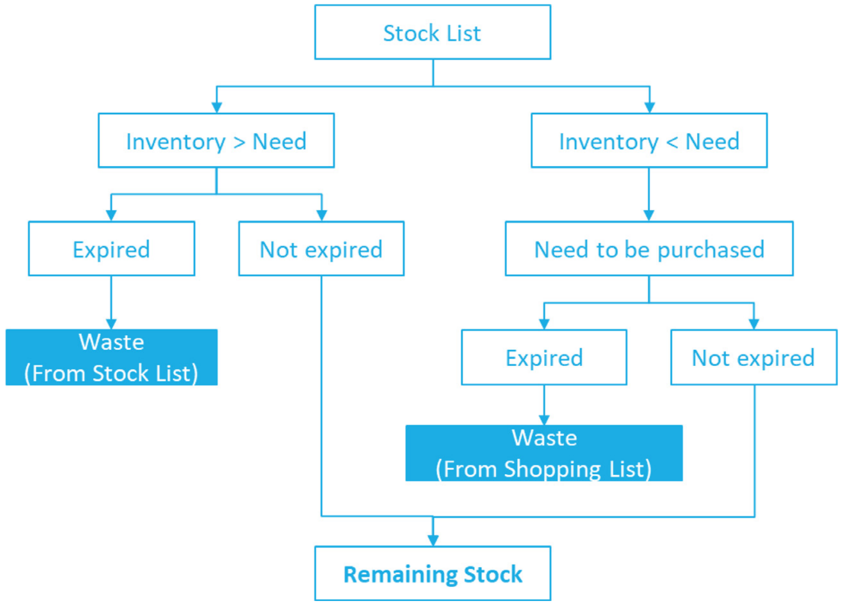

Fig. 8. Food waste characterisation procedure.

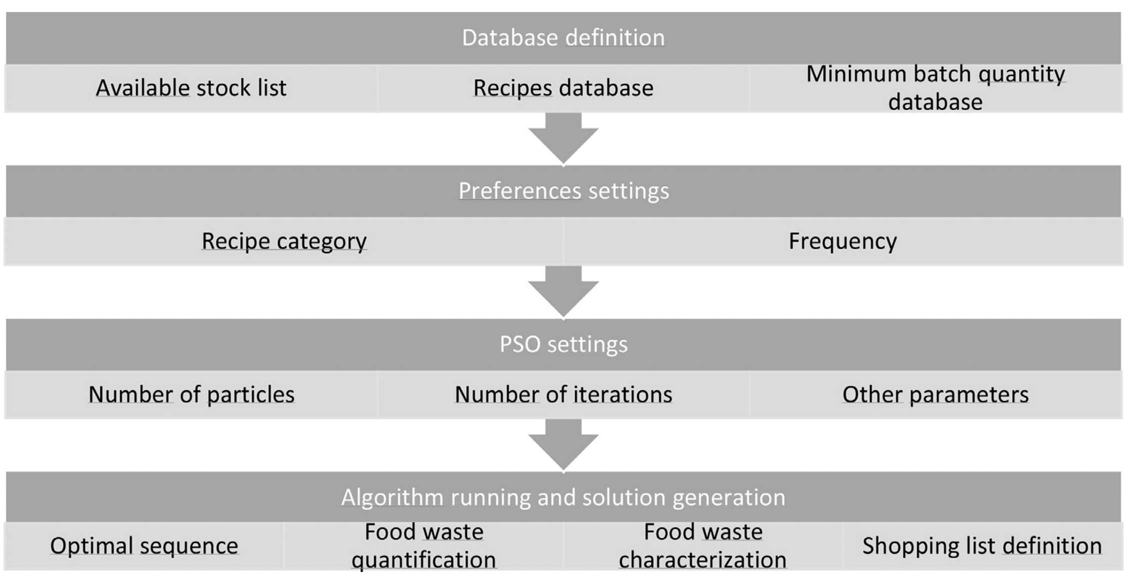

Fig. 9. Case study flow chart.

requirements and associated preferences. Such app systems could be linked to both retailer e-commerce systems and online recipe databases to provide a simplified user experience.

For demonstration purposes the recipes database contains 12 recipes, retrieved from (Food.com - Recipes 2021). (four Italian, four Chinese and four Japanese), as partially displayed in Table 3 and entirely reported in Appendix B. Recipes contain the list of ingredients, preparation method and meal description.

Regardless of whether items are purchase in-store or online, typically items can only be purchased in minimum commercial quantities (such as six eggs), or multiples thereof, which may be defined in a Minimum Batch database. Minimum batch sizes may be problematic if only a small quantity of the ingredient is needed as the majority will then be added to the Stock List, for which recognition of the expiry is required to support timely use. The current Recipe Suggestion tool considers ingredients used across more than one recipe. An example of the minimum batch quantities for the Shopping List is partially reported in Table 4 and entirely reported in Appendix C.

In this case study the user specifies the following preferences for the week:

- Chinese food: 3 times/week
- Japanese food: 2 times/week
- Italian food: 2 times/week

Given the 12 recipes in the database, such settings would generate 725,760 feasible sequences, i.e. those sequences which meet the preference requirements.

Fig. 10 shows the food waste of all the possible sequences calculated using the enumeration method. The process of calculating all the food waste outcomes without any optimization algorithms required about 2 h to finish on a standard modern laptop computer. The result shows that among all the possible sequences, the minimum food waste value is 280 g for the week. For such a small

Table 3
Recipes database excerpt.

	Name	Category	Ingredients			Source
			Item	Quantity	Units	
1	Fried rice	Chinese	Vegetable oil	25	ml	https://www.food.com/recipe/combination-fried-rice-415,972
			Eggs	2	units	
			Shrimps	250	g	
			…	…	…	
…	…	…	…	…	…	…
12	Bruschetta	Italian	Baguette	150	g	https://www.food.com/recipe/best-ever-bruschetta-443,987
			Garlic	25	g	
			…	…	…	

Table 4
Minimum batch quantity excerpt.

Item	Minimum Quantity	Units
Light soy sauce	300	ml
Arborio rice	500	g
Tuna steak	200	g
…	…	…

recipe database and straight forward user requirements, the computation time for the optimised solution is clearly too long, hence it is pertinent to utilise the optimisation module. For this task the PSO engine is configured with the following parameters:

- Number of particles $n = 100$
- Max. Number of iterations $i_{max} = 50$
- Inertia weight $\omega = 0.9$
- $\alpha = 2.5 - 2 \cdot \sin(\frac{i}{2 \cdot i_{max}}\pi)$, where i represents the current iteration
- $\beta = 0.5 + 2 \cdot \sin(\frac{i}{2 \cdot i_{max}}\pi)$

In the algorithm, a parameter, w, that indicates the willingness of user to accept food items that have passed the ‘best before’ date but have not yet expired is set to 0.6. The analysis of suitable recipe suggestions was repeated using the PSO-based selection engine; the intelligent platform requires around 60 s to compute the best solution using the same computer as before. The PSO iteration log is shown in Fig. 11. The index of the best sequence is 203,143, as the food waste amount of the optimal solution is 280 in grams. Fig. 10 reports the swarm optimization process in terms of objective function fitness value vs iterations.

The corresponding recipe sequence provided by the data processing module is reported in Table 5:

Table 5
Optimal sequence.

Day	Recipe	Category
Monday	Smoked Salmon Sushi	Japanese
Tuesday	Tuna Pasta Salad	Italian
Wednesday	Fried Rice	Chinese
Thursday	Wasabi Grilled Tuna	Japanese
Friday	Bruschetta	Italian
Saturday	Stir-Fried Pea Shoots	Chinese
Sunday	Simple Chinese Noodles	Chinese

Such solution is characterised by a total waste amount equal to 280 g with the waste characterisation summarized in Table 6. In accordance with Fig. 6, the tool differentiates between whether HFW is generated from unused stock or from the new items purchased that week.

In this case the new HFW generated originates from old items already held in the Stock List. If the system is used over several weeks, it would be anticipated that the number of items held in the Stock List would increase, but that they would be better utilised and so the amount of waste generated would reduce. It is also expected that waste generated from the items on the shopping list would remain low as the optimisation engine has most control over these items. Equally, it is expected that with a greater number of recipes, better optimisation could be achieved and that the amount of HFW generated would decrease, although computational requirements would increase, which suggest cloud-based database of recipes and Data Processing Module.

In order to obtain the required ingredients to fulfil the users’ requirements, a Shopping List is generated. The corresponding Shopping List for this case study is partially reported in Table 7 and entirely reported in Appendix D.

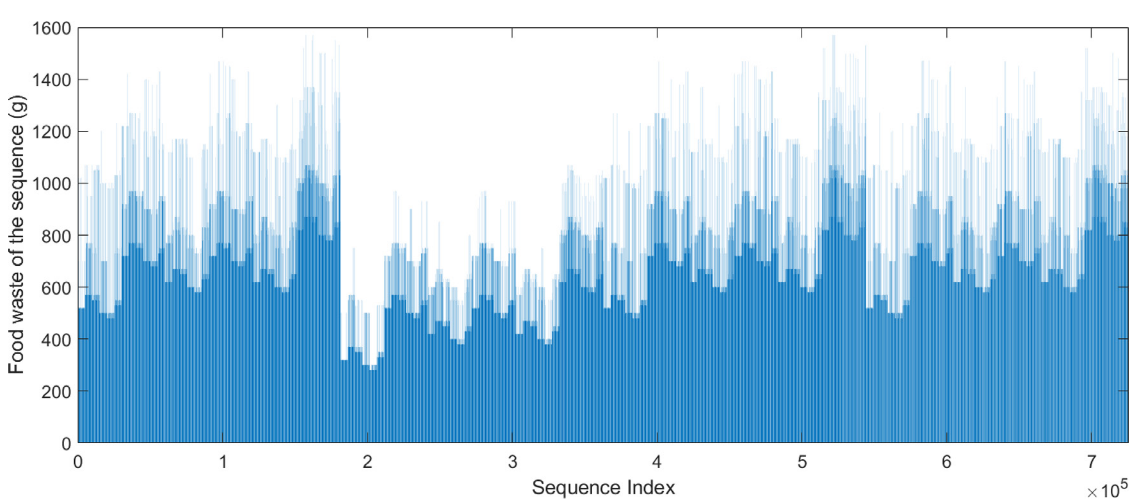

Fig. 10. Food waste of all the possible sequences.

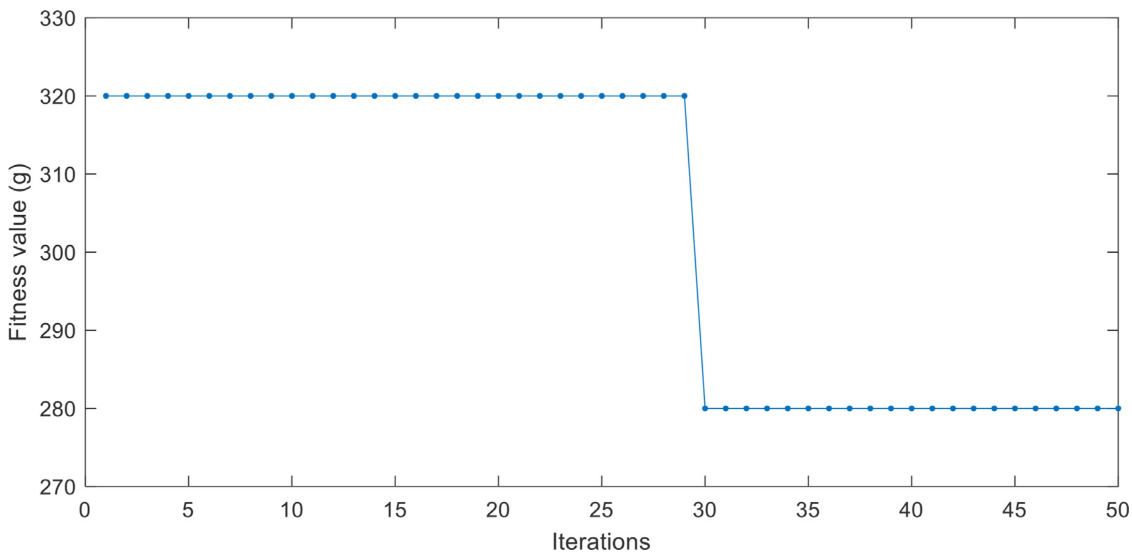

Fig. 11. PSO iteration log.

Table 6
Food waste characterisation.

	Item	Quantity	Unit	Source
1	Bacon rashers	250	g	Stock List
2	Celery	30	g	Shopping List
	TOTAL	**280**	**g**	

Table 7
Shopping List needed to realise the optimal sequence.

	Item	Quantity	Unit	Number of batches
1	Baguette	300	g	1
2	Balsamic vinegar	500	ml	1
…	…	…	…	…
25	Tuna steak	200	g	3

It should be noted that whilst an optimised solution is produced for, in this case, a week, in case there are changes in circumstances (e.g. a friend or relative comes to stay) the Recipe Suggestion tool could be run part-way through the week and would account for the existing Stock List to support the recipe suggestions.

There are a number of additional factors which may impact the recipes which are suggested by the tool. These include, but are not limited to:

- The willingness of consumers to consume items that are past their best before date. Depending on the food category (dairy, meat, bakery) the food availability function could have a linear or nonlinear trend indicating the willingness of user to accept food items that have passed the ‘best before’ date but are not yet expired.
- Consumers may be willing to substitute some ingredients with others already held in the Stock List (e.g. white pepper for black pepper, pork for chicken) which would better utilise existing available food and reduce the need for new purchases. In the tool, to query a food item, the food similarity assessment engine could display all the items in the available Stock List. The user is then asked to decide on the compatibility of an alternative food item to substitute the queried food item.
- Food availability and supply is not constant all year round, and can even be disrupted on the short timescale (e.g. due to flooding or drought). The tool could then be used to preferentially promote recipes with ingredients that are in surplus or reduce the frequency of suggestion of recipes with ingredients that are in shortage. Such an approach would enhance consumer engagement and communication and improve supply chain management. In this respect individual recipes (linked to ingredients) could be given a dynamic weighting by the system that would vary depending upon season, yield, supply perturbations, etc.

6. Conclusions

The need for approaches to address HFW generation is clear and there are economic, environmental and social drivers for this. This research has considered that the high levels HFW in developed economies is not an isolated issue for consumers, but is a consequence of the current market setup and associated interaction by consumers. The research therefore focusses on creating stronger communication and engagement links between the providers (manufacturers and retailers) and the consumers by incorporating a data-driven approach to food purchasing and consumption, with the objective of reducing HFW. In this regard, a novel framework has been designed to assist consumers with making better buying choices by creating a shopping list of required food items based on a) the consumer's meal requirements for a week and b) existing items the consumer already has in stock. The framework is sensitive to minimum purchasable batch sizes and food expiry dates. Due to the high number of possible permutations for solutions that fulfil a consumer's needs, a particle swarm optimisation engine has been employed to reduce computation time, but still provide optimised results. The implementation of the framework has been demonstrated on a simulated case study.

In this work it can be specifically concluded that a recipe suggestion tool, such as the one described, is one approach that may be used to better manage purchasing and consumption of food in terms of reducing HFW. However, due to the complexity of identifying optimised solutions for food purchasing, there is a need for a data-driven approach to support consumers and in this work PSO has been demonstrated to assist in reducing the computation time. The data driven approach is able to consider a number of factors that could not sensibly and cognitively be managed by a human including: all possible recipe combinations; the HFW associated with each combination of recipes; the restriction of minimum batch sizes and the implication of these on available inventory going forward; use by and best before dates of all products held in inventory; the origin of any HFW (i.e. from inventory or from new purchases).

In the context of industrial application, the novel recipe selection tool described in this research would be workable in conjunction with modern data-driven ecommerce systems and support the establishment of consumer-provider relationships (e.g. Jellil et al., 2018). In addition, by using a system such as this, the opportunity to better manage supply and demand in the food grocery sector could improve supply chain resilience and reduce food loss and waste across all supply chain actors. Also reducing household food waste through better engagement with consumers, as intended by the developed tool, could support efforts in corporate social responsibility and lead to improved sustainability performance of companies.

There are many possibilities to further enhance the described system which influence our ongoing work in this area. For example, the system could account for users' particular cooking skills and available equipment, consumers' willingness to consume food items past their expiry dates, automatically substitute ingredients for similar ones already available, or dynamically adapt mid-week based on preferences and changing circumstances.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by funds from the EPSRC *Centre for Innovative Manufacturing in Food* [EP/K030957/1], and Guangdong Province, *Inviting Famous Overseas Professors* [2020A1414010196].

Appendix A
Complete available stock list.

D	*Q*	*U*	*ED*	*EDT*	*d*
Bacon rashers	250	g	Nov/25/2020	Use By	0
Black pepper	20	g	Jun/12/2021	Best Before	10
Chicken breast	200	g	Nov/18/2020	Use By	0
Chicken thigh	150	g	Nov/19/2020	Use By	0
Egg	12	units	Nov/25/2020	Use By	0
Flour	500	g	Jul/05/2021	Best Before	3
Garlic	50	g	Dec/07/2020	Use By	0
Honey	200	g	Aug/01/2021	Best Before	5
Ketchup	50	g	Jun/17/2021	Best Before	5
Mayonnaise	80	g	Dec/17/2020	Best Before	4
Milk	300	ml	Mar/16/2021	Best Before	3
Mushroom	100	g	Nov/17/2020	Use By	0
Onion	250	g	Nov/21/2020	Best Before	3
Parmesan	50	g	Nov/20/2020	Best Before	6
Pasta	250	g	Jan/04/2021	Best Before	3
Pork chop	300	g	Nov/20/2020	Use By	0
Potato	200	g	Dec/01/2020	Use By	0
Salmon	300	g	Nov/21/2020	Best Before	4
Salt	100	g	May/28/2022	Best Before	10
Shrimp	200	g	Nov/19/2020	Use By	0
Soy sauce	500	ml	Apr/16/2022	Best Before	5
Tomato	40	g	Nov/23/2020	Use By	0

Appendix B
Complete recipes database.

Name	Category	Ingredients			Source
		Item	Quantity	Units	
Fried Rice	Chinese	vegetable oil	25	ml	
		egg	1	unit	https://www.food.com/recipe/combination-fried-rice-415972
		garlic	25	g	
		onion	250	g	
		bell pepper	50	g	
		shrimp	250	g	
		frozen peas	100	g	
		rice	500	g	
		soy sauce	30	ml	
Simple Chinese Noodles	Chinese	noodles	66	g	https://www.food.com/recipe/simple-chinese-noodles-141737
		ginger	10	g	
		onion	250	g	
		vegetable oil	15	g	
		oyster sauce	15	ml	
		soy sauce	10	ml	
		sesame oil	5	ml	
Sesame Chicken	Chinese	chicken breast	500	g	https://www.food.com/recipe/sesame-chicken-44321
		honey	90	g	
		soy sauce	60	ml	
		cornstach	80	g	
		ginger	20	g	
		red pepper	20	g	
		sesame seeds	10	g	
Stir-Fried Pea Shoots	Chinese	vegetable oil	10	ml	https://www.food.com/recipe/pea-shoots-stir-fried-pea-shoots-chow-dau-miu-146661
		sesame oil	5	ml	
		ginger	10	g	
		garlic	25	g	
		sugar	2	g	
		pea shoots	250	g	
		soy sauce	5	ml	
		oyster sauce	20	ml	
Wasabi Grilled Tuna	Japanese	wasabi powder	5	g	https://www.food.com/recipe/wasabi-grilled-tuna-9773
		vinegar	15	ml	
		mayonnaise	30	g	
		garlic	25	g	
		soy sauce	15	ml	
		vegetable oil	15	ml	
		mustard	5	g	
		tuna steak	500	g	
Smoked Salmon Sushi	Japanese	rice	200	g	https://www.food.com/recipe/smoked-salmon-sushi-346830
		nori	5	sheet	
		salmon	100	g	
		cream cheese	80	g	
		onion	15	g	
Yakitori	Japanese	mirin	150	ml	https://www.food.com/recipe/yakitori-74844
		soy sauce	90	ml	
		sugar	30	g	
		garlic	25	g	
		chicken thigh	200	g	
		onion	200	g	
Japanese Chicken Drumettes	Japanese	chicken drummette	150	g	https://www.food.com/recipe/japanese-chicken-drumettes-228780
		sugar	50	g	
		soy sauce	60	ml	
		red wine	60	ml	
		sesame seeds	20	g	
Italian Meatballs	Italian	ground beef	180	g	https://www.food.com/recipe/authentic-italian-meatballs-92095
		egg	1	unit	
		milk	25	ml	
		bread crumb	50	g	
		salt	10	g	
		parsley	10	g	
		garlic powder	5	g	
		black pepper	10	g	

(continued on next page)

Appendix B (*continued*)

Name	Category	Ingredients			Source
		Item	Quantity	Units	
Bruschetta	Italian	baguette	150	g	https://www.food.com/recipe/best-ever-bruschetta-443987
		garlic	25	g	
		olive oil	20	ml	
		parmesan	30	g	
		tomato	60	g	
		balsamic vinegar	40	ml	
		salt	10	g	
		black pepper	10	g	
Piccata Sauce	Italian	butter	20	g	https://www.food.com/recipe/piccata-sauce-19502?mode=Metric&scaleto=2
		garlic	50	g	
		olive oil	10	ml	
		flour	25	g	
		chicken broth	200	g	
		lemon juice	10	ml	
Tuna Pasta Salad	Italian	pasta	120	g	https://www.food.com/recipe/simple-tuna-pasta-salad-64320
		tuna steak	100	g	
		celery	20	g	
		frozen peas	80	g	
		mayonnaise	120	g	

Appendix C
Complete minimum batch quantity database.

Item	Minimum Quantity	Units
light soy sauce	300	ml
apple cider vinegar	500	ml
arborio rice	500	g
bacon rashers	250	g
baguette	300	g
baking powder	200	g
baking soda	200	g
banana	500	g
balsamic vinegar	500	ml
basil	100	g
bell pepper	250	g
black pepper	50	g
black pudding	200	g
bread	500	g
bread crumb	250	g
brown sugar	500	g
brussel sprout	250	g
butter	500	g
cayenne pepper	60	g
celery	50	g
cheese flavoured crackers	150	g
chicken breast	250	g
chicken broth	250	g
chicken drummette	250	g
chicken thigh	250	g
chilli	50	g
cod fillet	500	g
cornstach	200	g
cream cheese	100	g
egg	6	units
flour	500	g
french-fried onions	200	g
frozen peas	500	g
garlic	500	g
garlic powder	250	g
green beans	500	g
green onion	150	g
ginger	100	g
ground beef	250	g
ground pepper	250	g

(continued on next page)

Appendix C (*continued*)

Item	Minimum Quantity	Units
honey	150	g
ketchup	200	g
lemon juice	200	ml
lentil	50	g
mayonnaise	200	g
milk	500	ml
mirin	250	ml
mushroom	250	g
mustard	200	g
noodles	250	g
nori	5	sheet
olive oil	500	ml
onion	500	g
oyster sauce	250	ml
parmesan	200	g
parsley	100	g
pasta	250	g
pea shoots	250	g
porcini mushrooms	250	g
pork chop	500	g
potato	250	g
red pepper	50	g
rice	1000	g
salmon	250	g
salt	500	g
sausage	500	g
sesame oil	500	ml
sesame seeds	250	g
shallot	500	g
shrimp	500	g
soy sauce	500	ml
soymilk	500	ml
sugar	250	g
tomato	200	g
tomato sauce	500	ml
tuna steak	200	g
vegetable oil	500	ml
vinegar	500	ml
wasabi powder	50	g
white wine	500	ml

Appendix D
Complete shopping list needed to realise the optimal sequence.

Item	Quantity	Unit	Number of batches
Baguette	300	g	1
Balsamic vinegar	500	ml	1
Bell pepper	250	g	1
Celery	50	g	1
Cream cheese	100	g	1
Frozen peas	500	g	1
Garlic	500	g	1
Ginger	100	g	1
Mayonnaise	200	g	1
Mustard	200	g	1
Noodles	250	g	1
Nori	5	sheet	1
Olive oil	500	ml	1
Onion	500	g	1
Oyster sauce	250	ml	1
Pea shoots	250	g	1
Rice	1000	g	1
Sesame oil	500	ml	1
Shrimp	500	g	1
Sugar	250	g	1
Tomato	200	g	1
Tuna steak	200	g	3
Vegetable oil	500	ml	1
Vinegar	500	ml	1
Wasabi powder	50	g	1

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