Food for Thought: An Exploratory Study on User Understanding of a Food Waste Dashboard

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Abstract

Food is a vital part in human survival. Yet an estimated 820 million people were undernourished in 2018, as reported by the United Nations Food and Agriculture Organization (FAO). This makes the impact of food waste that more impactful. Not only does wasting food account for the inability to feed a growing world population, but also strains the planet due to the environmental and economic impact it bears. Companies in the HORECA sector (hospitality, restaurant, and catering) are the third largest food waste generator and, more importantly, is characterized as a sector with an overall low sense of awareness when it comes to food waste reduction technologies and challenges of minimizing food waste. This research draws on a tech startup that provides an innovative solution to HORECA firms in order to solve the food waste challenge. This exploratory research aims to determine how well the front end of such a food waste monitoring technology is understood by its users, which are often managers and chefs. Semi-structured interviews on the current level of data understanding were conducted with five active users of the system, which composed of four managers and one chef. Additionally, a between-subject questionnaire (N = 65) was used in determining what effect the type and content of a dashboard has on the users' understanding. Both the old and new version of the food waste dashboard were used in order to see whether the new iteration would perform better. Our analysis showed that the users of the food waste dashboard had a good level of data understanding and were able to make data driven decisions on the basis of that data. The results further indicated that the new dashboard did not significantly increase the level of perceived understanding, perceived usability, and perceived aesthetics. The dashboard elements that contributed the most to the interpretation of the data were the textual elements, such as the food categories table and the texts that present the user with a small written out summary or recommendation of the data. In terms of preferred text structure, we can conclude that participants seem to prefer a general overview of the data, and to see a combination of both monetary as well as kilograms information. We conclude that users of this dashboard have a sufficient understanding of the data, and implementing textual elements in a food waste dashboard increases not only the understanding of the user, but also of the entire kitchen staff, as textual data was found to be most often utilized by the users. Further research is needed however, on the possible implementations of larger and more diverse textual presentations.

Keywords: Food waste, dashboards, data understanding, dashboard evaluation, Food waste management technology

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1. Introduction

Food waste is a global issue that occurs throughout the whole food supply chain. Besides being unacceptable from an ethical point of view, food waste accounts for unnecessary use of energy and water, and high quantities of emissions of greenhouse gases (Raak et al, 2017). Beretta el al. (2013) identified the food service industry as the third largest source of food waste. The Dutch sector of food service is estimated to discard around 51.000 tonnes of food, with an estimated value of €235 million (Kouwenhoven et al, 2012). Kretschmer et al (2013) predicted this estimate to be significantly higher, around 446.000 tonnes of food waste. There are several factors that attribute to food waste in food service. For example, there is a lack of staff training on how to prevent food wastage due to managerial disbelief in the importance of such training (Filimonau et al, 2019). Additionally, poor, often manual, demand forecasting and inefficient food stock management are prime examples of managerial and staff competencies that lead to food wastage (Papargyropouluou et al, 2016). Finally, corporate decisions can prompt irresponsible consumer behaviour, such as the 'all-you-can-eat' model of food service provisions (Papargyropoulou et al, 2016). Existing research has proposed a number of approaches to management, and range from preventive (pro-active measures) to disposal-focussed (reactive) (Papargyropoulou et al, 2014). Filimonau (2019) recognizes that technological solutions can play an instrumental role in diverting food waste from the landfill, but also to generate extra profit in the process.

Despite the influential role technology can play for food service establishments, few studies have explored this role in food waste minimization. This is especially interesting due to the rise of larger, more comprehensive food management technologies. These technological innovations, known as sustainability-oriented innovations (SOI), have the capability to automatically quantify food waste, whilst simultaneously make changes to a company that create and realize environmental value and economic returns (Martin-Rios, 2021). Although Martin-Rios et al (2021) provided a first glance at how third-party technology providers can foster the innovative capacity of companies for food based SOI, there has been no study that has examined how effectively these technological sustainable solutions perform. Specifically, how the users interact with the system. This interaction is often enabled via different types of user interfaces, depending on the stage of the SOI. For example, during the measuring of the food waste, kitchen employees use a physical device to measure food waste volumes directly from the disposal unit (Martin-Rios, 2021). The final stage of the technical food based SOI however, revolves around reporting the food waste data back to the customer (e.g., data dashboard). Both interfaces have their separate goals and differ therefore significantly from each other. The focus of this study is on the final stage, data reporting. It is this area where managerial decisions on food waste are made that influence environmental and economic value of companies. It is therefore imperative that data presented in the dashboard is clear and easily understood. This is achieved by utilizing data visualizations. Some common examples of dashboard visualisations include charts, tables, and gauges (Janes et al, 2013). Additionally, text files are used to briefly summarize and inform the user of emerging data trends. While these techniques are used to increase the understanding the user has of their data, it is not fully understood how users understand these representations.

For this study, two iterations of a food waste dashboard from a company are used as a use case. This company had indicated that clients were having difficulties with interpreting the data that was shown on their dashboard. These clients often were managers and chefs, and had little experience with working with a data dashboard. This problem served as the main reason for this study to examine the user understanding of the food waste dashboard. The company released the latest iteration of the dashboard in an attempt to increase this understanding. This latest version of the dashboard includes visual, such as graphs and photos, and textual elements in an attempt to increase the users' understanding. This study focusses on evaluating whether these elements have increased the understanding of the user. Based on this, we can derive the following research question:

RQ: *In which way can the customers' food waste data be (re)presented textually or visually to provide the user with a good understanding of their own data?*

RQ 1.1: *How well do users understand their own food waste data via the use of textual files and visualisations?*

RQ 1.2: *How well do the textual files and visualisations make the user understand what actions to take next in order to reduce food waste?*

RQ 1.3: *Do the visual and textual elements of the new food waste dashboard lead to better perceived understanding of food waste data than the old food waste dashboard?*

RQ 1.4*: Do the visual elements of the new food waste dashboard lead to better perceived 'ease of use' and better perceived 'aesthetic appearance' than the visual elements of the old food waste dashboard?*

RQ 1.5: *What type of text structures that inform the user of their food waste are preferred?*

This exploratory study examines the usability of the user interface of one of these technological solutions, specifically in regard to data understanding. The term exploratory is used since no current study has examined this area or proposed a method that can measure user understanding of data in dashboards, regardless of the context of the domain. The focus of this study is on the food service industry. This research examines a startup that offers an automated technology-based artificial intelligence tool that monitors and quantifies food waste. A customer portal is launched at the time of this study that shows the customer a daily data report of their food usage. This dashboard is used as the platform that this research is based on. This study first provides an extensive background of related work. It then explains how qualitative data is collected in the method section. The qualitative result section provides the reader with results from the interviews. On the basis of these results, a questionnaire was designed. The quantitative method section of the questionnaire is there for presented after the qualitative result section and describes the design of the questionnaire. Results of the questionnaire are discussed afterwards. The discussion section provides the reader with the analyses and interpretation of both results. Finally, in the conclusion section, the research questions will be answered.

2. Related Work

2.1 Food waste

This study's contextual domain is the food waste management industry. This massive industry is expected to grow with an annual growth rate of 5.4% from 2020 to 2027 (Grand View Research, 2020). This growth is mainly related to the global rise of concern and awareness of food waste. Due to this increase of societal awareness, academic attention has also increased (Schanes et al, 2018). While there are many definitions of food waste given by academic literature throughout the years (Schneider, 2013; Östergren, 2014; Bellemare et al, 2017), this study uses the definition Parfitt et al (2010) has given. Similar to definitions of other authors, Parfitt et al make a distinction between food loss and food waste. Food loss refers to the decrease in edible food mass throughout the part of the supply chain that specifically leads to edible food for human consumption. Food loss takes place at production, postharvest, and processing stages in the food supply chain (Parfitt et al., 2010). Food losses occurring at the end of the food chain (retail and final consumption) are called "food waste", which relates to retailers' and consumers' behaviour. (Parfitt et al., 2010). Throughout this study, both concepts of food loss and food waste are used, but focuses primarily on food waste. This chapter provides a brief overview on the current state of food waste and the food service industry.

2.1.1 Global food waste

Global food waste is a significant and urgent problem that has faced humanity for the past decades. According to the Food and Agriculture Organization of the United Nations (FAO), an estimated 805 million people are undernourished in the world right now (Oliveira, 2016). Studies suggest that roughly one-third of food produced for human consumption is lost or wasted globally, which comes down to 1.3 billion tons of food (Gustavsson et al, 2011, FAO, 2013; Beretta, 2013; Gunders, 2012). This 2011 estimate of the FAO is currently being replaced by two separate indexes: The Food Loss Index (FLI) and the Food Waste Index (FWI), and is yet to present their new findings (FAO, 2020). The Coronavirus pandemic has only deepened the effects of the hunger crisis, where food security is put at risk due to factors such as a decrease in agricultural production, supply chain disruptions and income declines (Laborde et al, 2020). Besides the societal impact food waste has, there are numerous economic and environmental impacts that accompany this. Due to the resource-intensive nature of food production, there are a broad range of environmental impacts, such as soil erosion, deforestation, water, and air pollution, as well as greenhouse gas emissions that occur in the processes of food production (Mourad, 2016). The environmental impact of food waste is significant enough to account for a share of global carbon emissions equivalent to a medium-sized country (FAO, 2013). Due to these environmental, social, and economic concerns, global food waste is increasingly acknowledged as an urgent issue among many institutional bodies such as governments, businesses, NGOs, academics, and the general public (Schanes et al, 2017). The United Nations have addressed this mounting yet avoidable challenge by adopting a special target, called target 12.3, as part of the 17 Sustainability Development Goals: "*by 2030, halve per capita global food waste at the retail and consumer levels and reduce food losses along production and supply chains, including post-harvest losses*" (UN, 2017; Martin-Rios et al, 2018).

Food is lost throughout the entire food supply chain, from initial agricultural production to final household consumption (Gustavsson et al, 2011). However, the extent to which this food loss exists, differs severely per region. The main causes for food waste in low-income countries revolves around the processing phase, which is caused by technical limitations in harvesting techniques, packaging, and marketing systems. (Gustavsson et al, 2011). In contrast, food loss in the supply chain of medium to high-income countries revolve mostly around the final phase, which relates to the consumer behaviour as well as the lack of coordination between different actors in the supply chain (Gustavsson et al, 2011). This is more plainly illustrated by the fact that households represent the largest food waste faction throughout the entire supply chain (BIOIS, 2010). It is therefore important and most effective to focus on preventive measures on the consumer and retail level. One of the most effective methods that can be utilized in order to reduce food waste in industrialized countries, is to raise awareness and find a good and beneficial use for food that is currently being thrown away (Gustavsson et al, 2011; Mourad, 2016).

Tackling the issue of food waste on a consumer level can happen in multiple areas. Households are the largest contributing factor of food waste in Europe, with a share of 53%, followed by agriculture (19%) and the food service sector (12%) (Monier et al, 2010). The sector of food service, which is the main focal point for this study, is therefore the third largest food waste generator. Multiple studies have indicated that food waste in the service sector is avoidable to a great extent (Beretta et al, 2013; Betz et al, 2015). For example, food providers in gastronomy, catering and hospitality sectors have recently come under increasing scrutiny of their food management practices, with evidence that considerable amounts of food are being lost during the preparation of meals, or because food is thrown out since there are no ways in which the food can be either stored or reused (Betz et al, 2015). An estimated 75% of all the food thrown away in the food service could have been avoided (Filimonau et al, 2019). Meaning that 75% of food that was discarded, could have been eaten, but was not edible at the time of disposal (e.g., due to moulding or decomposition) (Oliveira, 2016). This shows that massive strides can be achieved in the service industry when it comes to food waste reduction.

2.1.2 Human Computer Interaction and sustainability

As addressed in the previous section, creating awareness is the most effective tool one has to prevent food waste. Throughout the years, several different methods have been used to increase this awareness. Many countries have used public campaigns to increase awareness, for example “Pay As You Trash” was a South Korean campaign that cut 200 tons of food waste a day over the span of two years (Zamri et al, 2020). However, with the growing influence of technology on peoples lives, more and more personal methods of raising awareness have become available. The field of Human Computer Interaction (HCI) has addressed the issue of food waste and how designing sustainable food systems can influence the food waste behaviour of users (Norton et al, 2017). HCI has proposed several means through which individuals, groups and society can be motivated to engage in behaviour change to reduce food waste, including personal informatics, persuasion, gamification, social influence and in a small number of cases coercion (Comber et al, 2013). Persuasive technologies have been the dominant field when looking at users' behaviour change, especially when it comes to environmental sustainability (Brynjarsdóttir et al, 2012). But despite its popularity, only a few persuasive systems have been developed to actively reduce individual's food waste in households.

One of those systems is called the BinCam system. The BinCam system is a persuasive technology that uses a mobile phone which is embedded in the lid of a household landfill bin (See Figure 1), which sends photos of the disposed food to a dedicated Facebook application (Comber et al, 2013). These photos were then used to provide the household with a dataset on their recycling and food waste behaviour, which were subsequently used to create a discussion amongst the household in order to create more user awareness (Comber et al, 2017). Another similar project is called The Grumpy Bin. While the premise of the technology remains the same, a system that sends the users photos of disposed food, the main difference is in the social consequences of the action of food disposal. The system encourages the household to collectively judge waste action, and expresses different moods depending on the type and amount of waste (Altarriba, 2017). While both systems did show to increase individuals' social and motivational effects to undertake a more sustainable consumer

Figure 1: The BinCam (Comber et al, 2013)

behaviour, long term effects were not proven (Stöckli et al, 2018). Additionally, several apps have been created to influence food waste behaviour among users, (e.g., WRAP's Love Food Hate Waste app) (Stöckli et al, 2018). These apps are simpler in design and provide the user mainly with household management tools such as leftover recipes and a food stock tracker. These apps however, also lack the evaluation that supports long term effectiveness (Stöcki et al, 2018). While these consumer-based systems are relatively new and lack results of long-term effects, larger already implemented systems exist in the food service industry.

2.1.3 Food Waste Management Technology

When we observe the food service industry, we know that the avoidable food waste is significant (75%). This high amount of food waste provides the sector with an opportunity to increase its food reduction. First, we need a frame of what food service entails. As a subsector of the food and beverage industry, the food service sector includes companies that serve meals for out-of-home consumption (Martin-Rios, 2018). The service industry consists of commercial and non-commercial services. Commercial services, like restaurants, cafeterias, fast-food restaurants, self-service, or take-away restaurants, have the primary goal of maximising profit from the end consumer (Oliveira, 2016). While non-commercial services, like education, healthcare, and staff catering, have the primary goal of providing a service to staff or other users, such as hospital patients or students (Oliveria, 2016). Both sectors are likely to maximise turnover and seek financial gain (Parfitt et al, 2013). When it comes to explaining food waste in the service sector, it comes down to three main reasons: consumers leave uneaten food on the plate, consumers' preference for given menu items, and overproduction due to inaccurate forecasting of consumers demand (Oliveria, 2016). One obvious solution to reduce food waste therefore would be to increase the awareness of the customers.

However, more recently, technological innovations have provided companies with an ability to quantify their food waste data (Martin-Rios, 2021). These innovations are known as sustainability-oriented innovations (SOI). A SOI is defined as: "*making* *intentional changes to an organization's philosophy and values, as well as to its products, processes or practices to serve the specific purpose of creating and realizing social and environmental value in addition to economic returns*" (Adams et al, 2016). In the food service sector, these innovations are used primarily to minimize the food waste of companies. As Beretta et al (2019) mentioned already, technology plays a central role in addressing the food waste challenge. Despite the urgency and significance of the global food crisis, little attention has been paid between technology, SOI and food waste management (Martin-Rios, 2021). From an academic standpoint, only one article has addressed this gap in literature, who provided an overview of the current SOI in food waste management technology (Martin-Rios, 2021). Nonetheless, there are currently five companies in the world that utilize a variety of these SOI solutions: Winnow Solution in the UK, LeanPath in the U.S., LightBlue in Singapore, Kitro in Switzerland, and Orbisk in the Netherlands (See Table 1) (Martin-Rios, 2021). All companies provide solutions that allows food service businesses to move away from manual measurements with pen and paper, towards digital automated solutions. The main differences in digital solutions lie in the use of manual input (Winnow, LeanPath, and LightBlue), versus automated input via AI (Kitro and Orbisk). While some companies rely on staff members to keep track of food waste by manually input the type and amount of data, other companies utilize AI to automatically classify and quantify the type of food data. Regardless of the method of input, all technical solutions allow companies to gain insight into their waste metrics. Their technological SOI can be summarized as a solution that integrates the data network connectivity with the waste disposal machine, a device that measures and shares food waste volume directly from the disposal unit, and an output that reports the measured data to assist managers and employees in identifying ways to prevent food waste (Martin-Rios, 2021). This research will focus mainly on the final stage of this technical solution, namely the data presentation of the food waste that is shown to the customers.

Company	Date of Establishment	Headquarters	Main Activity	Characteristics of the Technological SOI
LeanPath	2004	Portland, US	High volume kitchens (food not made-to-order)	A pool of tracking stations to measure food waste
LightBlue	2012	Singapore	Commercial kitchens	FIT Food Waste Monitoring Tech
Winnow Solution	2013	London, UK	High volume and commercial kitchens	Patented smart meter technology attached to food waste bin
Kitro	2017	Zurich, Switzerland	Commercial kitchens	Automatic food waste classification using machine learning
Orbisk	2019	Utrecht, Netherlands	Commercial kitchens (food made-to-order)	Computer vision and AI data recording terminal

Table 1: Overview of SOI (Martin-Rios et al, 2012

2.2 User Understanding

Information systems (IS) from a user's point of view must be usable. Especially since the range of users is steadily increasing. No longer are IS tools that can be managed and used by professionals only, but are nowadays firmly integrated into the life of the common individual. This widespread use has prompted academics to develop methods of usability testing, most notably the System Usability Scale (Bangor et al, 2008; Lewis, 2018). These methods allow the usability practitioner to assess the usability of a given product or service (Bangor et al, 2008). And whilst these methods are proven to be effective, they are limited to measuring usability. When one wants determine a different attribute, such as user understanding, a different method is needed. One can be unsure whether they fully understood the interaction with an interface of an IS, despite this interaction being easy and pleasant. Especially when one is expected to act upon this interaction in the real world. This chapter examines 'understanding' as a construct and how different domains measure this construct when applied to their users.

2.2.1 What is Understanding?

If one wants to measure an abstract process such as understanding, it will need a theoretical basis to base its measurements on. We therefore first need to look at the definition of understanding. The Oxford dictionary defines understanding as: *The knowledge that someone has about a particular subject or situation*" ("understanding", 2021), where Merriam-Webster simply defines it as having "*a mental grasp*" ("understanding", 2021). But what does it mean to have a mental grasp and knowledge about something? Nickerson (1985) suggests that these concepts appeal to intuition, that the concept of understanding is something that we understand intuitively. This outs itself in the human tendency to easily say "I understand" or "I do not understand" (Nickerson, 1985). But if asked to say what one exactly means with that statement, without using the word "understand" or a close synonym such as "comprehension", people may find it difficult to do so (Nickerson, 1985). Let us first examine how closely related words differ from understanding. When we talk about understanding and comprehension, both words are often interchangeable. However, understanding stresses the final result of having attained a firm mental grip of something, while comprehension stresses the process of coming to grips with something intellectually ("comprehend", 2021). Additionally, another important distinction must be made between understanding and knowledge. Knowledge is more factual based, being described as "information on tap" (Perkins, 1998). The value of understanding therefore seems to surpass that of knowledge, since one can know something without understanding it (Baumberger, 2017). This also becomes apparent when one looks at Blooms (1956) taxonomy. The well-known taxonomy represents learning as a process. In the revised version of 2001, remembering (knowledge) is the first level of learning, followed by understanding (Anderson et al, 2001).

To get a more in depth understanding of understanding, one has to look at academic literature. Wiggins and McTighe (2005) acknowledge that defining understanding is a complex and confusing target. In their view, to understand is to make connections and bind together knowledge into something that makes sense of things, whereas without understanding one might see only unclear or unhelpful facts (Wiggens et al, 2005). But understanding is not just a mental act, it also implies doing. As Bloom (1956) noted in his Taxonomy, a performance lies at the heart of understanding. To understand is therefore not only to know, but also to wisely and effectively transfer what we know. To apply knowledge and skill effectively in realistic tasks and settings (Wiggens et al, 2005). Bereiter (2005) proposes that understanding is a relational concept, where understanding implies something about the relation between a person and an object. This is due to the fact that understand is a transitive verb, a person always understands something. This something can be a person, an electronic device, or a computer interface. Understanding must therefore always be defined relative to the task or set of tasks the person wants to perform (Riley, 1985). Bereiter (2005) further states that: "*Understanding refers to that aspect of a relationship that has to do with its potential to support intelligent action"*. One is able to undertake something intelligent with that object once it is understood. Understanding is therefore a precondition of intelligent action, no understanding means no intelligent action (Bereiter, 2005). Perkins (1998) stresses this relation, however, adds that understanding is the ability to think and act flexibly with what one knows. He sees understanding as a flexible performance, comparable to learning to improvise jazz, hold a good conversation or rock climb, as opposed to learning facts (Perkins, 1998). Finally, Nickerson (1985) mentions that the most important point is that understanding, or grasping something, should be demonstrable in a variety of ways. But what does it mean to grasp something well? In literature about understanding, it is commonplace that understanding requires more than believing or knowing isolated pieces of information (Baumberger, 2017). One must grasp or see how these information pieces hang together: understanding requires "*seeing the way things fit together*" (Riggs 2003). If what is grasped is a representation of an object, grasping is only a necessary condition for understanding a phenomenon (Baumberger et al, 2017)

To briefly conclude this section, understanding is a complicated and broad concept, one that is not clearly and unanimously defined. What we can conclude however, is that understanding revolves around a person and an object of knowledge. It is not only a mental act, but enables people to intelligently apply this knowledge in real life settings. In order to let a person undertake intelligent action, one must understand this object. And that the person can act flexible around this knowledge component and utilize that knowledge in multiple settings. The discussion of what understanding is in the context of this study is informal, focussing primarily on examples provided by human computer interfaces. Cognitive theories have and are currently being developed that express the specifications of understanding in more detail (Baumberger et al, 2017).

2.2.2 Measuring understanding

Now that we have a basic understanding of what understanding entails, let us examine how different fields have used understanding as a measurement. While, for this study, the main focus is the HCI field, showing examples of different domains can help us frame understanding as a measurement better. The accounting field has a large history when it comes to measuring the understandability of financial report messages (Adelberg, 1979; Smith & Taffler, 1992; Jones and Smith, 2014). Most of the focus in this research lies in analysing user understanding of textual complexities in financial reports. By using a procedure called the Cloze procedure, which uses the principle that if individuals can understand a piece of text, they will be able to fill in missing words correctly, as a proxy of understanding (Jones & Smith, 2014). Another prominent area that looks into measuring user understanding is business process models (Gadatsch & Laue, 2010; Melcher et al, 2010; Dikici et al, 2017). These studies examine how increasingly larger and complex processes influence the understanding of the processes, and to what extent the reports can be easily understood by a reader of that model. Furthermore, in regard to software, understandability is one of the major quality attributes used to measure understandability of code. Many methods exist to evaluate the understandability of software architecture (Jin-Cherng & Kuo-Chiang, 2006; Stevanetic & Zdun, 2015; Saifan et al, 2018; Simone et al, 2019). Finally, the most well-known area in which understanding is measured is education. The technique most often used to measure understanding of theoretical material is exams (Sato et al, 2019). Whereby course grades and cumulative GPA are conventional measures of certifying success (Wiggins et al, 2005). As we know from the previous chapter, understanding is relative to the object that is being measured. And while it is useful to gain knowledge from these existing methods, the different contexts make it impossible to use any of these methods outside of their designated domain. Every domain uses their own proxies to determine the level of understanding. We therefore need to look further at how user understanding is measured within HCI focussed information systems, which are systems specifically designed to foster interaction between humans and computers.

2.2.3 User evaluations of Information systems.

The original goal of information systems (IS) is described as: "the effective design, delivery, use and impact of information technologies in organizations and society" (Keen, 1987). Evaluations of information systems have therefore always been prevalent in measuring if these organizational goals are achieved. Throughout the years, a variety of measurement methods have been developed to determine various factors of IS. One of the most prominent user measurements is user acceptance. In general, acceptance is defined as: *"an antagonism to the term refusal and means the positive decision to use an innovation*" (Taherdoost, 2019). User acceptance models have been developed to explain this acceptance of users to adopt new innovations and technologies. While there is a plethora of user acceptance models (e.g., TRA, TPB, DoI, MPCU, UTAUT2) (Tamilmani & Dwivedi, 2020), the most widely applied model remains the Technology Acceptance Model (TAM) (Marangunic & Granic, 2015). The TAM utilizes two variables, Perceived Usefulness and Perceived Ease of Use, to determine an individual's information system acceptance (Davis, 1989). Beside acceptance, IS effectiveness is another prominent measure. Several indicators have been proposed as measurements when it comes to measuring IS success or effectiveness. These include measures such as system use, IS performance and IS effectiveness (Delone & McLean, 2016). The most widely used single measure and indicator of IS success is user satisfaction (Veazi et al, 2016). Here, satisfaction refers to the result of the evaluative process of the user, which is the satisfaction that derives from a user experience (Oliver, 2010; Vaezi, 2016). Another measurement that is becoming increasingly relevant, is user engagement. Due to the increasing emphasis on user experience, systems are no longer just designed to be usable (Blythe & Monk, 2018). Successful technologies therefore engage users (O'Brien & Toms, 2008). The

User Engagement Scale (UES) has been developed to measure user engagement (O'Brien et al, 2018).

A variety of measurement methods have thus been scientifically proven, and are currently being used in practise to evaluate information systems. For the context of this study, we are interested in ways of measuring the construct of understanding. Academic literature has spent little attention on this area. Only one article has discussed the impact of user understanding. Riley (1986) provided a framework for characterizing user understanding and how this plays a role in performance and learning. She explored to what extent a user needs to understand a system or program to become a skilled user. This understanding has a multi-dimensional nature, where it is related to three characteristics of the user's knowledge: internal coherence, validity, and integration (Riley, 1986). While Riley (1986) does examine user understanding, she does so from a problem-solving perspective. What we want to find out in this study is how well the user understands the information that is presented to them in an information system. More specifically, how well does the user interpret the data that is shown on a user interface?

2.3 Dashboards

Presenting data through a user interface is often accompanied by visualisations that represent abstract information. These information visualizations can be defined as: "*the use of computer-supported, interactive, visual representations of abstract data in order to amplify cognitions* (Card & Mackinlay, 1999). The goal of information visualization systems is to provide "*tools and techniques for gaining insight and understanding in a data set, or more generally to amplify cognition*." (Zuk et al, 2006). Common examples of these information visualization tools are dashboards and scatter plots. This section examines the different types of dashboards and the current field of dashboard evaluations.

2.3.1 Dashboard types

Most companies nowadays generate enormous amounts of data. In order to gain insights in this data, an increasing number of organizations use dashboards to visualize their data. There are three main fields that currently utilize dashboards, education (e.g., learning analytics, student facing dashboards) (Schwendimann, 2016), healthcare (Dowding et al, 2015) and business management (Rahman et al, 2017). Sustainability dashboards are slowly becoming more prevalent due to the growing demand for sustainability management and reporting (Shields & Shelleman, 2020). Dashboards are cognitive tools that help users visually identify trends, patterns, anomalies and help them guide toward effective decisions (Brath & Peters, 2004). While various definitions exist, Wexler et al (2017) provides a broad definition: "*a visual display of data used to monitor conditions and/or facilitate understanding*", which include narrative visualizations and infographic elements. Examples of such visualizations are charts, tables, and gauges (see Figure 2).

Generally, data dashboards are used for three purposes: strategic, analytics, and operational (Smith 2013). Strategic dashboards are most common and provide management with a top-down view of the performance of a program or organization, having a refresh cycle that is typically monthly or quarterly (Few, 2006). Operational dashboards have the aim to provide a constant flow of information, with a refresh cycle often less than a minute (Smith 2013). This type is primarily used for formative, quality assurance or safety purposes (Smith, 2013). Lastly, dashboards for analytical purposes are interactive and allow the user to delve into the details of the data and support explorations and examination (Smith, 2013). The refresh cycle for this type of dashboard could be daily, weekly, monthly, quarterly, or yearly (Smith, 2013). Analytical dashboard are well suited for food management, due to the daily updates and options to make flexible changes in purchasing strategies.

Visual elements of all types of dashboards can be presented in two scenarios, the pull and push scenario (Janes et al, 2013). In the push scenario, the dashboard is designed in such a way that the information is pushed to the user, to the extent that the user should have as little interaction with the dashboard as possible (e.g., a car's dashboard) (Janes et al, 2013). More interestingly for this study however, is the pull scenario. In the pull scenario, the user wants to acquire specific pieces of information and uses the dashboard to obtain it (Janes et al, 2013. The dashboard should help the user to understand the context of the data (e.g., why is it collected, how should it be interpreted and how can it be used in the future), and help understand the meaning of the data (e.g. minimal effort to convey the visualizations, be coherent, allow the user to choose the detail of the data) (Janes et al, 2013). If is important to note that there is no right or wrong way of dashboard design, it depends on the requirements the dashboard has to fulfil (Brath & Peters, 2004; Janes et al, 2013). A factor that is nonarbitrary however, is limiting the dashboard design to a single screen. As Smith (2013) explained: "Having everything to monitor within a single eye span enables the user to make comparisons, evaluate, and draw conclusions that are not possible when data are fragmented onto separate screens or when scrolling is required" (p.32). It becomes apparent that increasing the data understanding of the user is a significant factor of the designing and implementations of dashboards.

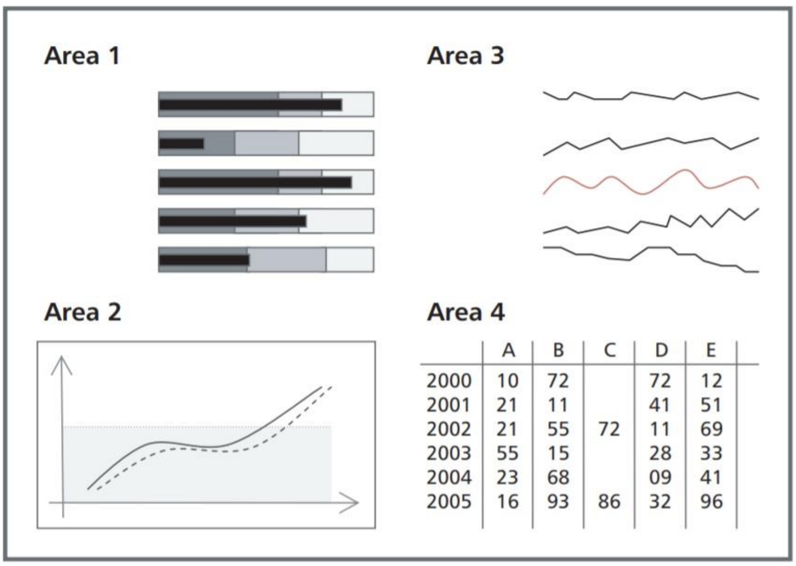

Figure 2: A typical dashboard (James et al, 2013)

2.3.2 Aesthetics vs usability

A factor that influences usability performance, is aesthetics (Sonderegger & Sauer, 2010). Dashboards are primarily used as a tool to convey information via visuals. It is therefore important to understand how aesthetic influences the usability of dashboards. Studies have shown that aesthetically appealing products were perceived to be more useful that unappealing products (Hartmann, Sutcliffe & De Angeli, 2007; Sonderegger & Sauer, 2010). However, other studies could not find this relation (Hassenzahl, 2004; Van Schaik & Ling, 2009; Alexandre et al, 2012). Based on the empirical findings of these previous studies, it is currently unclear under which circumstances perceived usability is influenced by the aesthetics of an interface (Alexandre et al, 2012). While the effect of aesthetics on usability is still largely unknown, Cawthon & Moere (2007) did prove that attractive visualisations correlated strongly with task abandonment, in which users looked more closely at attractive visualizations, displaying a higher level of user patience.

2.3.3 Dashboard Evaluations

In order to get a sense of the success of these dashboards, and subsequently how well they increase this understanding of users, we need to look at how dashboards are currently being evaluated. Vasquez-Ingelmo et al (2019) provided an overview of the current state of evaluations of tailored dashboard. The main critic that resulted from this study was the lack of formal testing regarding the perception of the end-users on the proposed dashboard solution. The evaluations that were elaborated in these studies were mostly mentioned as future work. This finding is similar for healthcare dashboards, where a review of clinical dashboards showed that only a margin of the examined literature performed empirical evaluations (Dowding et al, 2015). Schwendimann et al (2016) encountered the same problem while examining learning dashboards. Of 55 included papers, only 15 papers portrayed actual evaluations of the proposed dashboards (Schwendimann et al, 2016). These findings highlight the need to, not just implement, but also evaluate proposed implementations.

While a variety of evaluation methods were shown in the meta studies mentioned in the previous paragraph, most dashboard evaluations revolved around the concept of usability. In context of learning dashboards, over three quarters of all examined dashboard evaluations addressed general constructs such as usability, usefulness, or user satisfaction (Schwendimann et al, 2016). The earlier mentioned System Usability Scale (SUS) is a method often used in measuring system usability (Brooke, 1996; Dowding et al, 2019; Maceli & Yu, 2020). Zhuang et al (2020) provided a framework for evaluating dashboards in Healthcare that illustrates the current usability focus in the evaluation field. On the basis of 81 papers, seven evaluation scenarios were derived. These scenarios were grouped into three themes: *interaction effectiveness, user experience,* and *system efficacy* (Zhuang et al, 2020), where the interaction effectiveness group is particularly interesting for this study. The goal of this evaluation is to measure how effective the dashboard is when the user is interacting with it. The three scenario's that are part of this group are: *task performance, behaviour change,* and *interaction workflow* (Zhuang et al, 2020). Task performance is a usability-based scenario (e.g., percentage of completed task and time to completion), and is often mentioned in evaluation studies (43 out of 82, 52,44%). Behaviour change and interaction workflow are relative new evaluations fields with respectively only five out of 82 (6.1%) and seven out of 82 (8,54%) evaluation studies (Zhuang et al, 2020). This demonstrates that most dashboard evaluations are still directing their attention on usability performance.

Janes et al (2013) proposes to use aspects of the earlier mentioned TAM in order to evaluate dashboards, specifically perceived usefulness and perceived ease of use. In line with technology acceptance, Dolan et al (2013) applied a questionnaire based on the Unified Theory of Acceptance and Use of Technology (UTAUT) and WebQual instrument to a healthcare decision dashboard, in order to evaluate how nurses experienced the dashboard's ease of use and acceptability. Smith (2013) introduced a standard set of four questions to determine if the design of the dashboard communicates effectively to stakeholders. One of the main goals of this evaluation is to increase the understanding the user has. Furthermore, Dowding and Merrill (2018) developed a heuristic-based evaluation of dashboard visualizations. The evaluation checklist is based on heuristic principles from Nielsen, combined with heuristic principles developed by prior research specifically to evaluate information visualizations (Forsell & Johansson, 2010; Dowding et al, 2018). As of yet, no method has been developed that looks purely into the understanding the user has of the data presented in the dashboard, specifically how well this data is interpreted.

3. Use Case Background

Orbisk is a startup that was founded in 2019 with the main goal of reducing food waste by implementing technical solutions. The company strives to bring back the value of food, while at the same time provide companies with sustainable solutions that positively impact businesses. With a focus on the hospitality sector, Orbisk provides an IoT-solution that quantifies all food waste related data for food waste management. Orbisk is based in The Netherlands and currently has a team of 20 people. Most customers are companies or private and public organizations that operate canteens for staff or customers, or hotels. These include hospitals such as the Leids Universitair Medisch Centrum (LUMC) and hotels such as the Krasnapolsky (Amsterdam). The leftover products of these canteens consists generally of buffet surplus, surplus meals, unused or spoiled raw foods and ingredients used for cooking, and food leftovers that are lost during the cooking process, such as imperfect cuts, and plate leftovers. In addition to a wide range of clientele, Orbisk has received various awards for their innovative and sustainable solution. Awarded by organizations such as the Postcode Lotteries Green Challenge.

The solution that Orbisk offers is an IoT based food waste system that automatically quantifies and analyses food waste data. Orbisk targets the hospitality

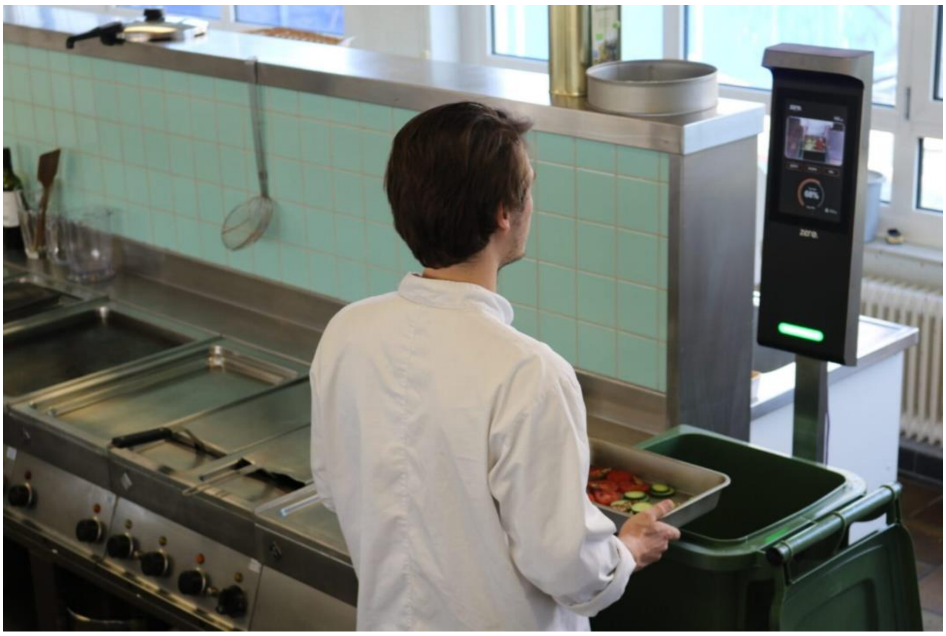

Figure 3: Orbisk Hardware system (from Orbisk.com)

sector by installing their system in larger, commercial kitchens. This system comprises of both a software and hardware system. The hardware part consists of a scale that can weigh the contents of the bin, and a camera that captures the content of waste bin (Figure 3). Whenever a plate of food is positioned below this camera, a photo is taken of this plate. This photo will be used to identify the amount and type of food waste that is being thrown out. The scale keeps track of the amount of weight of every deposit. This physical machine also has a small user interface that shows the user whether the food deposit was successful, alongside additional information such as the amount of food waste that was deposited on that day.

The next part of the quantification process is the analysis phase. The input for this phase includes sequences of images captured by the camera, and weight data captured by the scale sensor. Orbisk applies AI-technology to these photos to automatically classify what type of food is being thrown away. This software can recognize and differentiate between avoidable waste (e.g., leftover plates) and unavoidable waste (e.g., peelings). The annotation process, or classification process, is partly done automatically via AI, and partly manually via human annotators. Whenever the AI returns a certainty level below a threshold (95%), a human will manually check and annotate these images. Once all the images of a given period have been analysed, a feedback report is presented to the client. This report allows floor managers and executive chefs to make data-driven decisions.

In the relative short period that Orbisk has been operational, there have been three different iterations of feedback reports. During the early days of development of the Orbisk technology, there was no existing dashboard that could be used to present the clients data. PowerPoint presentation (Figure 4) for clients were presented every other week, that would contain all the data of the food waste of the previous week. This was a demanding and time-consuming task for the employees at Orbisk. A transition was made to Google Data Studio. This data visualization tool is a platform provided by Google that allows users to build interactive and customizable dashboards, and has been in use by Orbisk since 2020. This dashboard provides the customers with an overview of food waste data and trends (Figure 5). The final iteration of the food waste report is an interactive dashboard designed and implemented by Orbisk itself, which is currently being tested by a small group of clients (Figure 6). Operating their own dashboard allows Orbisk to have more control and accessibility to how and when data is presented to clients. New features of the dashboard include descriptive text files that are based on the food waste, and the option to view the photos of the food waste that were made by the hardware system. Existing elements such as graphs and categories tables remained the same in functionality, but received a new design. The graphs functioned the same, however was made more compact by having the option to view multiple variants of the graph in the same presentation (e.g., having the option to view either the kilograms or the money, as opposed to having to separate graphs).

Having data presented in this dashboard format, provide the floor managers with insights into their sources of waste, food waste components, quantities, and costs. These insights are expected to lead to more resource-efficient processes and a reduction in food waste and food cost, especially in the catering business (Shakman et al, 2008). Based on previous measurements and external case studies of similar food waste systems, it is anticipated that avoidable food waste reductions of up to 70% are achievable (Martin-Rios, 2021), and it is this goal that Orbisk is striving to achieve. By reducing food waste, companies are not only reducing food expenditures, but also preventing unnecessary environmental impact (e.g., water use, CO2 emissions, land use, etc.). This allows companies to strive for sustainability without having extra costs.

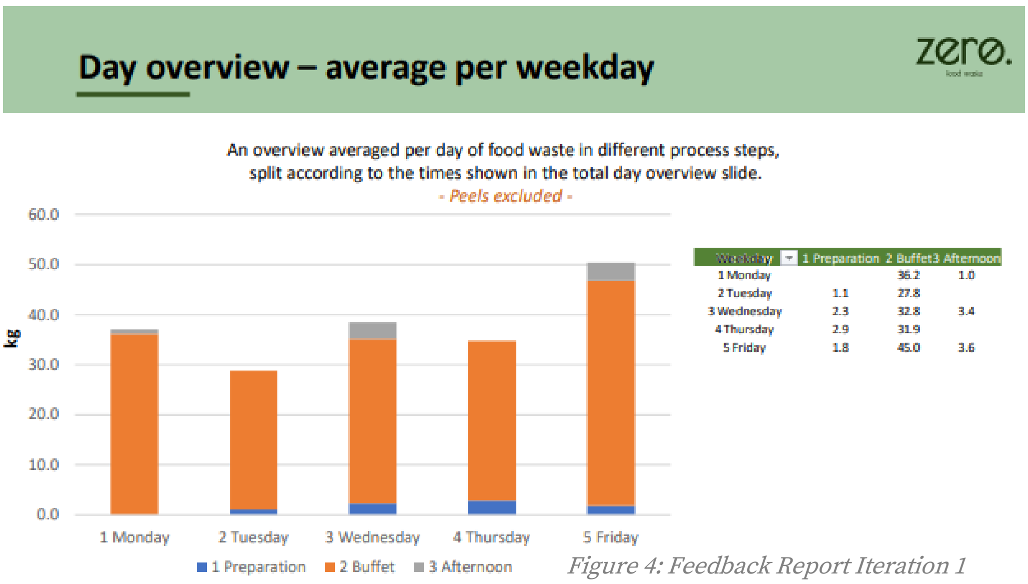

Figure 4: Feedback Report Iteration 1

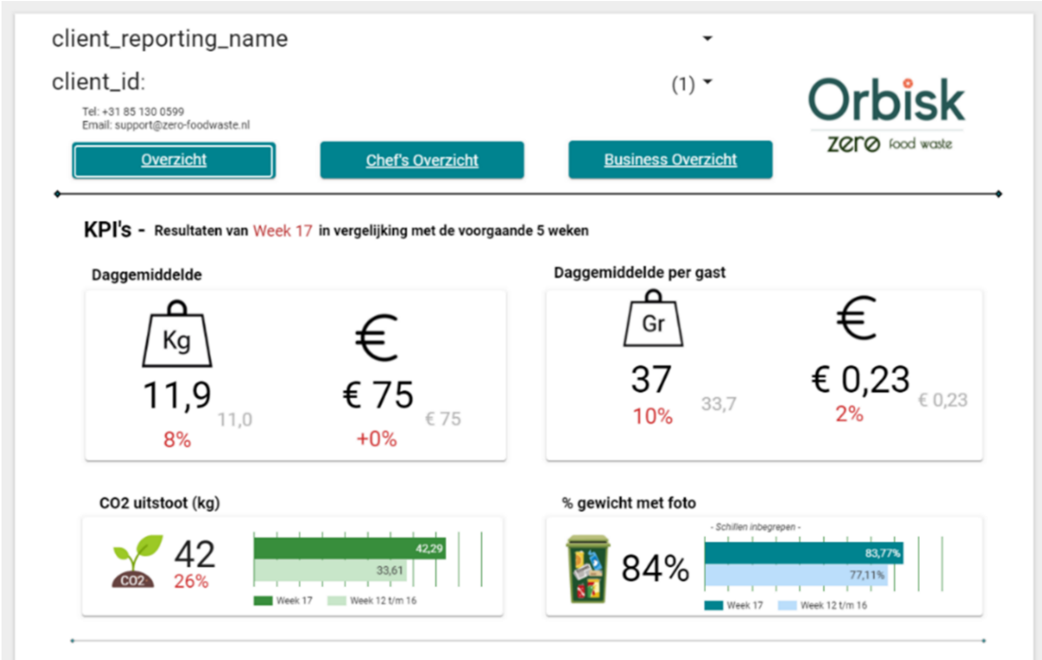

Figure 5: Feedback Report Iteration 2

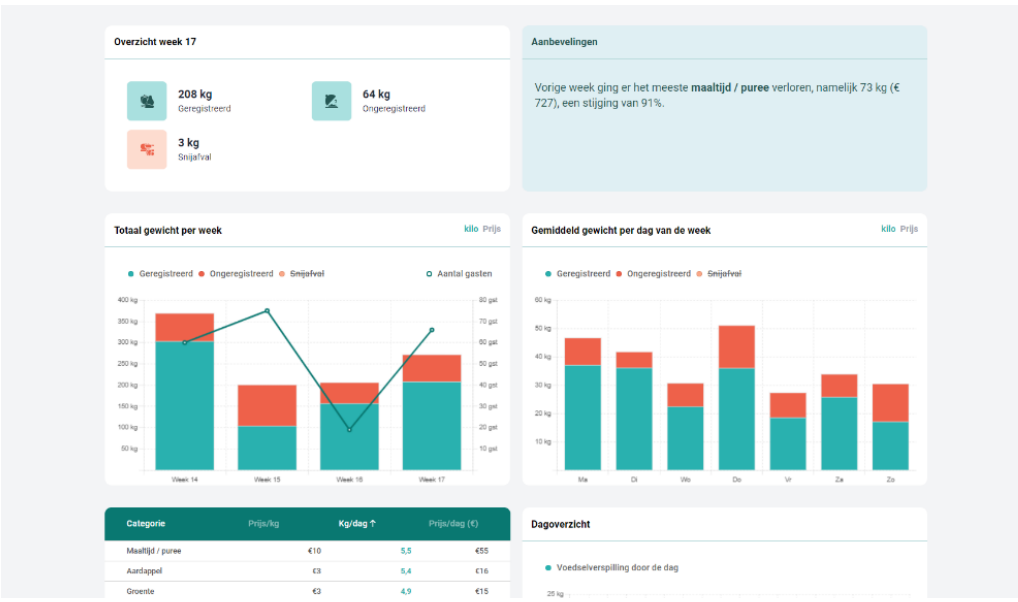

Figure 6: Feedback Report Iteration 3

4. Qualitative Methodology

This method part examines qualitative data. For this method part, qualitative data will be used to answer the first two research questions. By using a qualitative approach, insights into the thought process are more easily found. In-depth information is gathered via interviews that highlights more precisely where the exact problem of data interpretation of the customers lie. This information is subsequently used as the backbone of the second part of the study, which is the quantitative part. This research uses both primary data, gathered by the research itself, and secondary data from a company.

4.1 Participants

Participants of the pilot interviews were recruited via e-mail communication. All participants (N = 3) were clients of Orbisk that had a Orbisk food waste system implemented and had experience with using this system. Of the three clients that were interviewed, two were male and one was female and were between the ages of 35 and 58. Of the three interviews, all three had a managerial function, however one manager was also active in the kitchen as a chef. Convenience sampling was used. All clients of Orbisk were approached to participate in these interviews, and three clients volunteered to participate. The interview's took place online via Google Meet.

Participants of the interviews were recruited via e-mail communication. All participants (N = 2) were clients of Orbisk that had a Orbisk food waste system implemented and had experience with using this system. Of the two interviews, two interviewees were female, and one was male. As one interview was conducted on two people. The age of the interviewee's ranged from 36 to 51. All three interviewees had managerial functions. Convenience sampling was used. Four clients were approached for these interviews, from whom only two responded and agreed to participate. Only four clients were approached as these four clients were the only people who had not participated in any previous user test or interview before. The interviews were conducted online via Google Meet.

4.2 Design

Semi structured interviews were used to provide an in-depth understanding of what the participant perceived when analysing their data via the dashboard. This is especially important due to the new nature of the dashboard. The interviewees have not interacted with this system and therefore need to be questioned in detail on their first impressions. Most questions were designed by the researchers themselves and looked at either specific understanding of a single element, or examining how the dashboard is being used in daily operation. Additionally, one question of Smiths (2013) four standard evaluation questions, was used in the interviews. The interviews were transcribed, and a thematic analysis was conducted. NVivo was used to code the transcriptions of the interviews. The process of open coding was used to determine trends and themes within the interviews (Blandford, Furniss, & Makri, 2016). The diagram application Lucidchart was used to visualize the hierarchical structure of the codes into a visual hierarchical tree (Lucidchart, 2021). Each theme was examined to gain understanding of the thought process of the dashboard user. The interviews were conducted in Dutch, so the quotes in the results section have been translated to English.

4.3 Procedure

For the pilot interviews, participants were told that the interview would be about how they interpreted and understood elements of the dashboard. Consent was asked in the beginning of the interview to allow an audio recording to be made. These interviews focused on gathering feedback on the visualisations and text messages of the Orbisk dashboard that were understood and not understood. The interview comprised of seven questions that looked into how clients perceived to understand several elements of the new dashboard (Appendix A.1). Questions were designed to force the interviewee to make an explanation on a particular topic, in order to determine how well they understood it on the basis of that explanation. The pilot interviews were generally completed within 20 minutes. Afterwards, the clients were thanked for the participation, and were dismissed.

For the interviews, participants were also told that the interview would be about how they interpreted and understood elements of the dashboard. Consent was asked in the beginning of the interview to allow an audio recording to be made. These interviews focused on getting more of a general overview on how the experiences with interacting with the dashboard has been. Questions were broader and focussed less on forcing the interviewee to make the explanation. This was changed as the clients of the pilot interviews had no issue with explaining the dashboard. The interview comprised of 15 questions (Appendix A.2). The interviews took an estimated 30 minutes to complete. Afterwards, the clients were thanked for the participation, and were dismissed.

5. Qualitative Results

In this section, results of the qualitative part of this study are presented. Firstly, qualitative results from the pilot interviews are presented, followed by the qualitative results from the interviews.

5.1 Results of interviews

Five interviews with Orbisk clients were conducted to examine what the current state of user understanding is within the new Orbisk dashboard. The focus of the interviews was specifically on two aspects. Firstly, how the clients understood the visualisations and the text files. Secondly, to what extent do they understand what actions to take next.

5.1.1 Coding theme's

Several themes emerged during the open coding process of the interviews that visualised the thought process of the dashboard user. This process identified six key themes: *Dashboard element opinions, Dashboard appearance, Understanding of data, Frequency of dashboard usage, Motivation, Understanding of next step*. The hierarchical structure of NVivo was used and transformed into a hierarchical tree using the diagram tool Luchidchart (See figure 7). Two themes are especially interesting when looking at our research questions RQ.1 and RQ.2: *understanding of data* and *understanding of the next step.*

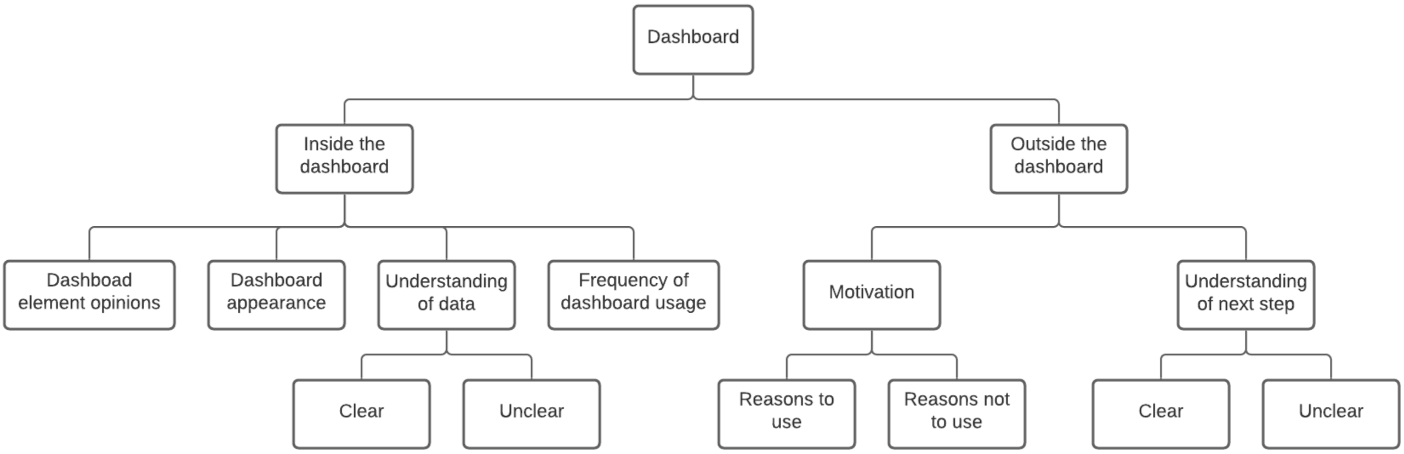

Figure 7: Hierarchical structure of coding

5.1.2 RQ 1.1 – Understanding of data

In this theme, remarks of clients were placed that revolve around understanding the data in the dashboard (defined as 'Clear'), or having trouble understanding the data in the dashboard (defined as 'Unclear'). Overall, clients seem to have a relatively good understanding of the data they were questioned about. This also became visible when examining the number of quotes that were within the two codes 'Clear' and 'Unclear'. The code 'Clear' had 65 quotes on understanding data, whereas the code 'Unclear' only had 27 quotes on not understanding the data.

5.1.2.1 Clear

In the interviews, clients were asked to describe data within certain elements of the dashboard. All five clients were having little trouble interpreting the data correctly. For example, when asked if they could interpret the data from the recommendation element, a client said:

"*It basically shows that I threw away potatoes the most. It also shows the amount of kilo's I threw away in Week 12. So, 84 kilos of potatoes, which is quite a lot.*"

This shows that client is able to interpret the data and know what impact it has. Having a recommendation section that writes out the data was positively received by the clients. As one client explained:

> *"It gives a different portrayal of the data than just numbers, having text is a welcoming change. And it is nice that there is now text that tells you: watch this ingredient, watch that product. I am not a chef, and I am only seeing data, so seeing only data can be difficult for me sometimes."*

The client sees the implementation of text as an additional factor that increases its understanding. As a manager and not a chef, food-based decisions are not always a logical step to undertake, as indicated in this quote. Having text to assist users therefore appears to increase the user's understanding. One manager indicated that the introduction of these recommendation texts was vital for allowing chefs to use the dashboard in case of absence. As the manager noted:

> "*For when I am not around, and one of the chefs has to use the dashboard".*

Another example of a clear data interpretation is an outlier in a graph that was shown to an interviewee. That person was able to quickly understand what the outlier in the graph meant:

> "*That was an outlier, and that outlier is completely clear to use, because our fridge broke down. Everything that was in the fridge was prepared in the kitchen which naturally causes more food waste.*"

This is an important quote, since the client shows that he is able to move flexible around the concept of knowledge, which is the graph. Clients also pointed out that the introduction of photos of the food waste helped with understanding certain data portrayals of the dashboard. An interesting finding for the use of photos in the dashboard was that it acted as a learning tool for chefs that worked in the kitchen.

Managers that are in control of the dashboard would use the photos as a communication tool to illustrate the impact that food waste has on their organization. As one client noted:

> "*My staff in the kitchen are low-skilled workers or not schooled at all, and for them photographs say more than reading texts. (...) And if she sees a tray full of vegetables, she thinks: oh yes! And is able to follow the food waste story.*"

Managers themselves identified only one way that the photos would benefit their understanding process of the data. Namely that ingredient that they did not recognize in the categories table, could be traced back in the photo's section of the dashboard. Finally, clients were asked to combine multiple elements of the dashboard to be able to determine their food waste trends. This way the interviewee would display a good understanding of the data since it would have to look at specific information spread out in the dashboard. The interviewee's appeared to not have difficulties with combining elements, as one client noted:

> "*I look at the area of the highest waste. Which in this case is meals and components. I then click on that and see what is the highest, in this case vegetable mix. And I often look simultaneously at the week where the peak is the highest, and on what day. So that I can take that information and can examine what dish, what vegetable mix did not do well last week.*"

It shows that the client knows where and how certain data can be found and combined in order to understand their food waste data better.

5.1.2.2 Unclear

When asked to describe certain elements of the dashboard, clients also indicated that some parts were not quite understood. But in contrary with the previous part on understanding the general idea of the dashboard, clients indicated that they only had trouble with understanding specific parts of the dashboard. No interviewee indicated that they had trouble understanding the data that was presented in the general overview of the dashboard. One trend that emerged was that clients could not fully relate the data to their current situation. As one client indicated:

> "*It says 'an increase of 25%', but seeing that this is the first week, it must be 25% of all my food waste. Because I do not think that we threw away 25% less potatoes in week 11, than we did in week 12."*

In this instance, the increase of the amount food waste could not be related back to the own situation of this client, which therefor caused confusion. A similar example from another client exhibited the same problem:

> *"I expected more waste between 8 and 11, very strange. Because there is still plenty of mise-en-place going on before the lunch. So either they have waited literally until 11 o'clock to throw away the waste, but they did not. I know for a fact that waste is thrown away in the meantime. Very strange."*

Interestingly, by indicating that the time-based graph in question was not working as expected, the client did show that the general concept of the graph was understood. They understood the working of the data and could therefor identify whether or not it was functioning right. But confusion still remains nevertheless. Another trend that emerged was lack of understanding on certain ingredients. Clients indicated that they often had issues with identifying and recognizing certain ingredients that the dashboard displayed. These portrayals were all written out and included ingredients that were automatically annotated by the machine learning models. As a result, ingredients written out in text are not 100% accurate. As one client explained:

> *"I recall that sometimes items are being described in the reports for example, and it shows items that we do not even have. It is being described as 'brown gravy' for*

example, you have the descriptions in the dashboard from which I know that we do not sell that. So what could it be then?"

This shows that the dashboard user can become confused on the nature of the waste. One client did indicate that they did not understand a piece of data that was presented to him. As he stated:

"I only see an increase in week 12 and I am curious what that increase is. How it suddenly increased so much. It could be that it has been busier in the hospital, I would have to check that. That could be it, no clue really what that is about."

This clearly shows that the client is confused about where this increase in the data comes from. This proves that the dashboard is not fully understandable in some cases. However, the lack of trend for these types of quotes indicate that this is more of an outlier than a commonality. Finally, all interviewees explained that chefs and kitchen staff did have difficulties interpreting the data from the dashboard. As can be seen in chapter 5.1.2.1, this has various reasons such as staff that is low-skilled or not schooled at all.

5.1.3 RQ 1.2 - Understanding of next step

In this theme, remarks of clients were placed that revolve around understanding the next step of food waste reduction on the basis of the data in the dashboard (defined as 'Clear'), or having trouble understanding what next step to undertake on the basis of the dashboard data (defined as 'Unclear'). Overall, clients seemed to understand how they could act on the data presented. This also became visible when examining the number of quotes that were within the two codes 'Clear' and 'Unclear'. The code 'Clear' had 19 quotes on understanding the next step, whereas the code 'Unclear' only had 5 quotes on not understanding what step to take next. Both areas having significantly less quotes than the quotes on data understanding. It is important to clarify that there is no fixed method of reducing food waste, each client does it in their own way. These results purely look into whether they have an idea of an approach to reducing food waste.

5.1.3.1 Clear

In the interviews, clients were asked if they understood what follow up actions to take after reviewing the food waste data in the dashboard. They were forced to explain what follow up steps to take. Overall, clients were able to give a good explanation on how they would use the presented data in the dashboard. As one client noted:

> "*It is being viewed as this: The first thing we look at is what do we throw away the most. And how much of that do we throw away? Those are always the first two questions.*"

Another client explained their process:

> "*But yes, I am going to look at the text to see what I actually did, what I actually threw away. So that I can go ahead and discuss with my food supplier, but also with our dietitian, if I look at this data, I am throwing away too many potatoes. Can we increase the size of that steak and reduce the number of potatoes for example. To still get the right nutritional value.*"

Both quotes show that these clients have a clear understanding of what exact steps they have to take next. In both instances, the interviewee's indicated that they first look at the dashboard data to decide what was thrown away and how much. This shows that the clients both understand the data, and understand what data is necessary to make additional steps on. When talking about how time-based graphs could be integrated in the decision-making process, one manager explained:

“ *What I get from that graph, I am not really looking at, do I have to make smaller portions of potatoes or smaller vegetable portions. I am more specifically looking at, perhaps we should spread the food weight more over the rest of the day”.*

“*Look at the graphs and see what we throw away on a weekly basis. That is a lot of money, perhaps we should do something about that. Preparing the meals later on the day for example. (...) Those type of things are what I am thinking about, how do we handle that in the best way so to say.”*

Both examples show that the client is able to identify in what areas they can improve. Both do show to have a strategy available. However, both also show that they are not completely sure in whether their strategy would work. Having a successful strategy differed from clients. As one client showed:

“*By now, we know that they do not like udon noodles. That is always leftover, it is a very specific example. But you can clearly see that it increases our waste quite substantially. We buy less of it. We prepare less of it, more à la minute if possible. In that way we try to reduce the waste, we do it step by step. If we first made 10 kg, we would do 8. And lower that until we are at the right weight.*

As shown in the example, this manager has a concrete strategy to lower food waste. Showing that they clearly understand what food should be reduced, and in what manner.

5.1.3.2 Unclear

There were no clients that had no idea what steps to take next. However, as shown in the previous paragraph, some clients were unsure whether their steps would be effective. One example of such an uncertainty:

“*just to name something, we do not cook for a day and observe, if we do not cook on Friday, what obstacles do I run in to? Do I have enough? Because I have been over producing for all these days, or should I produce extra, or do I have too little? The reaction between reducing our order quantities and observing how that effects our production. If I throw away 20 kilos of food per day and reduce our order with 20 kilos to see what it does to our production. And I still see that I am throwing away potatoes, I think to myself, how is this possible?*

It is clear that this client is struggling with coming up with a good strategy. Even to the point of becoming a little frustrated. It is this trend of being uncertain on what strategy to use that was corroborated by another client:

“ *What are we going to do about that? Are we going to produce less, put it on the menu less often? Those type of things are what we should be thinking about. Should we mix it with something else, to make it appear more delicious so that they would want to eat it?”*

In this case, the client is proposing some good ideas on how to handle the food waste, but is not settled on a single best approach. This finding was observed with three of the five interviews, and does indicate that, despite clients understanding how they can reduce food, they do not know the most efficient ways.

5.1.4 RQ 1.4 – Usability & Appearance

During the interviews, feedback was given on the look and feel of the new dashboard. These comments were coded under the theme ‘dashboard appearance’. This feedback was mostly the first impression the interviewees had of the new dashboard, and revolved mostly around the new aesthetics. The new look of the dashboard appeared to be received positively by the clients, as two clients noted:

"But yes, at first glance it looks really great. So definitely an upgrade compared to the old dashboard."

"The dashboard looks a lot calmer, based on the colours."

Both clients appreciated the new design, and indicated that it is a step up from the old dashboard. This improved appearance also influenced the usability aspect of the new dashboard. Clients indicated that the clear overview helped with finding the right data. As two clients explained:

"*I think it looks pretty clean right now. In the previous dashboard, you had to click on that button so you would go deeper into the dashboard. I think this makes it clearer."*

"Yes, it is portrayed more clearly. You have the time period graphs and the categories table clearly visible at the top. You don't have to go to the bottom of the graph and click on it to go deeper into the dashboard."

Changing the design of the dashboard appeared to have also influenced the usability of the dashboard. Clients indicated that the change in presentation made certain data appear more accessible. Where in the old dashboard, clients needed to take extra steps to obtain data, the new dashboard makes this data instantly and more ease accessible.

5.1.5 RQ 1.5 - Money vs Kg

Another interesting theme that emerged, was the motivation of the client to reduce food waste. It became apparent after the interviews that clients prioritised either reducing food waste for monetary reasons, or reducing the amount of food waste for environmental reasons. When clients prioritised for monetary reasons, they mostly did to reduce costs for their company. As two clients explained:

“*What I find interesting, is just plain euros. Do we throw away one hundred kilos of potatoes because it saves me five euro, or do we throw away ten kilos of meat, which is 500 euros. (...) In the end, that is what you are being accounted for, for the reduce in money and not for the reduce of kilos.*”

“*Look at the graphs and see what we throw away on a weekly basis. That is a lot of money, perhaps we should do something about that.*”

Both examples clearly state that clients have their priority set on reducing costs. On the contrary, other clients prioritised reducing the amount of kilo’s due to environmental reasons. As two clients explained:

“*Because we want to try and do better for the environment. The waste really needs to go down.*”

“*People often look at the money and that is where I stop. Because for me, that is not the most interesting at the moment, it is just a nice bonus*”.

Both quotes exhibit a different priority than focusing purely on money. From the five interviews conducted, three prioritised money over amount of kilos, where two prioritised environmental reasons over reducing money.

5.2 Conclusion

This section highlighted the key findings of the interviews that were conducted. As a result of the open coding process, several themes were identified and analysed to be able to answer the research questions. When examining ‘understanding of data’, the overall results indicate that managers have a good understanding of the data. Difficulties in understanding data were mostly single cases that could not be related back to the real-life situation, or related to kitchen staff that had difficulties with the dashboard. When examining ‘understanding of the next step’, the overall results indicated that managers were generally aware on what actions they could take in order to reduce food waste, but were unsure on the effectiveness of these actions. When examining 'Motivation', we could observe a split in monetary vs environmental reasoning for food waste reduction. This finding will be further observed in the quantitative section, where an analysis has been performed to determine if there are underlying preferences to be found.

6. Quantitative Methodology

This method part addresses the quantitative study. Quantitative data is used to answer the third, fourth and fifth research question, that required an analytics approach. The questionnaire is an effective method to gather larger amounts of user feedback, which enables us to create a good representation of the average user. Since no standard questionnaire currently exists that attempts to measure perceived user understanding, this study created a questionnaire that attempts to measure perceived user understanding. Correct responses on knowledge questions were used as a proxy for understanding. On the basis of the qualitative results, this questionnaire also attempts to determine the preferred type of textual presentation. These text files are used to suggest the most urgent types of food waste changes the user can make.

6.1 Participants

Participants were recruited via the use of a third-party website called Prolific. The amount of required responses for the questionnaire was set to a total of 60. An additional five participants filled out the questionnaire. Most of the participants (N = 60) were unknown to the researchers as it existed of the prolific participant base, which amounts to over 140.000 users. The remaining five participants were known to the researcher. A total of N = 65 participants ended up filling out the questionnaire. Convenience sampling was used, no restrictions were present, except for participants having to be over 18 years old. Due to the between-subject design of this study, participants would fill out either one of the questionnaires. In order to reduce the number of participants that would fill out both of the questionnaire, the two questionnaires were released on different times. Of the 65 participants, 32 were male and 33 were female. The age ranged from 18 to 60, where the largest group (70.77%) consisted of 18–25-year-olds. Group A consisted of 14 males and 19 females, where the largest group (75.76%), were 18–25-year-olds. Group B consisted of 18 females and 14 males, where the largest group (65.63%) were 18–25-year-olds. Participants had little to average experience with using a dashboard. 80% indicated that they never, rarely, or sometimes used a dashboard, with sometimes being the largest group (36.9%). The never, rarely, or sometimes group for Group A was 72.72% in total, where that same group for Group B was at 87.5%. The questionnaire could be filled out online in the homes of the participants. Participants took an average of 15 minutes to complete the questionnaire. The questionnaire was available online from 27-06 till 29-06. All participants were informed on the questionnaire beforehand and provided written informed consent (Appendix B.1).

6.2 Materials

Participants required a laptop to fill out the questionnaire. Qualtrics was used to design and distribute the questionnaire. One question of the System Usability Scale from Brooke (1996) was used to determine how participants would rate the 'ease of use' of the proposed screenshots. One question of the UUP (Utility, Usability and Presentation Score) was used to determine how participants would rate the look and feel of the screenshot (Myles, 2019). Screenshots of the second and third iteration of Orbisk dashboards were used as reference material in the questionnaire. Questionnaire A used screenshots of the second iteration of the dashboard, whereas questionnaire B used screenshots of the third iteration.

6.3 Design

The questionnaire used a between-subject design since we wanted to compare the two types of dashboards. The choice for a between-subject design was made since we required participants to answer certain knowledge question. Repeating these questions for a different dashboard would cause unreliable results for either of the two dashboards, as participants had already answered these. Before release of the questionnaire, five participants tested the questionnaire for grammar and functionality. After processing this feedback, the final questionnaire design was finished. The questionnaire consists of two parts. The first part is on the effect of the type of dashboard on user understanding, usability, and aesthetics. The second part is on preferred text structures. For the first part, the independent variable was the type of dashboard, either old or new. The dependent variables were 'correct answers', ‘ease of use’ and ‘aesthetically appealing’. The experimental group (Group B) answered questions when looking at screenshots of the new dashboard. These screenshots of the new dashboard can be found in Appendix B.1 and consist of figure 15, 17, 19, 21 and 23. The control group (Group A) answered the same questions, only looking at screenshots of the old dashboard. The screenshots of the old dashboard can be found in Appendix B.1 and consist of figures 14, 16, 18, 20 and 22. The answers were presented in a multiple-choice format. For the questions on ‘ease of use’ and ‘aesthetically appealing’, a five-point Likert Scale was used, where 1 was ‘strongly agree’ and 5 was ‘strongly disagree’.

The second part on text structures was introduced as a result of the interviews. In which interviewee’s indicated that they had different motivations for using the dashboard. These text files were designed appropriately, where money versus kg texts were used. In this part of the questionnaire, participants were asked to rank sentences that inform them on food waste in their preferred order. They were given four sentences to rank from 1, being most useful to either 3 or 4, being least useful. The dependent variable was ‘type of text structure’, whereas the dependent variable was ‘order of preference’.

6.4 Procedure

This questionnaire was designed to determine whether the new dashboard had increased the data understanding of the user as compared to the old dashboard. These questions were formulated in such a way that participants needed to make an extra thought step in order to be able to answer the questions correctly. Since the participants had no previous domain knowledge when it comes to food waste, foreknowledge that was needed to answer the question was provided with every question. Participants of both groups had to answer two of these type of questions per screenshot, where the answers were presented in a multiple-choice format. Participants first saw the screenshot of the dashboard element, and below this screenshot the two knowledge questions were visible.

Additionally, after answering two knowledge questions per screenshot, participants were asked to indicate on a five-point Likert scale how they perceived the 'ease of use' and 'aesthetic appearance' of that screenshot. After answering the two knowledge questions, participants clicked on next an saw the same screenshot but with the two Likert scale questions. In total, five screenshots were presented to the participant, in which they had to answer ten knowledge questions and five usability questions. In the second part of the questionnaire, participants were asked to rank text structures from most useful to least useful. The first four ranking questions were four sentences that had the following structures: 'General insights', 'Times Series', 'Correlating Ingredients' and 'Day of the Week'. After four of these rankings were completed, participants had to rank another four text structures. These sentences had the following structures: 'normal presentation', 'high kg', and 'high money'. Participants saw four texts per page, and needed to rank these four texts in order to go to the next page. Afterwards, the clients were thanked for the participation, and were dismissed.

6.5 Analysis

Before the analysis of the questionnaire data, the dataset was first prepared. It was checked for outliers and any missing data. No corrections were needed. The data was then analysed using statistical software IBM SPSS Statistics for Windows, Version 27.0. In order to analyse the data correctly, the two SPSS files were merged into one file. A variable called 'version' was added to both files in order to differentiate between the two groups, with group A called 'old' and group B called 'new'. RQ 1.3 is tested by using a Chi-squared test. In order to determine significance of results, a chi-squared test of independence was performed to examine the relation between the type of dashboard and the correct answer to the question. Crosstabs were used to summarize the relationships between different variables of categorical data. The test of independence is used because we want to see if two variables are related. The ten knowledge questions were individually hypothesised and analysed. A difference is deemed significant if $p < a$, with $a = 0.05$.

RQ 1.4 is tested by using a Chi-squared test. In order to determine significance of results, a chi-squared test of independence was performed to examine the relation between the type of dashboard and the perceived 'ease of use' and 'aesthetic appearance'. The Chi-squared test was used because the data that needed to be analysed was data from a Likert Scale, which is ordinal. Taking the average of ordinal data has an unclear meaning, as you cannot take the average of "strongly agree" and "agree" (Sullivan & Artino, 2013). Tests like the T-test or regression analysis have to use the average, which is why these were not applicable for this analysis. Crosstabs were used to summarize the relationships between different variables of categorical data. For both ease of use and aesthetics, five Likert scale questions were individually hypothesised and analysed. A difference is deemed significant if $p < a$, with $a = 0.05$. Additionally, the median of every Likert scale result was measured. The median was used as the measure of central tendency because Likert Scale data is ordinal. SPSS was used to generate these median scores via frequency tables.

RQ 1.5 is tested by using the Friedman's ANOVA. Friedman's ANOVA is used to test data that does not conform to normality. Since we worked with ranked data, the data is not normality distributed. The Friedman's ANOVA allowed us to compare differences in ranked data in order to highlight significant preferences. No weights were added to the ranks. The groups were not split for this analysis, since the type of dashboard has no influence on the text files. A difference is deemed significant if $p < a$, with $a = 0.05$.

7. Questionnaire Results

In this section, the analysis of the questionnaire data and overall scores are presented. An overview of all the results can be found in Appendix B.2 and B.3.

7.1 RQ 1.3 - Influence of new dashboard on data understanding

This paragraph will provide results for the sub research question 1.3: *Do the visual and textual elements of the new food waste dashboard lead to better perceived understanding of food waste data than the old food waste dashboard?*

To answer RQ 1.3, ten knowledge questions were analysed and checked for significant differences by using the Chi-Squared test. The independent variable for this analyses is 'type of dashboard', where it was either the new or the old dashboard. The dependent variable was 'amount of correct answers'. Conceptual models have been created to show the hypothesis of relationships between RQ 1.3 and the variables (Figure 8).

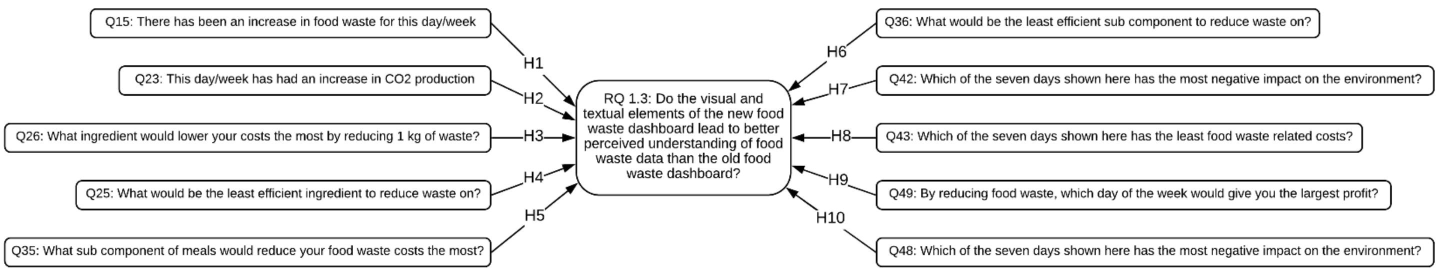

Figure 8: Relationship of variables to RQ 1.3

The following hypothesis were tested:

H_1: RQ 1.3 is associated with Q15. For H_1, the hypothesis can be accepted. Users of the new dashboard answered Q15 significantly better than users of the old dashboard, X^2 (1, N = 65) = 6.67, p = 0.010 (Appendix B.3 - Table 16)

H_2: RQ 1.3 is associated with Q23. For H_2, the hypothesis must be rejected. Users of the new dashboard did not answer Q23 significantly better than users of the old dashboard, X^2 (1, N = 65) = 1.65, p = 0.199 (Appendix B.3 - Table 17)

H_3: RQ 1.3 is associated with Q26. For H_3, the hypothesis must be rejected. Users of the new dashboard did not answer Q26 significantly better than users of the old dashboard, X^2 (3, N = 65) = 3.16, p = 0.367 (Appendix B.3 - Table 18)

H_4: RQ 1.3 is associated with Q25. For H_4, the hypothesis must be rejected. Users of the new dashboard did not answer Q25 significantly better than users of the old dashboard, X^2 (3, N = 65) = 4.78, p = 0.189 (Appendix B.3 - Table 19)

H_5: RQ 1.3 is associated with Q35. For H_5, the hypothesis must be rejected. Users of the new dashboard did not answer Q35 significantly better than users of the old dashboard, X^2 (3, N = 65) = 4.80, p = 0.187 (Appendix B.3 - Table 20)

H_6: RQ 1.3 is associated with Q36. For H_6, the hypothesis must be rejected. Users of the new dashboard did not answer Q36 significantly better than users of the old dashboard, X^2 (3, N = 65) = 1.98, p = 0.578 (Appendix B.3 - Table 21)

H_7: RQ 1.3 is associated with Q42. For H_7, the hypothesis must be rejected. Users of the new dashboard did not answer Q42 significantly better than users of the old dashboard, X^2 (3, N = 65) = 2.17, p = 0.537 (Appendix B.3 - Table 22)

H_8: RQ 1.3 is associated with Q43. For H_8, the hypothesis must be rejected. Users of the new dashboard did not answer Q43 significantly better than users of the old dashboard, X^2 (1, N = 65) = 3.24, p = 0.114 (Appendix B.3 - Table 23)

H_9: RQ 1.3 is associated with Q49. For H_9, the hypothesis must be rejected. Users of the new dashboard did not answer Q49 significantly better than users of the old dashboard, X^2 (2, N = 65) = 1.15, p = 0.564 (Appendix B.3 - Table 24)

H_{10}: RQ 1.3 is associated with Q48. For H_{10}, the hypothesis must be rejected. Users of the new dashboard did not answer Q48 significantly better than users of the old dashboard, X^2 (2, N = 65) = 2.68, p = 0.262 (Appendix B.3 - Table 25)

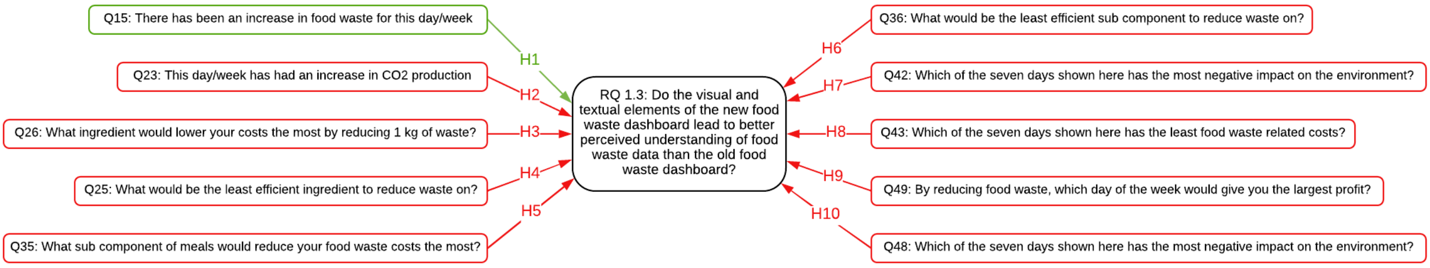

Figure 9: Significant differences of variables in relation to

After testing all hypothesis, only Q15 proved to be significantly better answered by the users of the new dashboard. The remaining nine questions showed no significant difference in responses from both groups.

7.2 RQ 1.4 - Perceived ease of use and aesthetics

This paragraph will provide results for the following sub research question 1.4: *Do the visual elements of the new food waste dashboard lead to better perceived 'ease of use' and better perceived 'aesthetic appearance' than the visual elements of the old food waste dashboard?*

To answer RQ 1.4, five usability questions, and five aestethic questions were analysed and checked for significant differences by using the Chi-Squared test. The independent variable for this analyses is 'type of dashboard', where it was either the new or the old dashboard. The dependent variable was 'score on Likert scale'.

7.2.1 Ease of use

A conceptual model has been created to show the hypothesis of relationships between RQ 1.4 and the ease of use Likert scale questions (Figure X).

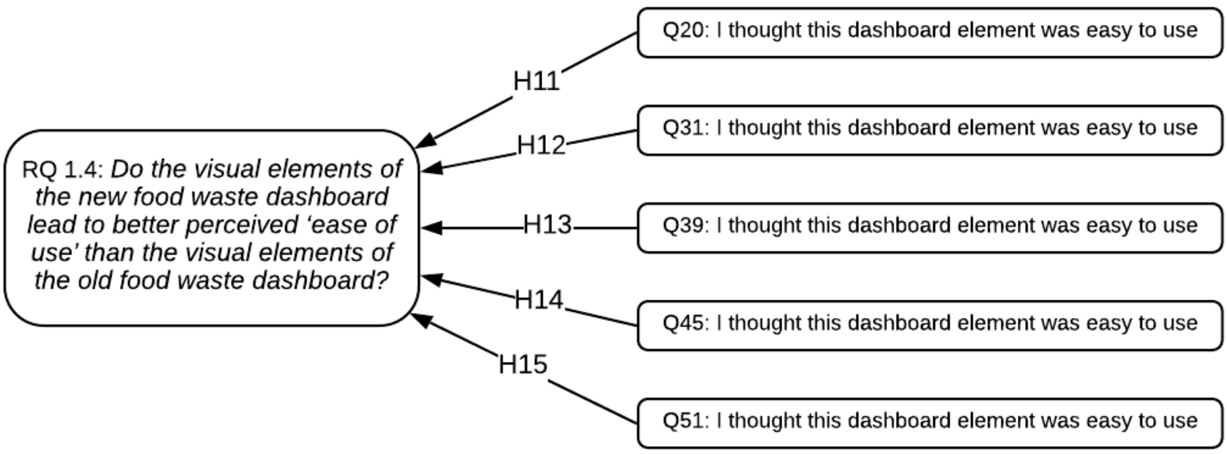

Figure 10: Relationships of variables to RQ 1.4

The following hypothesis were tested (Figure 11):

H_{11}: RQ 1.4 is associated with Q20. For H_{11}, the hypothesis can be accepted. Users of the new dashboard did perceive Q20 to be significantly easier to use than users of the old dashboard, X^2 (4, N = 65) = 14.47, p = 0.006 (Appendix B.4 - Table 26).

H_{12}: RQ 1.4 is associated with Q31. For H_{12}, the hypothesis must be rejected. Users of the new dashboard did not perceive Q31 to be significantly easier to use than users of the old dashboard, X^2 (4, N = 65) = 7.48, p = 0.113 (Appendix B.4 - Table 27)

H_{13}: RQ 1.4 is associated with Q39. For H_{13}, the hypothesis must be rejected. Users of the new dashboard did not perceive Q39 to be significantly easier to use than users of the old dashboard, X^2 (4, N = 65) = 3.88, p = 0.422 (Appendix B.4 - Table 28)

H_{14}: RQ 1.4 is associated with Q45. For H_{14}, the hypothesis must be rejected. Users of the new dashboard did not perceive Q45 to be significantly easier to use than users of the old dashboard, X^2 (4, N = 65) = 2.10, p = 0.718 (Appendix B.4 - Table 29)

H_{15}: RQ 1.4 is associated with Q51. For H_{15}, the hypothesis must be rejected. Users of the new dashboard did not perceive Q51 to be significantly easier to use than users of the old dashboard, X^2 (4, N = 65) = 4.95, p = 0.292 (Appendix B.4 - Table 30)

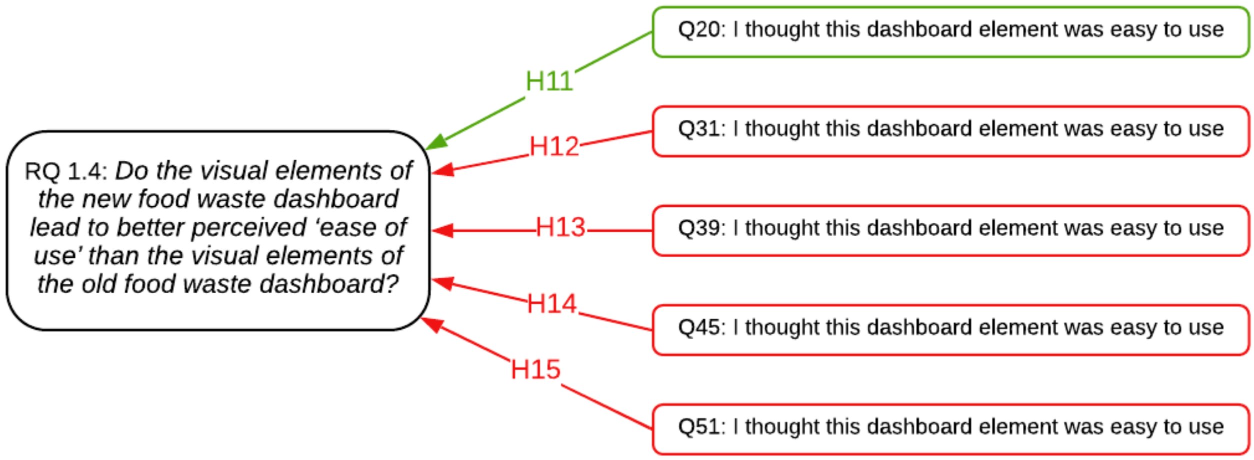

Figure 11: Significant differences of 'ease of use' variables in relation to RQ 1.4

After testing all hypothesis, only the screenshot of Q20 proved to be significantly better answered by the users of the new dashboard. The remaining four screenshots showed no significant difference in perceived ease of use from both groups. Median scores indicate that there is a difference between the two groups in Q31, but that this difference is not significantly relevant based on the Chi-Squared test (Table 1).

Median scores of 'ease of use'. 1 = Strongly Agree, 5 = Strongly Disagree	Q20: general overview	Q31: categories table	Q39: categories table	Q45: Kg waste graph	Q51: Costs graph
Old dashboard (Group A)	4	2	2	1	2
New dashboard (Group B)	2	3	2	1	2

Table 2: Median scores of 'ease of use' Likert scale questions for both groups

7.2.2 Aesthetics

A conceptual model has been created to show the hypothesis of relationships between RQ 1.4 and the aesthetic appearance Likert scale questions (Figure 12). The following hypothesis were tested (Figure 13):

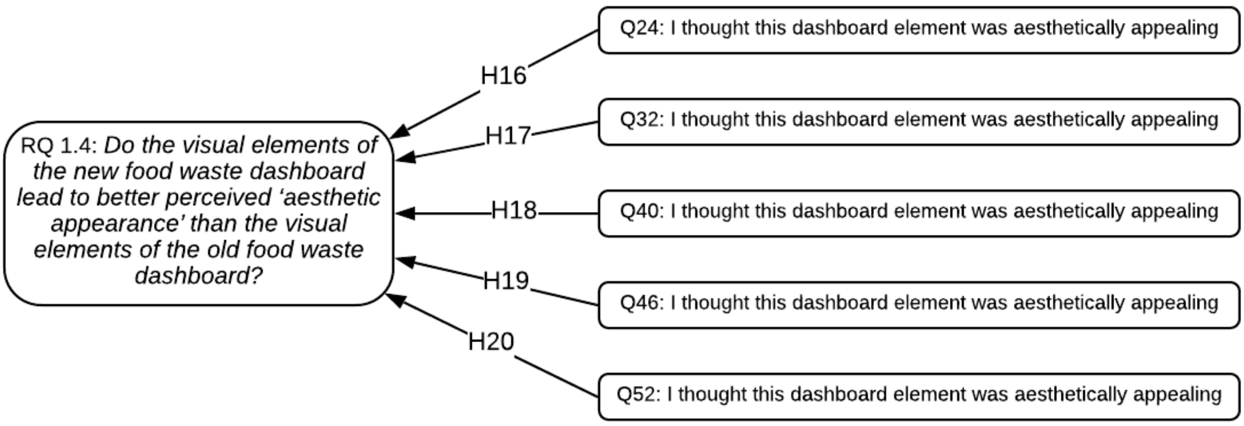

Figure 12: Relationships of variables to RQ 1.4

H_{16}: RQ 1.4 is associated with Q24. For H_{16}, the hypothesis must be rejected. Users of the new dashboard did not perceive Q24 to be significantly more aesthetically appealing than users of the old dashboard, X^2 (4, N = 65) = 6.68, p = 0.154 (Appendix B.4 - Table 31)

H_{17}: RQ 1.4 is associated with Q32. For H_{17}, the hypothesis must be rejected. Users of the new dashboard did not perceive Q32 to be significantly more aesthetically appealing than users of the old dashboard, X^2 (4, N = 65) = 5.42, p = 0.247 (Appendix B.4 - Table 32)

H_{18}: RQ 1.4 is associated with Q40. For H_{18}, the hypothesis must be rejected. Users of the new dashboard did not perceive Q40 to be significantly more aesthetically appealing than users of the old dashboard, X^2 (4, N = 65) = 4.41, p = 0.353 (Appendix B.4 - Table 33)

H_{19}: RQ 1.4 is associated with Q46. For H_{19}, the hypothesis must be rejected. Users of the new dashboard did not perceive Q46 to be significantly more aesthetically appealing than users of the old dashboard, X^2 (4, N = 65) = 5.75, p = 0.219 (Appendix B.4 - Table 34)

H_{20}: RQ 1.4 is associated with Q52. For H_{20}, the hypothesis must be rejected. Users of the new dashboard did not perceive Q52 to be significantly more aesthetically appealing than users of the old dashboard, X^2 (4, N = 65) = 4.35, p = 0.360 (Appendix B.4 - Table 35)

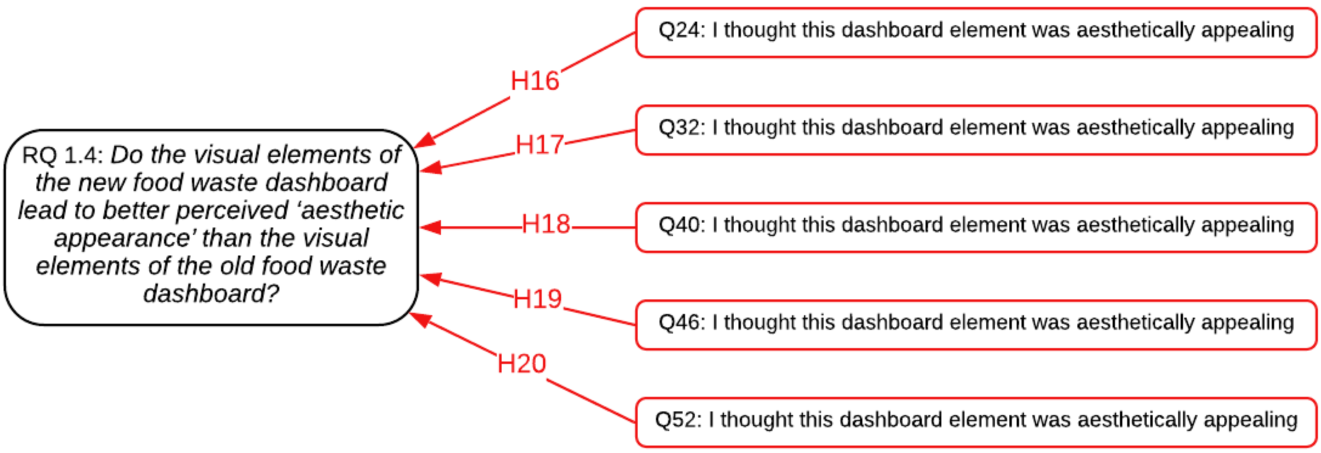

Figure 13: Significant differences of 'aesthetically pleasing' variables in relation to RQ 1.4

After testing all hypothesis, none of the questions on ‘aesthetically appealing’ proved to be significantly better answered by the users of the new dashboard. Median scores indicate that there are differences between the two groups for Q31, Q39 and Q45, but these differences are not significantly relevant on the basis of the Chi-Squared test (Table 2)

Median scores of ‘aesthetically appealing’. 1 = Strongly Agree, 5 = Strongly Disagree	Q20: general overview	Q31: categories table	Q39: categories table	Q45: Kg waste graph	Q51: Costs graph
Old dashboard (Group A)	2	2	2	2	2
New dashboard (Group B)	2	3	3	1	2

Table 3: Median scores of 'aesthetically pleasing' Likert scale questions for both groups

7.3 RQ 1.5 - Preference of text structure

This paragraph will provide results for the following sub research question 1.5: *What type of text structures that inform the user of their food waste are preferred?*

To answer RQ 1.5, different type of text structures were analysed. The first four questions revolved around the type of text structure, and the final four questions revolved around textual presentation preferences for either amount of money or amount of kilograms.

7.3.1 Text structures

The four types of text structures consist of the following: General Insights, Time Series, Correlating Ingredients and Day of the Week. There were three settings for the texts. There was a normal setting when information on the kilograms and money was average. The setting of High Costs resembled high costs versus low amounts of kilogram. The setting for High Kg resembled high amounts of kg versus low amounts of kg. For the ranks, 1 was the most preferred text structure, as opposed to 4 being the least preferred.

There was not a statistically significant difference in preferred text structures for Q57 under normal settings, $X^2(3) = 3.960$, $p = 0.266$ (Appendix B.5 – Table 36). The text structure that was preferred the most for Q57 was General Insights (Table 4).

Ranking Q57 - Normal	Mean Rank	Median Score
General Insights	2.35	2
Time Series	2.77	3
Correlating Ingredients	2.45	2
Day of the Week	2.43	2

Table 4: Mean rank and median scores for text structures of Q57

There was a statistically significaat difference in preferred text structures for Q44 under normal settings, $X^2(3) = 17.455$, $p = 0.001$ (Appendix B.5 – Table 37). The text structure that was preferred the most for Q44 was Time Series (Table 5).

Ranking Q44 - Normal	Mean Rank	Median Score
General Insights	2.29	2
Time Series	2.20	2
Correlating Ingredients	3.06	3
Day of the Week	2.45	2

Table 5: Mean rank and median scores for text structures of Q43

There was a statistically significaat difference in preferred text structures for Q43 under high costs settings, $X^2(3) = 17.455$, $p = 0.001$ (Appendix B.5 – Table 38). The text structure that was preferred the most for Q43 was General Insights (Table 6).

Ranking Q43 – High Costs	Mean Rank	Median Score
General Insights	2.18	2
Time Series	2.28	2
Correlating Ingredients	3.05	3
Day of the Week	2.49	2

Table 6: Mean rank and median scores for text structures of Q44

There was a statistically significaat difference in preferred text structures for Q50 under high kg settings, $X^2(3) = 29.640$, $p < 0.000$ (Appendix B.5 – Table 39). The text structure that was preferred the most for Q50 was General Insights (Table 7).

Ranking Q50 – High Kg	Mean Rank	Median Score
General Insights	1.98	2
Time Series	2.26	2
Correlating Ingredients	3.15	3
Day of the Week	2.60	3

Table 7: Mean rank and median scores for text structures of Q50

Overall, the text structure that had the lowest mean rank in three of the four settings was General Insights. The text structure that had the highest mean rank was Correlating Ingredients, where three out of four times this structure was rated the least preferred. There appeared to be a clear difference in preferred text structures, as three of the four questions scored significanly.

7.3.2 Kg Vs Money

The three texts have the following structure: text that present only kilogram information of the ingredient, text that present only monetary information of the ingredient, and text that combine the two and present both kilogram information and monetary information. There was a statistically significant difference in preferred text structures for Q46 under normal settings, $X^2(2) = 9.631$, $p = 0.008$ (Appendix B.5 – Table 41). The text structure that was preferred the most for Q46 was Combination (Table 8)

Ranking Q46 – Normal	Mean Rank	Median Score
Kilograms	2.31	3
Money	1.98	2
Combination	1.71	1

Table 8: Mean rank and median scores for text structures of Q46

There was a statistically significant difference in preferred text structures for Q49 under normal settings, $X^2(2) = 10.338$, $p = 0.006$ (Appendix B.5 – Table 40). The text structure that was preferred the most for Q49 was Combination (Table 9)

Ranking Q49 – Normal	Mean Rank	Median Score
Kilograms	2.31	3
Money	1.94	2
Combination	1.75	1

Table 9: Mean rank and Median scores for text structures of Q49

There was a statistically significant difference in preferred text structures for Q48 under high costs settings, $X^2(2) = 11.108$, $p = 0.004$ (Appendix B.5 – Table 43). The text structure that was preferred the most for Q48 was Combination (Table 10).

Ranking Q48 – High Costs	Mean Rank	Median Score
Kilograms	2.32	3
Money	1.92	2
Combination	1.75	1

Table 10: Mean rank and Median scores for text structures of Q48

There was a statistically significant difference in preferred text structures for Q47 under High kilogram settings, $X^2(2) = 11.723$, $p = 0.003$ (Appendix B.5 – Table 42). The text structure that was preferred the most for Q47 was Combination (Table 11)

Ranking Q47 – High Kg	Mean Rank	Median Score
Kilograms	2.31	3
Money	1.98	2
Combination	1.71	1

Table 11: Mean rank and Median scores for text structures of Q47

Overall, the text structure that had the lowest mean score was the combination of both kilograms and money. For all settings, combination was significantly more preferred than the other two text presentations. A clear order of preference became noticeable when looking at the median scores of the three texts, with combination the most preferred, followed by money, and finally the kilograms. Changing the setting to focus on either money or kilograms appeared to have no effect on what texts were preferred.

8. Discussion

The purpose of this study was to gain a better understanding of how visual and textual elements could be presented in a food waste dashboard to provide the user with a good understanding of their own data. Therefore, the main research question was formulated as the following: *In which way can the customers' food waste data be (re)presented textually or visually to provide the user with a good understanding of their own data?*.

8.1 Interviews

Based on the results of the interviews, clients proved to have a good understanding of how the data is portrayed in the dashboard. Clients proved that they understood the general overview of the dashboard and generally understood what every specific dashboard element was telling them. This result was somewhat unexpected, as results of the secondary data showed that clients indicated to have trouble understanding the data. The likely explanation for this result lies with the target group. The interview results indicated that the group that had the most problems understanding the data were the kitchen staff, and not the managers. Seeing as most of the clients that were interviewed were managers, results showed mostly users that did perceive to have a good understanding of the data. There was not a single dashboard element, textual or visual, that was difficult to interpret. One of the key concepts of understanding was moving flexible around a knowledge component, as pointed out by Perkins (1998). This is an important aspect that clients proved, as they were able to interpret the data, but also to identify if data was incorrect or could not be related back to the kitchen. This is substantiated by Wiggins and McTighe (2005), who see understanding as making connections and bind together knowledge into something that makes sense of things. While clients indicated to sometimes have trouble with navigating the dashboard, they also proved to be able to connect multiple elements of data from the dashboard, such as ingredients and temporal information, which each other to form a larger picture. This is an important aspect, as Riggs (2003) explained that understanding requires: "*seeing the way things* *fit together*". The results did show that there is confusion in some areas. Specifically, ingredients having the wrong label in the texts, and data that could not be related back to the real-life situation. This however did not prevent clients from understanding their data. The addition of written out data did enhance the understanding of all users, not only to the managers but also to the chefs. The addition of texts, as well as the addition of photo's, was originally meant to increase the understanding of the dashboard user. However, interview results indicated that it gained a secondary function, namely that of a communicative function. Kitchen staff were found to be the group that had the most problems with interpreting data. Utilizing texts and photos as a communication mean increased the understanding of the kitchen staff, albeit indirectly via the manager.

When it comes to understanding the next step, we can conclude that the clients understood what actions to take next on the basis of the data. The interview results clearly showed that all five interviewees had an idea or strategy that they used or could use on the basis of the data. This shows that the client could use the dashboard data and utilize it in their business. This is in line with Nickerson (1985), who explained that understanding something means you can demonstrate it in a variety of ways. Clients demonstrated that they could devise a strategy on the basis of the dashboard data. The strategy that was predominantly used involved focussing on a single ingredient, which was often the ingredient that had the highest waste. This explains why textual elements of the dashboard were often primarily used, as they are effective at singling out a single outlier as a highlight, whether that is in the ingredient table, or as a recommendation. After reducing the waste of this single ingredient, clients would then monitor the effects of this change in the dashboard, thus proving again that they know what steps to undertake to efficiently reduce waste. These successful follow up steps are crucial in determining whether or not someone understands the data. As Bereiter (2005) mentions that one is only able to undertake something intelligent with a knowledge object once it is fully understood. Even though clients were able to identify and act upon this data, clients were not certain whether this approach would be effective. This does not however affect the level of understanding the client has, rather proves that clients were uncertain of its effectiveness.

8.2 Questionnaire

The results of the questionnaire indicate that users of the new dashboard did not understand the data significantly better than the users of the old dashboard. Apart from the overview element, that did prove to be significantly better understood in the new dashboard. This result was somewhat to be expected. This was mainly due to the fact that the information on both versions of the dashboard had to be identical, otherwise one group would logically answer better than the other. So the main differences was in presentation. This presentation proved to be only significantly relevant for the overview element. The presentation of the other elements like the graphs and tables appeared not to be significantly better. It is important to note that just examining individual elements of a dashboard is not representative of how an actual interaction with the dashboard would be. In order to make informed data driven decisions, a combination of these elements have to be used. This is in line with the findings of Smith (2013), who emphasises that comparing, evaluating, and drawing conclusions is not possible when data is fragmented in multiple screens.

Since the results of the knowledge questions were expected, additional questions were added to the questionnaire that looked specifically at the presentation of the dashboard screenshots. These were checked by asking the participant their opinion on ‘ease of use’ and ‘aesthetically appealing’ for every dashboard element. It is important to note here that these questions were added to provide an indication of both perceived effects, as just one question is not sufficient to provide reliable results. We expected the new dashboard to score higher on usability and appearance due to the new design of the dashboard and the feedback of the interviews, in which clients expressed themselves positively when it came to overall appearance and new layout. On the basis of the interview results, we can conclude that the overall feel and look of the new dashboard is perceived to be better than the old dashboard. However, for the questionnaire part, only one element scored significantly higher on the ‘ease of use’ scale in the new group. The remaining four ‘ease of use’ scales did not score significantly better. For the appearance scales, none of the five scales scored significantly higher, which was the most surprising finding of the two scales. The new dashboard focused heavily on design and layout, therefor the result came unexpected. This finding can therefore not be related to literature that looks at how aesthetics influence usability performance. Because the aesthetics scores needed to be higher than the usability scores in order to have, either effect (Sonderegger & Sauer, 2010), or no effect (Alexandre et al, 2012). Based on the median scores we can conclude that there was not a single element that scored higher on both the usability scale and the aesthetics scale. A possible explanation for this result could be that the elements were individually rated, not as a whole. As results of the interviews indicated that clients did appreciate the new dashboard when it was observed as a whole. This observation of better perceived usability would again be in line with the findings of Smith (2013). As clients indicated in the interviews that having a single screen was a positive change, as they would not have to go 'deeper' in the dashboard anymore. This in combination with the fact that the element were graphs and tables that could only be improved so much aesthetic wise, since the overall presentation of a graph and table is simple. This showed especially in the median scores for the categories table, where the group of the new dashboard rated the element worse than the group of the old dashboard.

The results of the questionnaire prove that participants had a preferences for the structure and content of the text files. For the text structure, the structure that was ranked first the most often was General Insights. This result was expected since it provided the user with the most broad and nonspecific information of the four text structures, thus appealing to the most participants. The type of setting did not change what text structures were preferred. For the difference in textual content, the combination of both money and kg had a strong preference in all settings. Money came in at a clear second place, and texts with information on kilograms was least preferred. It was expected that settings of either high money or high kg, would positively influence the money or kilogram texts respectively. However, only a miniscule change was visible that indicated that no real change took place. A possible factor that influenced these results could have been the type of ingredient that was used as an example. Personal experiences with the ingredients could account for a different reaction.

8.3 Limitations

There were several limitations for this study that limit the generalizability of the results. The sample size for the qualitative part of the study was small, only five interviews were conducted. This posed two limitations. The small sample size made it difficult to generalize some results from interviewees, as some quotes were not substantiated by other clients. Additionally, of the five interviews, only one had a background as a chef. As most interviewee's had managerial functions, the results reflected the views of the chef in a limited manner. While the representation of the average dashboard user was accurate, as most of the dashboard users are managers, chefs proved to have less understanding of data and should therefore have had a bigger representation. The reason only five interviews were conducted, was that these were the maximum number of clients that could be interviewed. Orbisk is a startup that was founded in 2019, while they are steadily growing, they still have a limited client base. On top of that, due to Covid-19 having a substantial impact on the catering industry, numerous kitchens of clients had to be closed. This limited the number of clients that were actively using the Orbisk system.

This lack of access to clients also impacted the questionnaire. In order to be reliable, the questionnaire needed to have a substantial sample size. Using only clients as the sample would have severely limited the number of respondents. A choice was therefore made to modify the questionnaire in such a way that people with no domain knowledge or dashboard experience could participate in the questionnaire. This way, the sample size was sufficient. This however posed a different limitation, namely the quality of the data. Having respondents that are familiar with the system and domain would result in more reliable responses.

Since there is no standard questionnaire on data understanding in dashboard, the researchers designed this questionnaire themselves. Certain design choices might have influenced the results of the study. The lack of significant results should therefore not immediately disprove a possible effect.

For RQ 1.4, one usability questions and one aesthetic question were put in the questionnaire. Having just two questions limited the generalizability of these questions. As this usability and aesthetic aspect of the study was not the main focal point, only two questions were added. This in contrast with the System Usability Scale that uses a standard set of ten questions to measure usability.

8.4 Recommendations

Future studies should take several aspects into account. Firstly, future research is needed to further investigate the possibility of designing a standard, tested survey that examines and measures system understanding. There is currently no questionnaire that can be used to test how well users understand the content of the system. This questionnaire needs to be designed in a broad and general way, so that domain specific information should not be a factor.

When examining or testing data understanding of dashboards or systems, future research should consider that compartmentalizing the system or dashboard should only be done if no other options are available. If one wants to measure understanding, a combination of the elements is necessary. Using a controlled experiment is a suitable method for collecting data while the participant is using the entirety of the system.

The automatically generated textual elements of the dashboard proved to be preferred and vital in food waste strategy decision making. As this study only examined a limited area of how texts could be presented, future research is needed to establish in a more comprehensive manner how texts could be integrated in a dashboard, that often primarily displays visual elements.

Finally, future research is needed to establish how chefs and kitchen staff would interact with such a food waste dashboard. This group has been identified to have the most problems with the dashboard. Doing additional research on how this group interacts with the system, might expose some areas of data understanding that this study could not find.

9. Conclusion

This research aimed to identify how customers' food waste date can be presented textually or visually to provide the user with a good understanding of their own data. Based on a qualitative and quantitative analysis of the use of a food waste dashboard, it can be concluded that primarily textual elements, such as the categories table and recommendations, are important factors that contribute to the increase of perceived data understanding of customers. The results indicate that, in order to understand the data and what steps to take on the basis of this data, clients often utilise textual data to establish a food waste reduction strategy. Visual elements also positively influenced the perceived understanding, however this was found to have a lesser effect. The implementation of photos did appear to have a substantial effect of increasing the understanding of kitchen staff that were directly or indirectly related to the use of the dashboard.

The first sub question aimed to identify the current level of understanding the customer has of the data presented in a food waste dashboard. The results indicate that the dashboard users have a good level of data understanding. Clients were not only able to recognize and explain specific elements of the dashboard, but also showed the ability to combine the different dashboard elements in order to establish the entire perspective. While the primary dashboard users proved to understand the data, it must be noted that kitchen staff did exhibit a lack of data understanding. This has however, no effect on the sub question, since that specifically regards the user of the dashboard.

The second sub question aimed to identify to what extent the user knows what steps to take next on the basis of the data. The result indicate that clients sufficiently understood what steps to take next. During interviews, clients could explain multiple different strategies that all derived from data presented in the dashboard. Clients did indicate to be uncertain on the effectiveness of these steps. But this however does not affect whether they understood the data in the dashboard from which these steps could be taken.

The third sub question aimed to identify whether the new dashboard was perceived to be better understood. The results indicated that, overall, the new dashboard was not better understood than the old dashboard. Since individual elements of the dashboard were used to test the level of perceived understanding, we can conclude however that the ‘overview’ element was significantly better understood. The results of the remaining four elements remain significant however.

The fourth sub questions aimed to identify whether the visual elements of the new dashboard would lead to higher perceived usability and aesthetics. The questionnaire results indicate that the new dashboard was not found to be significantly easier to use or aesthetically appealing than the old dashboard. The results of the interview, however, did indicate that clients perceived the new dashboard to be more usable and aesthetically appealing. The results of the questionnaire in this case are statistically stronger, which is why we cannot conclude that the new dashboard is more usable or aesthetically appealing. However, this does indicate that further research is needed to investigate these two aspects of the dashboard.

The fifth sub question aimed to identify what text structures that inform the dashboard user on their food waste were preferred. Result indicated that text structures that display a general overview of the food waste data was preferred. Results further indicated that the contents of these texts should preferably include a combination of costs information, and information on amount of food in kilograms. Results of the interviews indicated a split between the clients, where one group preferred costs of kilograms, versus the other group that preferred kilograms over costs. We can therefor conclude that both options of presentation should be available in the dashboard, as this mostly involves the personal preference of the client.

This research played an exploratory role in looking at data understanding of a food waste quantification system. Food waste quantification technology is still surprisingly rarely reported in applied research. While societal pressure for sustainable products and regulations is increasing. The importance of this technology is particularly important for commercial foodservice companies that often lack a sophisticated food waste management strategy. Therefore, much is still unknown about the effectiveness of these dashboards in terms of data understanding, as no existing survey that measures this phenomenon exists in literature. This research attempted to provide a first glance at how such a survey would function. And while this research is a step in the right direction, further research is needed to establish a non-domain specific survey.

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Appendix A

A.1 – Pilot Interview

Pilot interview structure:

1. Kunt u voor mij uitleggen wat de grafiek linksboven, die gaat over XX, volgens u inhoudt?
2. Kunt u vervolgens voor mij uitleggen hoe u deze informatie zou gebruiken om voedsel afval te verminderen?
3. Kunt u voor mij uitleggen wat de teksten rechtsboven volgens u beschrijft?
4. Kunt u voor mij vertellen welke volgende stappen u zou ondernemen nadat u de teksten/aanbevelingen over aanpassingen voedsel afval heeft gelezen?
5. Zou u eerder kijken naar de grafieken of de tekstuele aanbevelingen, en waarom?
6. Zorgen de foto's onder in het dashboard voor een beter overzicht, en zo ja, waarom?
7. Is er data van het dashboard die u nog niet begrijpt?

Thank you for your time, and I will give Ilse time to ask some remaining questions.

A.2 – Interview

Beste,
Ten eerste, heel fijn dat je de tijd wilde nemen om met mij te zitten voor dit interview, dat wordt erg gewaardeerd. Zoals ik had vermeld in de mail ben ik op dit moment onderzoek aan het doen naar data begrip bij klanten. We hebben in het verleden meerdere signalen gekregen dat het dashboard moeilijk te interpreten was en dat klanten niet wisten wat ze met de data aan moesten. Nu wordt er op dit moment een nieuw dashboard ontworpen die de data toegankelijker probeert te maken. In dit interview ga ik aan de hand van dit nieuwe dashboard kijken wat de huidige situatie is van data begrip. Ik ga wat algemene vragen stellen over hoe je de data over jullie voedsel afval interpreten, en wat specifiekere vragen die echt gaan over jouw interpretatie van het dashboard. Dit duurt ongeveer 30 minuten, kan korter of langer zijn aan de hand van je antwoorden natuurlijk.

Algemeen

1. Wat is je huidige functie bij Optiver?
2. Hoe lang gebruik je het huidige dashboard al?
3. Hoe vaak gebruik je het dashboard?
4. Heb je al eerdere ervaring gehad met het gebruik van dashboards? En zo ja met welke?
5. Wat zijn belangrijke punten van het huidige dashboard waar je vaak naar kijkt?
6. Hoe neem je de data uit het dashboard mee als er beslissingen genomen moeten worden over het verminderen van voedsel afval?

a. Welke onderdelen van het dashboard gebruik je dan vooral?
7. Zijn er op dit moment aspecten van het huidige dashboard of van de data die je nog niet goed begrijpt of onduidelijk zijn?

Elementen nieuw dashboard

8. Welke data/informatie zou jij graag willen zien uitgeschreven in de aanbevelingen?
9. Zou u eerder kijken naar de grafieken, de tekstuele aanbevelingen of de combinatie, en waarom?
10. Kunt u voor mij vertellen welke volgende stappen u zou ondernemen nadat u de teksten/aanbevelingen over aanpassingen voedsel afval heeft gelezen?
11. Welke grafieken zijn op dit moment het meest nuttig om te gebruiken?
    a. En voegen die op dit moment waarde toe aan je afval vermindering proces?
12. Wat is voor jou de toegevoegde waarde van de foto's die onderin te zien zijn?

Afsluitende vragen

13. Zijn er op dit moment aspecten van het dashboard of van de data die je nog niet goed begrijpt of onduidelijk zijn?
14. Zijn er aspecten van het dashboard die je niet gebruikt of denkt niet gaat te gebruiken?
15. Is er informatie in het dashboard die je op dit moment mist?

Dat waren mijn vragen. Hartelijk bedankt dat je hier even tijd voor wilde nemen en als het goed is zie je dit nieuwe dashboard binnenkort verschijnen. Fijne dag nog!

Appendix B

B.1 – Questionnaire

(Block 1) Introduction to Research
Welcome to this research study on data understanding.

Hello! We are conducting a study with the Utrecht University on data understanding of dashboards. For this study, you will be shown several screenshots and texts that are incorporated in a food waste dashboard. Questions will be asked on the contents of these screenshots to determine how well information is being portrayed by the dashboard and understood by you. Additionally, you will be asked to rank several sentences in your preferred order. You will not require any previous knowledge on food waste to be able to participate in this study. Your responses will be kept completely confidential.

The study should take you around fifteen minutes to complete. You have the right to withdraw at any point during the study. Thank you for your participation!

By clicking the button below, you acknowledge:

- Your participation in the study is voluntary.
- You are 18 years of age.
- You are aware that you may choose to terminate your participation at any time for any reason.

(Block 2) Basic Demographic Questions:

1. What is your gender?
   - Male
   - Female
   - Non-binary
   - Prefer not to disclose
   - Prefer to self-describe ________
2. What is your age?
   - 18-25 years
   - 26-40 years
   - 40-60 years
   - I am older than 60
3. What is the highest degree or level of education you have completed?
   - No schooling completed
   - High school graduate
   - Bachelor degree
   - Master degree
   - Doctorates degree
   - Other _____
   - I prefer not to say
4. What are your experiences with the use of a dashboard?
   - I never use a dashboard
   - I rarely use a dashboard
   - I sometimes use a dashboard
   - I often use a dashboard
   - I use a dashboard on a daily basis

(Block 3) Old vs New dashboard

In the following part, five screenshots of a food waste dashboard are presented to you. For every screenshot, two questions are asked about the content of the image. Additionally, you are asked to rate the dashboard element for its ease of use and appearance.
In order to be able to answer some questions, some foreknowledge is required:

- Food waste refers to any type of food that is thrown away but still able to be consumed
- Cutting waste refers to the leftover foods that occur after cutting (e.g., peels)
- Unregistered food refers to food that the system was unable to identify, but waste nonetheless
- **Higher food** waste amounts to **higher costs**
- **Higher food** waste amounts to **higher outputs of CO2**

(**Q15**): There has been an increase in food waste for this day/week.
- Answer: **Yes**

(**Q23**): This day/week has had an increase in CO2 production
- Answer: **Yes**

(**Q20**): I thought this dashboard element was easy to use
Strongly agree - agree – Neutral – Disagree – Strongly disagree
(**Q24**): I though this dashboard element was aesthetically appealing
Strongly agree - agree – Neutral – disagree – Strongly disagree

A.1

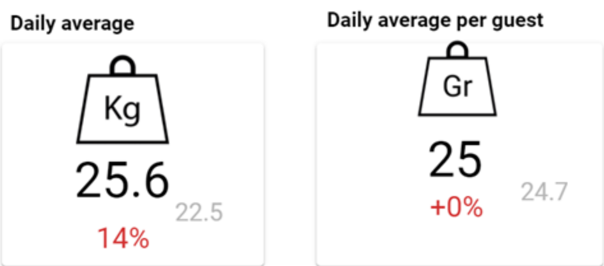

Figure 14: Screenshot of old dashboard overview Q15 & Q23

B.1

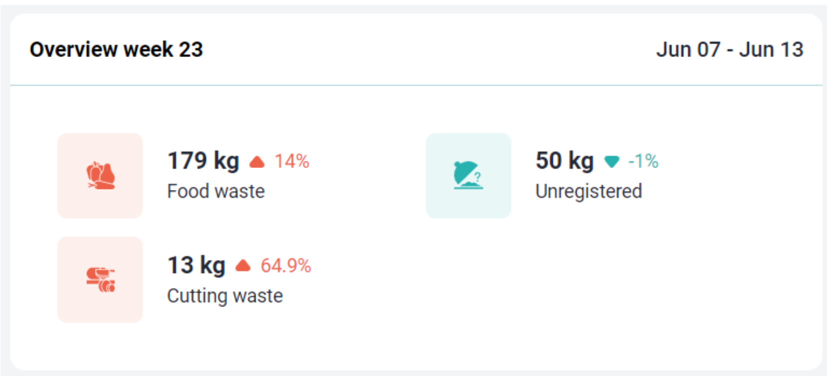

Figure 15: Screenshot of new dashboard overview Q15 & Q23

(**Q26**): What ingredient would lower your costs the most by reducing 1 kg of waste?
- Answer: **Either Soup & Sauce or Meals and components**

(**Q25**): What would be the least efficient ingredient to reduce waste on?

- Answer: **Snacks**

(Q31): I thought this dashboard element was easy to use
Strongly agree - agree – Neutral – Disagree – Strongly disagree
(Q32): I though this dashboard element was aesthetically appealing
Strongly agree - agree – Neutral – disagree – Strongly disagree

A.2

Category	Price / Kg	kg / day ▾	Cost
Soup & sauce	3	8.8	€26
Meals and components	10	1,8	€18
Bread	3	1.4	€4
Vegetable	4	1.2	€5
Potato	3	0.9	€3
salads	10	0.6	€6
Pasta / rice	2	0.5	€1
Snacks	5	0.2	€1

1 - 10 / 18

Figure 16: Screenshot of old dashboard categories table Q26 & Q25

B.2

Category	Price/kg	Kg/day ↑	Price/day (€)
Soup & sauce	€3	8,6	€26
Meals and components	€10	1,8	€18
Vegetables	€4	1,7	€7
Bread	€3	1,3	€4
Potato	€3	0,9	€3
Salads	€10	0,5	€5
Pasta and rice	€2	0,5	€1
Snacks	€5	0,2	€1

← 1 2 3 →

Figure 17: Screenshot of new dashboard categories table Q26 & Q25

(Q35): What sub component of meals would reduce your food waste costs the most?
- Answer: **Vegetable mix**

(Q36): What would be the least efficient sub component to reduce waste on
- Answer: **Stuffed peppers**

(Q39): I thought this dashboard element was easy to use
Strongly agree - agree – Neutral – Disagree – Strongly disagree
(Q40): I though this dashboard element was aesthetically appealing
Strongly agree - agree – Neutral – disagree – Strongly disagree

A.3

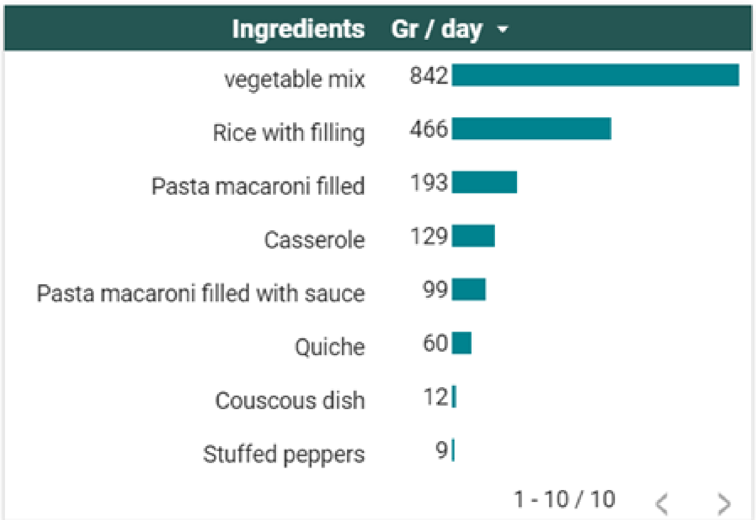

Figure 18: Screenshot of old dashboard categories table Q35 & Q36

B.3

Meals and components	Price/kg	Gr/day ↑	Price/day (€)
Go back			
Vegetable mix	€10	821,7	€8
Rice with filling	€10	454,8	€5
Macaroni pasta with pieces	€10	188,8	€2
Casserole	€10	125,7	€1
Macaroni pasta with sauce and pieces	€10	97	€1
Quiche	€10	58,5	€1
Couscous dish	€10	11,8	€0
Peppers stuffed	€10	8,7	€0

← 1 2 →

Figure 19: Screenshot of new dashboard categories table Q35 & Q36

(Q42): Which of the seven days shown here has the most negative impact on the environment?

- Answer: Thursday

(Q43): Which of the seven days shown here has the least food waste related costs

- Answer: Sunday

(Q45): I thought this dashboard element was easy to use

Strongly agree - agree – Neutral – Disagree – Strongly disagree

(Q46): I though this dashboard element was aesthetically appealing

Strongly agree - agree – Neutral – disagree – Strongly disagree

A.4

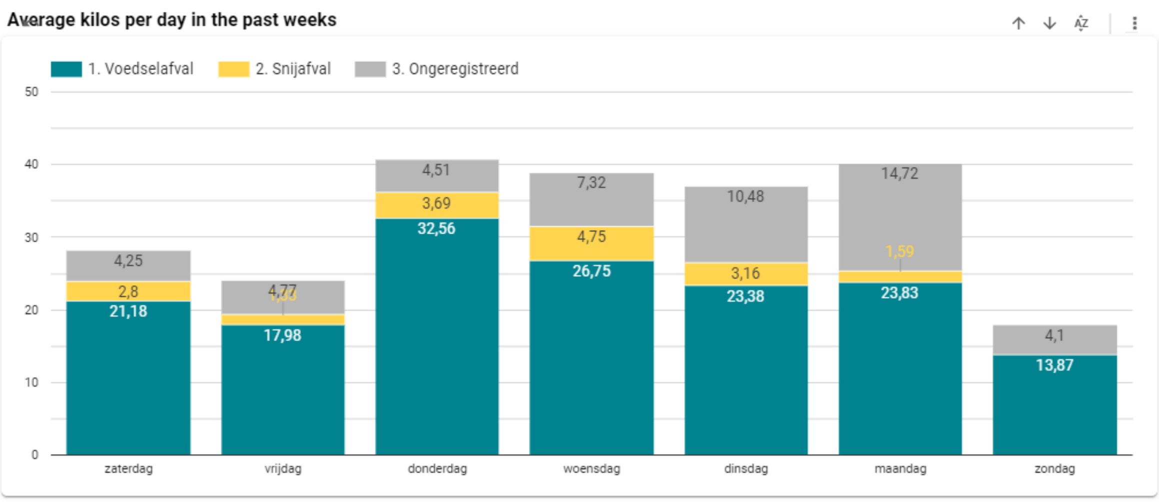

Figure 20: Screenshot of old dashboard kilogram graph Q42 & Q43

B.4

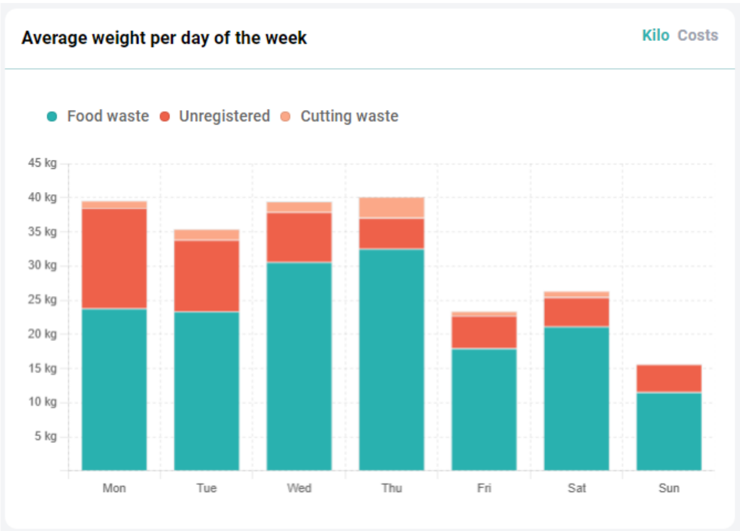

Figure 21: Screenshot of new dashboard kilogram graph Q42 & Q43

(Q49): By reducing food waste, which day of the week would give you the largest profit?
- Answer: Thursday

(Q48): Which of the seven days shown here has the most negative impact on the environment?
- Answer: Thursday

(Q51): I though this dashboard element was aesthetically appealing
Strongly agree - agree – Neutral – disagree – Strongly disagree
(Q52): I thought this dashboard element was easy to use
Strongly agree - agree – Neutral – Disagree – Strongly disagree

A.5

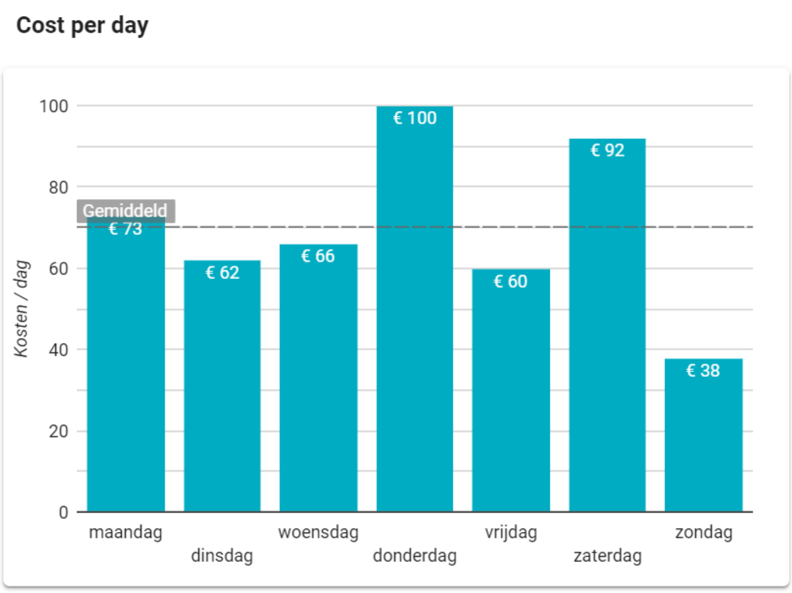

Figure 22: Screenshot of old dashboard costs graph Q49 & Q48

B.5

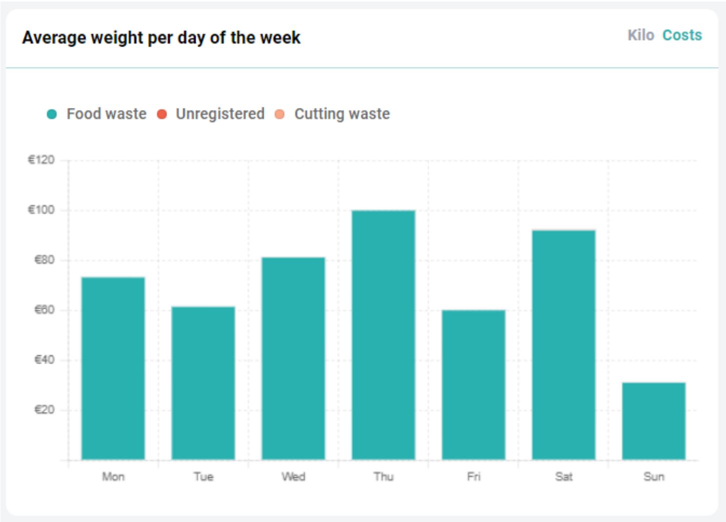

Figure 23: Screenshot of new dashboard costs graph Q49 & Q48

(Block 4) Ranking text structures: Rank the text in order of most understandable

The following part will display a number of example texts on your use of food throughout the week. These texts are designed to inform the reader on their food waste. Rank the following text structures in order of information you would deem as most useful for reducing food waste at your home.

Part A.

- (**Q57**) The following four texts inform you on your use of tomatoes. If you were to reduce food waste at home, which information would be the most useful for reducing food waste? Rank the text structures on food waste in the preferred order, with 1 being the most useful and 4 the least useful:
    - This week, the ingredient that was lost the most was **tomatoes**, namely 2 kg (€ 2.60), an increase of 91% relative to the previous 5 weeks.
    - Per day, there is an increase of 285 gram (20%) of **tomatoes** waste, around €0.37 per day.
    - There is a pattern between **tomatoes** and **lettuce**. If the waste of one of these ingredients goes up, the other ingredient is likely to follow.
    - The waste of **tomatoes** is the highest every Saturday, around 500 grams more. While the waste of other days is around 250 gram.

- (**Q43**) The following four texts inform you on your use of **cheese**. If you were to reduce food waste at home, which information would be the most useful for reducing food waste? Rank the text structures on food waste in the preferred order, with 1 being the most useful and 4 the least useful:
    - This week, the ingredient that was lost the most was **cheese**, namely 1 kg (€ 20.28), an increase of 30% relative to the previous 5 weeks.
    - Per day, there is an increase of 143 gram (10%) of **cheese** waste, around €2.90 per day.
    - There is a pattern between **cheese** and **bread.** If the waste of one of these ingredients goes up, the other ingredient is likely to follow.
    - The waste of **cheese** is the highest every Saturday, around 500 grams more. While the waste of other days is around 100 gram.

- (**Q50**) The following four texts inform you on your use of **pasta**. If you were to reduce food waste at home, which information would be the most useful for reducing food waste? Rank the text structures on food waste in the preferred order, with 1 being the most useful and 4 the least useful:
    - This week, the ingredient that was lost the most was **pasta**, namely 2 kg (€ 2.24), an increase of 50% relative to the previous 5 weeks.
    - Per day, there is an increase of 285 gram (20%) of **pasta** waste, around €0.32 per day.
    - There is a pattern between **pasta** and **cheese**. If the waste of one of these ingredients goes up, the other ingredient is likely to follow.
    - The waste of **pasta** is the highest every Saturday, around 1 kg more. While the waste of other days is around 166 gram.

- (**Q44**) The following four texts inform you on your use of **potatoes**. If you were to reduce food waste at home, which information would be the most useful for reducing food waste? Rank the text structures on food waste in the preferred order, with 1 being the most useful and 4 the least useful:
    - This week, the ingredient that was lost the most was **potatoes**, namely 10 kg (€9.75), an increase of 180% relative to the previous 5 weeks.
    - Per day, there is an increase of 1.43 kg (20%) of **potatoes** waste, around €1.40 per day.
    - There is a pattern between **potatoes** and **salt**. If the waste of one of these ingredients goes up, the other ingredient is likely to follow.
    - The waste of **potatoes** is the highest every Saturday, around 4 kg more. While the waste of other days is around 1 kg.

Part B.

- (**Q46**) The following three texts inform you on the food waste of **tomatoes**. What information would you perceive as the most useful for your home situation? Rank the text on food waste in the preferred order, with 1 being the most useful and 3 the least useful:
    - For this week, the ingredient that was lost the most was **tomatoes**. You lost over 1 kg of **tomatoes** this week, which is an increase of 90% relative to the previous 5 weeks.
    - For this week, the ingredient that was lost the most was **tomatoes**. This loss costed an estimated €0.65. Your costs are 90% higher than the previous 5 weeks.
    - For this week, the ingredient that was lost the most was **tomatoes.** You lost over 10 kg of **tomatoes** this week which amounts to €6.50. Your increase in kg is 90% relative to the previous 5 weeks, while your costs are 90% higher than the previous 5 weeks.

- (**Q47**) The following three texts inform you on the food waste of **potatoes**. What information would you perceive as the most useful for your home situation? Rank the text on food waste in the preferred order, with 1 being the most useful and 3 the least useful:
    - For this week, the ingredient that was lost the most was **potatoes**. You lost over 8 kg of **potatoes** this week, which is an increase of 180% relative to the previous 5 weeks.
    - For this week, the ingredient that was lost the most was **potatoes.** This loss costed you an estimated €7.80 Your costs are 40% higher than the previous 5 weeks.
    - For this week, the ingredient that was lost the most was **potatoes.** You lost over 10 kg of **potatoes** this week which amount to €7.80. Your increase in kg is 180% relative to the previous 5 weeks, while your costs are 40% higher than the previous 5 weeks.

- (**Q48**) The following three texts inform you on the food waste of **cheese**. What information would you perceive as the most useful for your home situation? Rank the text on food waste in the preferred order, with 1 being the most useful and 3 the least useful:
    - For this week, the ingredient that was lost the most was **cheese**. You lost over 1 kg of **cheese** this week, which is an increase of 30% relative to the previous 5 weeks.
    - For this week, the ingredient that was lost the most was **cheese**. This loss costed an estimated €20.28. Your costs are 150% higher than the previous 5 weeks.
    - For this week, the ingredient that was lost the most was **cheese.** You lost over 1 kg of **cheese** this week which amount to €20.28. Your increase in kg is 30% relative to the previous 5 weeks, while your costs are 150% higher than the previous 5 weeks.

- (**Q49**) The following three texts inform you on the food waste of **pasta**. What information would you perceive as the most useful for your home situation? Rank the text on food waste in the preferred order, with 1 being the most useful and 3 the least useful:
    - For this week, the ingredient that was lost the most was **pasta**. You lost over 3 kg of **pasta** this week, which is an increase of 60% relative to the previous 5 weeks.
    - For this week, the ingredient that was lost the most was **pasta**. This loss costed an estimated €3.36. Your costs are 50% higher than the previous 5 weeks.
    - For this week, the ingredient that was lost the most was **pasta.** You lost over 3 kg of **pasta** this week which amount to €3.36. Your increase in kg is 60% relative to the previous 5 weeks, while your costs are 50% higher than the previous 5 weeks.

B.2 – Demographic Data

What is your gender?

The old dashboard			Frequency	Percent	Valid Percent	Cumulative Percent
New	Valid	Male	18	56,3	56,3	56,3
		Female	14	43,8	43,8	100,0
		Total	32	100,0	100,0	
Old	Valid	Male	14	42,4	42,4	42,4
		Female	19	57,6	57,6	100,0
		Total	33	100,0	100,0	

Table 12: Demographic data - gender for both groups

What is your age?

The old dashboard			Frequency	Percent	Valid Percent	Cumulative Percent
New	Valid	18-25 years	21	65,6	65,6	65,6
		26-40 years	11	34,4	34,4	100,0
		Total	32	100,0	100,0	
Old	Valid	18-25 years	25	75,8	75,8	75,8
		26-40 years	5	15,2	15,2	90,9
		40-60 years	2	6,1	6,1	97,0
		I am older than 60	1	3,0	3,0	100,0
		Total	33	100,0	100,0	

Table 13: Demographic data - age for both groups

What is the highest degree or level of education you have completed?

The old dashboard			Frequency	Percent	Valid Percent	Cumulative Percent
New	Valid	High school graduate	15	46,9	46,9	46,9
		Bachelor degree	12	37,5	37,5	84,4
		Master degree	5	15,6	15,6	100,0
		Total	32	100,0	100,0	
Old	Valid	No schooling completed	1	3,0	3,0	3,0
		High school graduate	17	51,5	51,5	54,5
		Bachelor degree	10	30,3	30,3	84,8
		Master degree	5	15,2	15,2	100,0
		Total	33	100,0	100,0	

Table 14: Demographic data - level of education for both groups

What are your experiences with the use of a dashboard?

The old dashboard			Frequency	Percent	Valid Percent	Cumulative Percent
New	Valid	I never use a dashboard	8	25,0	25,0	25,0
		I rarely use a dashboard	6	18,8	18,8	43,8
		I sometimes use a dashboard	14	43,8	43,8	87,5
		I often use a dashboard	2	6,3	6,3	93,8
		I use a dashboard on a daily basis	2	6,3	6,3	100,0
		Total	32	100,0	100,0	
Old	Valid	I never use a dashboard	8	24,2	24,2	24,2
		I rarely use a dashboard	6	18,2	18,2	42,4
		I sometimes use a dashboard	10	30,3	30,3	72,7
		I often use a dashboard	7	21,2	21,2	93,9
		I use a dashboard on a daily basis	2	6,1	6,1	100,0
		Total	33	100,0	100,0	

Table 15: Demographic data - dashboard experience for both groups

B.3 - Questionnaire Analysis Results Knowledge Questions

Chi-square tests.

Statistic	*Value*	*df*	*Asymp. Sig. (2-tailed)*	*Exact Sig. (2-tailed)*	*Exact Sig. (1-tailed)*
Pearson Chi-Square	6.67	1	.010		
Likelihood Ratio	7.05	1	.008		
Fisher's Exact Test				.017	.010
Continuity Correction	5.23	1	.022		
Linear-by-Linear Association	6.56	1	.010		
N of Valid Cases	65				

Table 16: Chi-Squared test for Q15 (H1)

Chi-square tests.

Statistic	*Value*	*df*	*Asymp. Sig. (2-tailed)*	*Exact Sig. (2-tailed)*	*Exact Sig. (1-tailed)*
Pearson Chi-Square	1.65	1	.199		
Likelihood Ratio	1.66	1	.197		
Fisher's Exact Test				.277	.156
Continuity Correction	1.02	1	.312		
Linear-by-Linear Association	1.62	1	.203		
N of Valid Cases	65				

Table 17: Chi-Squared test for Q23 (H2)

Chi-square tests.

Statistic	*Value*	*df*	*Asymp. Sig. (2-tailed)*
Pearson Chi-Square	3.16	3	.367
Likelihood Ratio	3.22	3	.359
Linear-by-Linear Association	.95	1	.328
N of Valid Cases	65		

Table 18: Chi-Squared test for Q26 (H3)

Chi-square tests.

Statistic	*Value*	*df*	*Asymp. Sig. (2-tailed)*
Pearson Chi-Square	4.78	3	.189
Likelihood Ratio	5.41	3	.144
Linear-by-Linear Association	3.79	1	.052
N of Valid Cases	65		

Table 19: Chi-Squared test for Q25 (H4)

Chi-square tests.

Statistic	*Value*	*df*	*Asymp. Sig. (2-tailed)*
Pearson Chi-Square	4.80	3	.187
Likelihood Ratio	6.34	3	.096
Linear-by-Linear Association	4.37	1	.036
N of Valid Cases	65		

Table 20: Chi-Squared test for Q35 (H5)

Chi-square tests.

Statistic	*Value*	*df*	*Asymp. Sig. (2-tailed)*
Pearson Chi-Square	1.98	3	.578
Likelihood Ratio	2.03	3	.567
Linear-by-Linear Association	.00	1	1.000
N of Valid Cases	65		

Table 21: Chi-Squared test for Q36 (H6)

Chi-square tests.

Statistic	*Value*	*df*	*Asymp. Sig. (2-tailed)*
Pearson Chi-Square	2.17	3	.537
Likelihood Ratio	2.95	3	.400
Linear-by-Linear Association	1.50	1	.220
N of Valid Cases	65		

Table 22: Chi-Squared test for Q42 (H7)

Chi-square tests.

Statistic	Value	df	Asymp. Sig. (2-tailed)	Exact Sig. (2-tailed)	Exact Sig. (1-tailed)
Pearson Chi-Square	3.24	1	.072		
Likelihood Ratio	4.40	1	.036		
Fisher's Exact Test				.148	.114
Continuity Correction	1.46	1	.226		
Linear-by-Linear Association	3.19	1	.074		
N of Valid Cases	65				

Table 23: Chi-Squared test for Q43 (H8)

Chi-square tests.

Statistic	Value	df	Asymp. Sig. (2-tailed)
Pearson Chi-Square	2.68	2	.262
Likelihood Ratio	3.46	2	.178
Linear-by-Linear Association	1.75	1	.186
N of Valid Cases	65		

Table 24: Chi-Squared test for Q49 (H9)

Chi-square tests.

Statistic	Value	df	Asymp. Sig. (2-tailed)
Pearson Chi-Square	1.15	2	.564
Likelihood Ratio	1.53	2	.465
Linear-by-Linear Association	.00	1	.973
N of Valid Cases	65		

Table 25: Chi-Squared test for Q48 (H10)

B.4 – Questionnaire Analysis Likert Scale Questions

Chi-square tests.

Statistic	*Value*	*df*	*Asymp. Sig. (2-tailed)*
Pearson Chi-Square	14.47	4	.006
Likelihood Ratio	17.38	4	.002
Linear-by-Linear Association	12.23	1	.000
N of Valid Cases	65		

Table 26: Chi-Squared test for Q20 (H11)

Chi-square tests.

Statistic	*Value*	*df*	*Asymp. Sig. (2-tailed)*
Pearson Chi-Square	7.48	4	.113
Likelihood Ratio	7.72	4	.102
Linear-by-Linear Association	6.08	1	.014
N of Valid Cases	65		

Table 27: Chi-Squared test for Q31 (H12)

Chi-square tests.

Statistic	*Value*	*df*	*Asymp. Sig. (2-tailed)*
Pearson Chi-Square	3.88	4	.422
Likelihood Ratio	3.94	4	.415
Linear-by-Linear Association	1.78	1	.183
N of Valid Cases	65		

Table 28: Chi-Squared test for Q29 (H13)

Chi-square tests.

Statistic	*Value*	*df*	*Asymp. Sig. (2-tailed)*
Pearson Chi-Square	2.10	4	.718
Likelihood Ratio	2.53	4	.640
Linear-by-Linear Association	1.13	1	.287
N of Valid Cases	65		

Table 29: Chi-Squared test for Q45 (H14)

Chi-square tests.

Statistic	Value	df	Asymp. Sig. (2-tailed)
Pearson Chi-Square	4.95	4	.292
Likelihood Ratio	5.77	4	.217
Linear-by-Linear Association	1.41	1	.235
N of Valid Cases	65		

Table 30: Chi-Squared test for Q51 (H15)

Chi-square tests.

Statistic	Value	df	Asymp. Sig. (2-tailed)
Pearson Chi-Square	6.68	4	.154
Likelihood Ratio	8.64	4	.071
Linear-by-Linear Association	4.72	1	.030
N of Valid Cases	65		

Table 31: Chi-Squared test for Q24 (H16)

Chi-square tests.

Statistic	Value	df	Asymp. Sig. (2-tailed)
Pearson Chi-Square	5.42	4	.247
Likelihood Ratio	6.24	4	.182
Linear-by-Linear Association	4.50	1	.034
N of Valid Cases	65		

Table 32: Chi-Squared test for Q32 (H17)

Chi-square tests.

Statistic	Value	df	Asymp. Sig. (2-tailed)
Pearson Chi-Square	4.41	4	.353
Likelihood Ratio	4.51	4	.341
Linear-by-Linear Association	2.13	1	.145
N of Valid Cases	65		

Table 33: Chi-Squared test for Q40 (H18)

Chi-square tests.

Statistic	*Value*	*df*	*Asymp. Sig. (2-tailed)*
Pearson Chi-Square	5.75	4	.219
Likelihood Ratio	7.31	4	.120
Linear-by-Linear Association	4.89	1	.027
N of Valid Cases	65		

Table 34: Chi-Squared test for Q46 (H19)

Chi-square tests.

Statistic	*Value*	*df*	*Asymp. Sig. (2-tailed)*
Pearson Chi-Square	4.35	4	.360
Likelihood Ratio	4.84	4	.304
Linear-by-Linear Association	.11	1	.742
N of Valid Cases	65		

Table 35: Chi-Squared test for Q52 (H20)

B.5 – Questionnaire Analysis Text Structures

Ranks

	Mean Rank
Q57 - General Insights	2,35
Q57 - Time Series	2,77
Q57 - Correlating Ingredients	2,45
Q57 - Day of The Week	2,43

Test Statistics

N	65
Kendall's W[a]	,020
Chi-Square	3,960
df	3
Asymp. Sig.	,266

a. Kendall's Coefficient of Concordance

Table 36: Friedman's ANOVA for Q57

Ranks

	Mean Rank
Q44 - General Insights	2,29
Q44 - Time Series	2,20
Q44 - Correlating Ingredients	3,06
Q44 - Day of The Week	2,45

Test Statistics

N	65
Kendall's W[a]	,090
Chi-Square	17,603
df	3
Asymp. Sig.	,001

a. Kendall's Coefficient of Concordance

Table 37: Friedman's ANOVA for Q44

Ranks

	Mean Rank
Q43 - General Insights	2,18
Q43 - Time Series	2,28
Q43 - Correlating Ingredients	3,05
Q43 - Day of The Week	2,49

Test Statistics

N	65
Kendall's W[a]	,090
Chi-Square	17,455
df	3
Asymp. Sig.	,001

a. Kendall's Coefficient of Concordance

Table 38: Friedman's ANOVA for Q43

Ranks

	Mean Rank
Q50 - General Insights	1,98
Q50 - Time Series	2,26
Q50 - Correlating Ingredients	3,15
Q50 - Day of The Week	2,60

Test Statistics

N	65
Kendall's W[a]	,152
Chi-Square	29,640
df	3
Asymp. Sig.	,000

a. Kendall's Coefficient of Concordance

Table 39: Friedman's ANOVA for Q50

Ranks

	Mean Rank
Q49 - Kilograms	2,31
Q49 - Money	1,94
Q49 - Combination	1,75

Test Statistics

N	65
Kendall's W[a]	,080
Chi-Square	10,338
df	2
Asymp. Sig.	,006

a. Kendall's Coefficient of Concordance

Table 40: Friedman's ANOVA for Q49

Ranks

	Mean Rank
Q46 - Kilograms	2,25
Q46 - Money	2,05
Q46 - Combination	1,71

Test Statistics

N	65
Kendall's W[a]	,074
Chi-Square	9,631
df	2
Asymp. Sig.	,008

a. Kendall's Coefficient of Concordance

Table 41: Friedman's ANOVA for Q46

Ranks

	Mean Rank
Q47 - Kilograms	2,31
Q47 - Money	1,98
Q47 - Combination	1,71

Test Statistics

N	65
Kendall's W[a]	,090
Chi-Square	11,723
df	2
Asymp. Sig.	,003

a. Kendall's Coefficient of Concordance

Table 42: Friedman's ANOVA for Q47

Ranks

	Mean Rank
Q48 - Kilograms	2,32
Q48 - Money	1,92
Q48 - Combination	1,75

Test Statistics

N	65
Kendall's W[a]	,085
Chi-Square	11,108
df	2
Asymp. Sig.	,004

a. Kendall's Coefficient of Concordance

Table 43: Friedman's ANOVA for Q48