Resources, Conservation & Recycling: X 4 (2019) 100021

Contents lists available at ScienceDirect

Resources, Conservation & Recycling: X

journal homepage: www.journals.elsevier.com/resources-conservation-and-recycling-x

What gets measured gets managed – Or does it? Connection between food waste quantification and food waste reduction in the hospitality sector

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ARTICLE INFO

Keywords:
Food waste
Hospitality sector
Quantification
Waste prevention
Multiple linear regression
Kitchen

ABSTRACT

One innovation developed to tackle food waste in professional catering units is different versions of smart scales and softwares designed to simplify food waste quantification. The intention with this is to managing meal production more efficiently based on previous outcomes. However, quantification can be performed in different ways and having a catering unit quantify its food waste does not necessarily guarantee a reduction. Therefore this study sought to identify factors that could make food waste quantification more efficient in terms of waste reduction, and to determine the waste reduction payoff from more ambitious quantification set-ups. Data on 735 hotels, restaurants, and canteens in Europe, especially Sweden and Norway, that use a spreadsheet, a dedicated scale, or an internet-based service to track food waste were analyzed and parameters describing initial waste, number of guests and length, resolution, and completeness of quantification were determined. These parameters were then compared against the waste reduction achieved, in order to test their influence. It was found that 61% of the catering units studied had reduced their waste and that initial mass of waste per guest was the most influential factor for waste reduction. Catering units using more automated quantification tools recorded more data and reduced their food waste by slightly more, but also had a higher level of initial waste and therefore a greater opportunity for reduction. From this, it can be concluded that prioritizing catering units with the greatest waste volume could be an efficient strategy to reduce overall food waste in the most cost-efficient way.

1. Introduction

Food waste reduction is gaining interest as one aspect in making the food system more sustainable and merits specific mention in the UN Sustainable Goals (UN, 2016). However, as pointed out by Godfray et al. (2010) and Garnett (2011), reducing food waste is not only a way to make the food supply chain more environmentally sustainable, but can also save money and improve food security. Reducing food waste is also less controversial than, e.g., reducing meat consumption or increasing productivity by extending the use of genetically modified organisms.

In many countries, food waste in itself creates a problem if it is landfilled or left at illegal dumping sites. In other countries, landfilling of organic waste is prohibited and surplus food is considered a resource that can be used for biogas production or, with some restrictions, for feeding people in need (Eriksson et al., 2015; Eriksson and Spångberg, 2017). It is therefore not the wasted food that should be the main concern, but the wasteful behavior that results in unnecessary food production. However, the energy recovery options currently used are not those prioritized most highly in the European Union (EU) waste hierarchy (EC, 2008). In terms of food waste valorization, Eriksson and Spångberg (2017) report that the potential to reduce greenhouse gas emissions increases significantly by moving from energy recovery options to re-use options where surplus food is still used for human consumption. Waste prevention through source reduction can reduce the environmental impact even further, due to the high environmental burden of food production (Gentil et al., 2011; Bernstad Saraiva Schott and Andersson, 2015; Scholz et al., 2015; Eriksson et al., 2016; Beretta and Hellweg, 2019). Examples of actions that gives such source reduction in the hospitality sector include nudging procedures with smaller plates and information signs (Kallbekken and Sælen, 2013). It also includes redesigning portion sizes, service styles and menu designs to reduce the food waste generated by the guests (Lorenz et al., 2017) or using a employee participatory approach to reduce overproduction by

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https://doi.org/10.1016/j.rcrx.2019.100021
Received 26 June 2019; Received in revised form 24 September 2019; Accepted 26 September 2019
Available online 05 October 2019
2590-289X/

better aligning the quantity of meals produced to that required (Strotmann et al., 2017). However, in order to reduce food waste, it is necessary to understand the exact problem to be solved (e.g., Steen et al., 2018). According to Eriksson (2015), detailed quantification is an essential first step in this process. Moreover, accurate food quantification is needed in order to evaluate the effect of any waste-reducing measures taken in the process of continuous improvement (Lindbom et al., 2014).

An obstacle to conducting quantifications is the lack of a common standard for quantifying and reporting food waste, which makes results from different organizations difficult to compare (Corrado et al., 2019). The Food Loss and Waste Accounting and Reporting Standard (World Resource Institute, 2016) can be used to determine a reasonable trade-off between resources used for waste quantification and relevance, completeness, consistency, transparency, or accuracy. Eriksson et al. (2018a) extended the existing quantification methodology by demonstrating how different datasets can be compared and designed in a common framework. However, there have been no suggestions to date on the categories that should actually be recorded or for how long food waste should be quantified to support waste-reducing efforts. In the material presented by Eriksson et al. (2018b), there appear to be two main strategies for collecting data on catering units; as a continuous process or by sampling during a limited time. If catering units quantify their waste only during selected periods, the results are less generalizable than those from random selection of days or continuous quantification. Moreover, the 30 public catering units studied by Eriksson et al. (2017a) only quantify food waste during selected periods and, while these periods are fairly long and many observations are made per day. However, Eriksson et al. (2017a) did not consider what type of food waste quantification information that can be most important in facilitating waste reduction.

It is questionable whether food waste quantification by itself can be considered an action to reduce food waste. Nevertheless, it is clear that adequate quantification that supports design and implementation of tailored waste-reducing measures can play an important function in the process of continuous improvement, including waste reduction. However, not all food waste quantifications are the same and the form of quantification that leads indirectly to the highest waste reduction is still unknown, although it is easy to assume that investing more effort in quantification always leads to less food waste. There may be a threshold where small initial efforts to improve quantification can have a large impact, but where greater efforts might not be as efficient in terms of waste reduction. Accurate knowledge is needed in order to identify the best trade-off between accuracy and completeness of food waste quantification in relation to resources invested.

The main objective of this study was to evaluate the extent to which food waste quantification leads to waste reduction and determine whether more detailed, more complete, or longer quantification is correlated with a higher level of waste reduction. The overall aim was to help catering units identify efficient strategies for reducing food waste, thereby increasing the sustainability of the food system.

2. Materials and methods

The analysis was based on data on catering units in a number of European countries (Cyprus, Denmark, Greece, Portugal, Norway, Spain, and Sweden) but with major geographical representation from Sweden and Norway. A range of catering units in these countries have participated in different projects and a meta-analysis of the data obtained was performed in the present study. Two sources of quantification data were the KuttMatsvinn2020 project in Norway and the EU project UrBan Waste. The Swedish catering units contributing data were recruited among the customers of the company Matomatic AB, and some were recruited directly by the authors after being identified in previous studies (i.e., Steen et al., 2018; Eriksson et al., 2018b; Malefors et al., 2019). No quick service restaurants or convenience store was included in the study.

The catering units selected for the underlying projects were units previously engaged in food waste quantification projects, and no random sampling have been made to select participating units. Using this kind of convenience sample means that it is likely that the results are not representative (Reynolds et al., 2019). Since there was no random selection involved, it could be expected that the participating catering units were more interested and/or aware of the food waste issue than similar catering units not participating in any food waste-reducing initiative.

2.1. Quantification methodology

The catering units that supplied the data used different tools and methods to quantify food waste, but here the methods were classified into three types although some units used mixed methods. These were: automatic tools, semi-automatic tools, and manual tools. The automatic tools mainly consisted of scales designed for quantifying food waste, often called smart scales or food waste trackers. In the catering units covered in this meta-analysis, the scales used came from the companies eSmiley, Matomatic, Visma, and Winnow. These all comprise a heavy-duty scale connected to a computer with a touch screen, so that catering staff can easily weigh food waste and then record the amount in a specified category by selecting this menu on the touchscreen. Managers then receive the data compiled in a report and/or directly on a website, so that problems with specific categories of waste can be addressed and followed up. Some catering units used barcodes to scan the waste products instead of using a scale, but automatic tools have the common aim of making waste recording as automated as possible.

The semi-automatic tools consisted of websites or mobile applications where data compilation is automatic, but where the user has to manually enter the mass of waste. The tools used came from the companies Matomatic and Unilever, and work in a similar way to the automatic tools, but with less automation. Staff use their own scale to record the food waste and then type in the amount in an online form. The data are then compiled in a report and/or on the website, so that problems with specific categories of waste can be addressed and followed up.

The manual tools consisted of spreadsheets where observations were recorded manually and then compiled either directly via prepared calculations or afterwards. Since these spreadsheets are normally designed by each organization, a variety of designs and functions were used. However, the more advanced designs work in the same way as the semi-automatic tools, but in a simplified form, and data are sometimes used to give feedback to staff, but are mostly used by managers to follow up on the overall progress of the organization. Irrespective of the quantification tool employed, the catering units all used methodology similar to that described in previous studies (e.g., Eriksson et al., 2017a, 2018a) using a scale to quantify the mass of plate waste, serving waste and kitchen waste in relation to the number of guests. Table 1 displays the source of the data from what sector the data originates along with what tools where used by the different number of catering untis from the different projects and countries. A clear majority of the data orginates from Sweden, followed by Norway.

2.2. Data analysis

The data collected listed food waste in several categories, in accordance with the treestructure described by Eriksson et al. (2018a) and was also harmonized for overall comparability according to the treestructure. All included catering units recorded observations on a meal base (or daily base if only one meal was recorded), and the waste was related to the number of guests. Although the catering units employed customized adjusted quantification categories, the waste was summarized to the mass of food waste for each day quantified. Since each catering unit included (and excluded) different categories of food waste

Table 1
Information regarding source, how many kitchen units present from each source and sector, and the distribution of what quantification method used by the different units.

Country	Units (n)	Sector	Automatic tool (n)	Semi-automatic tool (n)	Manual tool (n)
Cyprus	7	Restaurants and hotels	7		
Denmark	5	Hotels	5		
Greece	7	Restaurants	7		
Portugal	4	Restaurants and hotels	4		
Norway	197	Hotels and Canteens	56	105	36
Spain	11	Restaurants and hotels	11		
Sweden	605	Public canteens and restaurants in schools, pre-schools, elderly care homes and hospitals	7	25	573

and potentially used different definitions of food waste, there was potential for variation between catering units due to the lack of common standard. However, since the reduction was evaluated for each catering unit individually, differences between units were of less importance for the purposes of the present meta-analysis, which focused on the improvement in each catering unit. Moreover, most catering units identified similar categories as their main solid food waste flows.

In order to rid the dataset of possible errors, outliers were removed, e.g., when staff were suspected to have confused grams with kilograms and therefore recorded a value 1000 times the real value. To tackle the problem of skewness and missing data points in the dataset, the second-level criteria described by Malefors et al. (2019) were used. This level only aggregates data for a catering unit if any waste is recorded for a given data point, together with the number of portions. By using this level, the roughest differences between quantification granularity for catering units can be evened out. For instance, if a catering unit had forgotten to record the number of portions for a specific meal, this data point would not reach the final aggregation, while the same would apply if the catering unit had recorded the number of portions, but not the waste. Different organizations use different ways of indicating that a data point is missing; this was handled by treating all suspected missing values, including all zero-value, as missing values when analyzing the data.

There is a methodological difficulty in evaluating a quantification process and its correlation with waste reduction, since there cannot be a baseline quantification before the action starts and there is no quantification afterwards with which to compare. There is only the actual quantification period. To handle this issue, the quantification periods considered in this meta-analysis were divided into two parts for each catering unit included, and the first 50% of days when food waste was quantified (first half-period) were compared with the last 50% days (second half-period). If the quantification period included an uneven number of days, the middle day was allocated to the first half-period.

The dataset originally contained 937 catering units that quantified food waste for a total of 52 792 days and used between 1 and 15 categories to quantify food waste. The quantification period in the catering units ranged from 1 to 410 days of actual quantifications but, since not all performed continuous quantification, the first observations was recorded in 2012 and the last in 2019. In order to include only time series long enough to display an actual reduction, only quantification periods including at least 10 days of complete observations were included. This resulted in 735 catering units being used for the meta-analysis.

2.3. Identification of quantification parameters

There are certain aspects of food waste quantification that determine the quality of the data, but also the resources needed to conduct quantification. According to the Food Loss and Waste Accounting and Reporting Standard (World Resource Institute, 2016), there is normally a trade-off between resources used and relevance, completeness, consistency, transparency, and accuracy in waste quantification. In order to evaluate different quantification designs, some quantifiable parameters were identified, e.g., number of food waste quantification days and number of food waste categories. These parameters represent different aspects of food waste quantification, and devoting more efforts to recording any of them will require more resources. However, a reasonable hypothesis is that more ambitious data collection (in every aspect) results in better information that leads to better decisions, and ultimately a greater reduction in food waste.

Since catering units typically have limited resources, they cannot give all parameters the same level of attention. The choices they make are likely to influence how efficiently they can use the recorded information to design and implement measures to reduce waste, and their ultimate success in reducing the waste. It was not possible to quantify the exact parameters (relevance, completeness, consistency, transparency, accuracy) defined by World Resource Institute (2016). However, these parameters were used for inspiration when seeking to identify quantifiable parameters that reflect the complex content of food waste quantification.

The quantifiable parameters identified were: number of quantification days (length), number of days with observations during the quantification period (completeness), and number of recorded food waste categories (resolution), as illustrated in Fig. 1. Length was represented by the total number of days on which food waste was recorded, since tracking the information over time should better help to

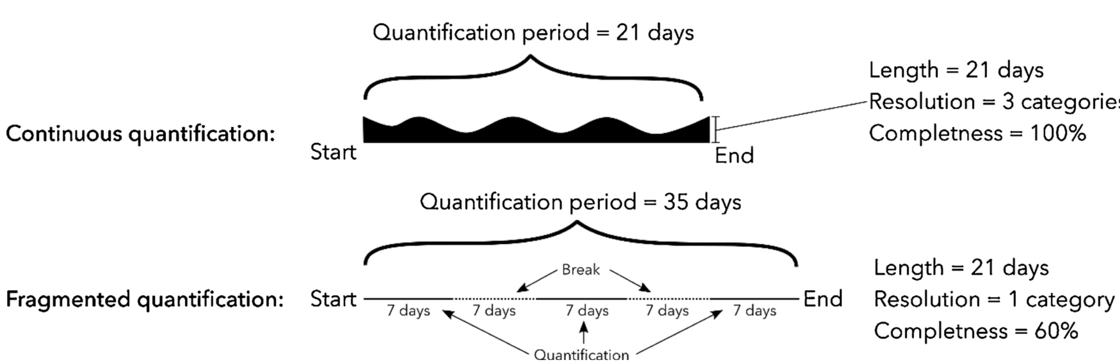

Fig. 1. Illustration of how the three parameters length, resolution, and completeness can diverge in different types of datasets.

Table 2
Comparison of quantification parameters for catering units that increased/decreased their food waste. All values represent mean of units included in each group, standard deviation within parenthesis.

Food waste change	No. of units	First half- period waste (g/ portion)	Second half- period waste (g/ portion)	No. of days with observations (n)	No. of days with complete observations (n)	No. of categories used (n)	Completeness (%)	No. of guests per meal (n)
Decrease	453	118 (521)	87 (432)	72 (76)	66 (74)	2.8 (1.7)	28 (34)	276 (301)
Increase	282	79 (191)	114 (433)	55 (61)	51 (59)	2.6 (1.3)	33 (34)	251 (281)
Difference		39	−27	17**	15**	0.15	−5.1*	24

***p < 0.001, **p < 0.01, *p < 0.05.

identify trends and assess the performance of the reporting entity. The length parameter came in two versions, number of days with any waste quantification (called waste measurement days) and quantification days with both waste and portion data (called complete measurement days), where the latter is what Malefors et al. (2019) call second-level criteria. Completeness was represented by the number of days with observations in relation to the total number of days within the quantification period, where the total number of days in the quantification period was taken as the number of days between the first and last measurement day. Resolution was represented by the daily average number of actual food waste categories used for the quantification, since better resolution of data potentially gives the user more relevant information than aggregated information would provide.

These three parameters identified as potentially influencing food waste quantification effectiveness were complemented with parameters on situational factors, such as initial waste (i.e., mean waste per portion during the first half of the quantification period), size of catering unit (mean number of portions served per meal), and initial mass (i.e., mean daily mass of food wasted during the first half-period). These parameters have little to do with waste quantification, but could still provide important obstacles or opportunities for food waste reduction. A high amount of food waste represents an opportunity, since there is greater potential to reduce food waste if it is high initially. This could be confounded by catering units that quantify with greater ambition finding more waste, when high waste levels would be an indicator of strong engagement, not a major problem. Having many guests represents an opportunity, since low volumes and turnover are normally correlated with higher waste (Eriksson et al., 2014; Brancoli et al., 2019).

2.4. Multiple linear regression (MLR)

In order to quantify the impact of significant, influential factors on food waste reduction, a multiple linear regression (MLR) model was developed for the catering units that successfully reduced their waste. According to Uyanik and Güler (2013), the advantage of using an MLR model instead of diverse correlations is the ability to quantify the total effect from relevant factors on the model outcome, as demonstrated by Steen et al. (2018) and Eriksson et al. (2014, 2016). The reason for selecting only the units reducing the waste was to asses the sucessfactors only for the successful ones, in terms of waste reduction.

Backward elimination was used to choose the best performing MLR models. All explanatory variables significantly correlated to the food waste quantity in relation to the number of guests were included in the different models. Explanatory variables that were not significant for the model outcome ($p > 0.05$) were eliminated step by step, until all remaining explanatory variables significantly influenced the variation in the response variable ($p < 0.05$) (Helsel and Hirsch, 2002).

To improve model performance, different interaction terms were then added through backward elimination. The best performing model was chosen with respect to the coefficient of determination, R^2, and the number of explanatory variables with the use of AIC. According to Helsel and Hirsch (2002), a good model explains as much of the variation in the response variables with as few explanatory variables as possible. As the R^2 value naturally increases with each explanatory variable included in the model, adjusted R^2, which considers the number of explanatory variables, was used to determine the best performing model (Helsel and Hirsch, 2002) combined with the knowledge gained from calculating and comparing the AIC result from the models (Burnham et al., 2002).

3. Results

Of the 735 catering units covered by this meta-analysis, 61% reduced their food waste in terms of mass wasted per guest during the second half of the quantification period in relation to the first half-period. This indicates that food waste quantification can be a useful activity to reduce food waste in catering units, but also that quantification alone is not a guarantee of reduced food waste. However, there were differences between the groups of units that increased/decreased their waste during the study period (Table 1). The catering units that decreased their waste had 33% higher initial waste, 23% longer quantification period, 9% more guests per meal, and used 5% more categories (e.g. categories such as plate waste, serving waste, etc) to quantify food waste, on average, than those units that increased their waste. The opposite trend was observed for the number of days with observations, since the catering units that had increased their waste had 19% more days with observations in the dataset than those that decreased their waste. This indicates that the most influential factors for the success of quantification in reducing waste are to have high initial waste and to perform quantification over a longer time (Table 2).

The catering units used different tools to quantify food waste. There was on average a greater reduction in waste for catering units using automatic tools than for catering units using less automated tools, such as apps or spreadsheets (Table 2). Catering units using automatic tools achieved an average reduction of 12 g per guest served, those using semi-automatic tools a reduction of 0.22 g/guest served, and those using manual tools a reduction of 9.4 g/guest served. However, it should be noted that the catering units using automatic tools had almost five times as much initial waste as those using semi-automatic tools, and therefore had much greater potential for waste reduction. Waste during the second half-period was also much higher for the catering units using automatic tools (311 g/portion) than for the other units (67–76 g/portion). While the waste reduction was small for the units using semi-automatic tools, the average waste level in these catering units was also somewhat smaller than for users of other tools (Table 3). This indicates that the level of waste, rather than the tool, influenced the food waste reduction.

The number of observations increased with use of more automated quantification tools. Both number of days with observations and number of days with complete observations were highest for the users of automatic tools and lowest for the users of manual tools (Table 3). A similar trend emerged for number of waste categories used and number of days with observations. The users of semi-automatic tools showed intermediate values for all parameters investigated.

The benefit of using more automated tools for food waste quantification seem to be that the quantification period is longer and more complete, i.e., more data are collected. However, for the users of automatic tools, it was impossible to determine whether the reduction in waste per guest depended on more ambitious data collection, on the very high level of food waste generated during the first half-period, or on whether the tool detected more of the waste generated. The relative reduction for the catering units using manual tools was greater, since they had a much lower initial level of waste.

The 453 catering units that reduced their food waste were assessed with different MLR models (Table 4). These were selected in order to asses the sucessfactors of the successful units, in terms of waste reduction. Model 1 included all units with reduced waste, while Models 2 and 3 included the same units, but divided based on days of quantification; Model 2 included units quantifying food waste during 10–29 days and Model 3 included those quantifying food waste during ≥ 30 days. For all time spans, initial waste had a significant positive correlation with waste reduction, indicating that the most critical factor for waste reduction is to have a large initial problem, irrespective of the length of the quantification period.

Number of days with complete observations had a significant negative correlation with food waste reduction for all models, indicating that there is no benefit for catering units to increase their quantification period. However, this is contradicted by the results shown in Table 2. It could be interpreted as indicating that quantification period length is important to achieve any waste reduction, but that a longer period does not necessarily bring about an additional reduction. This could be due

Table 3
Comparison of quantification parameters for catering units using different types of tools to quantify their food waste. All values represent mean of units included in each group.

Tool type used	No. of units	First half- period waste (g/port)	Second half- period waste (g/port)	Waste reduction (g/port)	No. of days with observations (n)	No. of days with complete observations (n)	No. of categories used (n)	Completeness (%)	No. of guests per meal (n)
Automatic	70	323	311	12	149	119	5.4	67	264
Semi-automatic	189	67	67	0.22	72	70	3.6	49	206
Manual	476	85	76	9.4	51	48	1.9	17	290

Table 4
Results of multiple linear regression where: Model 1 represents all values (> 9 days), Model 2 short quantification periods (10–29 days), Model 3 longer quantification periods (≥ 30 days), Model 4 manual tool users, Model 5 semi-automatic tool users, and Model 6 automatic tool users. Non-significant results are not shown.

Variable	Coefficient (with standard error)					
	Model 1 (≥10 days)	Model 2 (10-29 days)	Model 3 (≥30 days)	Model 4 (Manual)	Model 5 (Semi-automatic)	Model 6 (Automatic)
No. of categories used	−2.7** (0.97)	−21*** (6.1)	n.s.	−25*** (3.4)	−2.4* (1.2)	n.s.
No. of days with waste observations	0.24* (0.12)	1.8*** (0.40)	n.s.	0.66* (0.30)	n.s.	n.s.
No. of days with complete observations	−0.29* (0.12)	−2.3* (1.1)	−0.053*** (0.014)	−0.66* (0.29)	n.s.	−0.26*** (0.068)
No. of days with complete observations	n.s.	38* (19)	n.s.	n.s.	n.s.	n.s.
Initial waste (g/guest)	0.16*** (0.0046)	0.16*** (0.0066)	0.26*** (0.018)	0.75*** (0.021)	0.35*** (0.024)	0.16*** (0.0048)
Initial mass (kg/day)	0.85*** (0.014)	1.6*** (0.35)	n.s.	−0.49*** (0.12)	n.s.	2.6*** (0.51)
Guests (guests/meal)	−0.065*** (0.014)	−0.15*** (0.036)	n.s.	0.045*** (0.010)	n.s.	n.s.
Intercept	21*** (4.0)	76** (23)	4.5* (2.3)	n.s.	n.s.	n.s.
N	453	182	272	309	98	46
AIC	3557	1549	1586	2101	498	365
Adjusted R^2	0.77	0.82	0.44	0.82	0.69	0.96

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

to a strong reduction in waste at the start, when interest is likely to be highest.

The parameters that were significant for Model 1 were also significant for Model 2, indicating that these parameters are most important for shorter time series, although they also apply to longer time series. However, adjusted R^2 was higher for Model 2 than for Model 1, indicating a better fit during the shorter period than for the whole period.

As shown in Table 4, number of waste categories used had a negative correlation with waste reduction, meaning that increasing the resolution in quantification does not pay off in terms of increased waste reduction. A similar trend was observed for number of days with complete observations, but not number of days with waste observations (Table 4).

Initial mass of food waste was correlated positively with reduced food waste, indicating that a larger mass of waste initially increases the potential to reduce waste. In contrast to initial waste, wasted mass is more dependent on the size of the establishment, since only larger units can waste much mass per day, while any unit can have high waste per guest served. However, number of guests is related to catering unit size and could therefore be expected to show a similar positive correlation to waste reduction as initial mass, but in fact showed a negative correlation to reduced waste. This indicates that catering units with smaller numbers of guests can reduce food waste more than those with larger numbers of guests. This could be due to the smaller units having more initial waste, especially because they have more fluctuation in the number of customers, providing them with an opportunity to improve.

Models 4–6 included the results divided per type of quantification tool used (Table 4). From the adjusted R^2 values and relative AIC, it is clear that Model 6 most accurately explained the waste reduction, especially since this model was based on the smallest part of the dataset. However, only initial waste per guest and initial mass of waste showed a significant positive correlation, meaning that catering units using automatic tools reduced their food waste more if they started with more waste. For number of days with complete observations there was a significant negative correlation, which means that users with shorter quantification times achieved a greater waste reduction.

The results for users of semi-automatic tools were similar to those for users of automatic tools, but number of categories used, rather than number of complete observations, showed a significant negative correlation for these users.

For the largest group, users of manual tools, the model (Model 4) included the largest number of significant correlations (Table 4). Number of days with observations showed a positive correlation, but number of days with complete observations showed a negative correlation, as with Model 1. This indicates that observation of waste at all is more important for waste reduction than precise recording of waste per guest. This could possibly be due to the extra time and effort needed to conduct the added work of recording portions, diverting attention from actions needed to reduce waste. It could also be because the number of waste observations is always larger than the corresponding number of complete observations. Incomplete observations are thus unused information, since the methodology used in the present meta-analysis focused on the complete observation days. However, it appears unlikely that number of days with waste observations and number of days with complete observations correlate differently to the waste reduction achieved, and therefore this may need deeper investigation.

Model 4 also had significant correlations for initial waste per guest and initial mass or waste, but a negative correlation for initial mass. This indicates that, for users of manual tools, low efficiency (represented by the waste per guest) resulted in reduced waste, but the opposite was found for the actual mass wasted.

4. Discussion

Quantifying food waste is normally considered to be a good first step in reducing food waste. However, according to the results obtained in this meta-analysis, food waste quantification is far from being a perfect tool to reduce food waste, since only 61% of the catering units included actually reduced waste. Even when food waste is recorded, the information obtained is apparently commonly not acted upon, or action is taken but is unsuccessful. It must also be borne in mind that there was no random selection involved in sampling, and therefore the catering units represented by the data could be expected to be more interested, aware, and eager to reduce food waste than the average catering unit. Consequently, the share of catering units in the whole population actually reducing their waste is likely to be smaller. Moreover, many catering units do not quantify food waste at all, so those included in this meta-analysis can be seen as representing the top in terms of food waste reduction efforts. Thus the results are not fully generalizable.

There are also methodological weaknesses in this meta-analysis. One lies in the definition of waste reduction, since there was no phase before and after implementation of waste quantification that could be compared. However, dividing the period into two halves and comparing the first with the second can be seen as a reasonable compromise. Another option could be to specify an exact time for the baseline, but then the problem would be to decide what this time should be and whether it could be the same for all catering units, since the implementation will vary in time depending on staff and management. This also relates to the risk of not having the routines set at the beginning and therefore having lower waste due to missed recordings. However, this would lower the estimated waste reduction, so the reductions presented here should be seen as moderate.

Another weakness is that seasonality is not included in the analysis, even though season most likely affects the level of waste for some of the catering units represented by the data. Moreover, the possibility that the catering units have introduced a wide range of different waste-reducing measures, giving the time series a declining trend, was not assessed. However, even if there are seasonal and other trends in the generation of food waste, these trends were not obvious in the waste records, which just showed single days with unusually high waste. This is a very similar pattern to that reported in Eriksson (2015), where the waste had no clear trend depending on the time of year, but an extreme level of variation in some individual weeks. Depending on the half-period in which these days occur, the results can be heavily influenced. However, since the present meta-analysis included a large number of different catering units from different countries that quantified their waste partly during different time periods, the risk of single extreme events or seasonality influencing the results must be considered small.

To our knowledge, no previous study has investigated whether food waste quantification actually leads to a waste reduction and the most important parameters to consider. Therefore, it is difficult to verify the results against other findings and future studies are needed. However, some of the results simply confirm what can be viewed as common knowledge, and therefore might not need verification. For example, it is known that catering units using more automated tools for quantification record more data. They also reduce food waste to a slightly larger extent than units using basic spreadsheet tools. However, in this meta-analysis it was not possible to determine whether this reduction was due to use of more automated tools, or to the larger amount of initial waste at the units concerned. It is also possible that the situation is even more complex, since catering units with much initial waste should be more motivated to invest in waste reduction, therefore investing in more automated tools and taking the time to use them properly. There is also a possibility that the catering units with the most initial waste and using automated tools might have been more prone to record faulty data unknowingly, since the automated tools might have hidden this feedback from the users. More automated tools are thus simply a means to channel the desire to solve a problem, with more engagement leading to better results. It is not possible to claim a causality just because there is a correlation. However, there might be a endogeneity (reverse causality) present e.g. hotels that aim to reduce food waste likely have some strategy for quantification and not necessarily the other way around.

The MLR results revealed that the effect of certain efforts was most important at the beginning of a quantification period. Both number of days with observations and number of days with complete observations showed a positive correlation with waste reduction for shorter time series. However, the most important factor was clearly the amount of initial waste, indicating that it is more important to focus efforts on catering units with the largest problems, rather than on all catering units in an organization. This also indicates that waste reduction is not dependent on how the quantification is conducted, but on situational factors. However, this could be due to the rather short quantification times analyzed.

In comparison with other professional sectors, data collection performed in the food service sector is both limited and inconclusive. For example, the retail sector (in Sweden) is thoroughly described in a multitude of publications, e.g., by Brancoli et al. (2017, 2019); Eriksson et al. (2012, 2016, 2017b), Ghosh and Eriksson (2019), and Mattsson et al. (2018), where data on thousands of items were recorded daily for several years. The retail sector also has advanced and automated support systems to simplify data collection, and the information collected is reviewed in weekly meetings, making it possible to reduce the waste. Even catering units with the most automated and advanced tools for food waste tracking still have much to do before they can quantify food waste on the same level as retailers usually do. This lack of well-established quantification effort can explain part of the difference in waste level between retailers, which can have waste levels of 1–2% (Katajajuuri et al., 2014), and representatives for the hospitality sector, which generally report waste levels of around 20% (Malefors et al., 2019).

In order to increase quantification efforts in the hospitality sector as a first step in the process of waste reduction, there might be a need to introduce control measures to quantify food waste. Such control measures could involve mandatory reporting of food waste quantities to external organizations, or political targets with a standard follow-up procedure. There could also be a local political drive to contribute to the target of halving per capita global food waste at retail and consumer levels by 2030, as stated in the United Nations sustainable development goals (UN, 2016). Standardized quantification could be a first act in fulfilling this goal. Based on the findings in this paper, there is an opportunity to design quantification with a primary focus on quantifying food waste in detail, rather than for a long time. However, the greatest waste reduction potential lies with the largest catering units that have both the resources to conduct more ambitious food waste quantification and most food waste to be reduced. This can save large sums for restaurant owners and taxpayers, besides making a significant contribution to reducing the environmental impact from the food supply chain.

Another option to explore in promoting waste reduction might be to start with short, straightforward quantifications to raise awareness among staff and give a rough idea of how much and what is wasted. Alternatively, the focus could be on acting on information, rather than just quantifying more intensively. However, some efficiency measures could be implemented without detailed or long quantifications, for example reduced plate size (Kallbekken and Sælen, 2013), going trayless (Thiagarajah and Getty, 2013), better demand forecasting and more effective stock management (Filimonau and Delysia, 2019), and prompting guests to take only as much food as they will eat (Whitehair et al., 2013). A way forward could be to design control measures that incentivize or force catering units to: 1) Conduct a short and simple quantification to raise awareness; 2) ensure that a handful of simple measures (or a checklist) are implemented based on findings during the quantification period; and 3) begin more ambitious quantifications, to form the basis for well-designed food waste reducing actions in a system of continuous improvements. Starting on the third step is possible, but may be too ambitious, since there seems to be a clear opportunity for solving fairly simple problems before identifying and designing countermeasures to more complex issues. Following steps 1–3 might reduce food waste just as much as focusing on detailed quantification, and starting simple might lower the barrier to getting started but also achieve cost-efficient waste reduction. Both provide opportunities for achieving the UN sustainable development goal of halving food waste in the hospitality sector by 2030.

5. Conclusions

It was found that only 61% of all waste-quantifying catering units included in this meta-analysis had reduced their food waste, indicating that quantification in itself is not a guarantee of waste reduction. It was also found that the units reducing their food waste by most had a higher initial mass of waste and quantified their waste for longer. However, increased quantification time and share of days with complete recording only had a significant correlation to reduced waste for shorter quantification times.

Use of more automated food waste quantification tools resulted in more ambitious data collection over longer periods, with more categories quantified and fewer data gaps. For catering units using more automated tools, the waste reduction observed was slightly larger, but it was not possible to determine whether this reduction was due to increased efforts or to the higher initial waste observed for these units.

Declaration of Competing Interest

The authors Mattias Eriksson and Christopher Malefors are founders and part owners of the company Matomatic AB that is a spinoff company from the Swedish University of Agricultural Science. Since customers of this company have supported the study with data there is a potential conflict of interest since it the authors have an indirect financial interest in organizations evaluated in the study.

Acknowledgments

The study was mainly funded through the project AVARE, financed by the Swedish Research Council for Sustainable Development (FORMAS), the Research Council of Norway, and the Finnish Ministry of Agriculture and Forestry. Since the study was partly based on data collected in other projects and by other partners, it was indirectly supported through the project UrBan Waste financed by the European Union´s Horizon 2020 research and innovation program under grant agreement No. 690452, the project KuttMatsvinn2020 funded by the research Council of Norway, and the Swedish company Matomatic AB, a spin-off company to the Swedish University of Agricultural Science. The authors would like to thank all contributing organizations and also the staff in all catering units included for their help and cooperation.

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