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**RICHFIELDS Working Package 5**  
**Deliverable D5.5**

**Report on gaps and needs**

*Definition of gaps and needs on quality and availability  
of data to answer the relevant questions on  
determinants of food purchase*

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## Executive summary

The aim of deliverable 5.5 was to define gaps and needs and identify potentials and limitations with the tools collected in the WP 5 inventory. The data collection process of the purchase tools were investigated and covered by considering what/who/why/how the tools met the food purchase purpose, the method/s used for data collection, contextual influences on the purchase and intentional or actual eating behaviour were also covered in the investigation.

The type of data which we found interesting from a RICHFIELDS perspective, potentially explaining consumer purchase behaviour was 1) the purpose of the tool (i.e. the user's motivation for using the app), 2) the purchase method "how was purchased", 3) the product characteristics "what unit", 4) "how much" and 5) possible contextual influences on users' purchase behaviour. These data have the potential to be used for key research questions (i.e., What/Who/Why/How).

Our result shows that the purchase apps in our inventory are a heterogeneous sample of mobile apps supporting the users in different phases of the purchase process. And apps in the same category do not even generate the same kind of data. Generated data can also be intentional purchase data, or actual, or both intentional and actual. This result makes it very difficult to draw any conclusion and characterise a typical app in each of the four categories (i.e. the four purposes). However, an integration of food purchase data with relevant contextual generated data has the potential to give a more reliable picture of consumer purchase and eating behaviour. And moreover, purchase data together with preparation and consumption generated data have a potential to give a more complete picture of consumer behaviour since food activities are complex and is influenced by many factors.

Some identified limitations are that the availability of publicly accessible data about the collected tools is limited. There is a lack of documentation about the procedures for data access and insufficient information about the technical infrastructure for data access. The limitations about e.g. the tools' documentation of options and methods for accessing and extracting data, technical infrastructure for data assess as well as what format the generated data has are connected to large challenges in the continuation of the RICHFIELDS

project. The last and final phase [phase 3] of the project aims to design the research infrastructure and its governance, intellectual property rights and ethical aspects. Specific information regarding access strategy, scientific case, business model, governance and ethics are thereby crucial factors for the platform.



## 1. INTRODUCTION

### 1.1 BACKGROUND

The overall aim of RICHFIELDS is to design a Research Infrastructure for the collection, integration, processing and sharing of consumer-generated data as related to food intake activities, food behaviour and lifestyle determinants. The current growth in ICT technologies brings opportunities for researchers to monitor and collect information on these behaviours, which have often been recorded within the behavioural context and close in time to the users' experiences. However, in order for the data to be valuable to users of RICHFIELDS it is essential that factors influencing the quality of this data are identified and thereby visualizing the potential opportunities with the infrastructure, as well as the gaps and needs with its quality.

The evaluation of the scientific, technical, legal and ethical aspects of consumer-generated purchase (and preparation, consumption and lifestyle) data is an important part of the RICHFIELDS project. The inventory of tools and the data collection includes tools collected from work package 6 and 7 (preparation and consumption tools); however, this deliverable presents data from the tools collected in WP 5 (the inventory is presented in D.5.1).

### 1.2 AIM

The current deliverable, D.5.5, has focused on the identification and definition of gaps and needs on availability and quality of data generated from the collected mobile applications (apps) in D.5.1. The aim is to improve the understanding on consumer behaviour in general and answer to relevant questions on determinants of food purchase in particular. The aim is furthermore to specify the potentials and limitations of present and future data and to answer key questions on what/who/why/how of the food purchase process, as well as the quality of these data. The intention and goal for this deliverable is not to answer the research questions within RICHFIELDS but discuss the conditions, possibilities and limitation with our data in relation to those research questions.

## 2. QUALITY ASSESSMENT

In order to get an indication about the quality of the collected tools, the typology, as presented in Deliverable D5.1, was used as a frame (see Appendix). The typology structures the purchase procedure into different phases and groups tools in sub-groups. Pre- purchase phase includes a search for increased *knowledge & understanding* as well as tools that ease for the *planning & organization* of a purchase to come. The actual *point of sale* includes tools where you can order food and post- purchase includes tools where consumers increase their *financial understanding* and uses different budget tools. For all tools, the data collection process, its purpose and method as well as contextual influences were investigated.

Contextual data, from an individual, interpersonal and environmental perspective will be discussed with a basis from the DONE framework as formulated by Symmank et al. (2017) and Stok et al (2017).

### 2.1 AVAILABLE INFORMATION

Data for the descriptive, scientific, legal and technical profile of the apps was collected from the descriptions and screenshots provided on iTunes or Google Play, from information on the homepage of the app and in the terms of use and privacy policy documents. If no information could be found in order to answer any quality criteria “no information” was given as an answer. Programmable web (<http://www.programmableweb.com/>) and Google search engine were used in order to answer the questions; if and how data from the tool was available via an API (Application Programming Interface). The inventory could not be seen as a quantitative study, meaning that the collected tools should not be seen as representative for all purchase tools available on the mobile app market. For further details about the tools, we refer to the inventory reported in Deliverable D.5.1.

The type of data which we found interesting from a RICHFIELDS perspective, potentially explaining consumer purchase behaviour was 1) the purpose of the tool (i.e. the user’s motivation for using the app), 2) the purchase method “how was purchased”, 3) the product characteristics “what unit”, 4) “how much” and 5) possible contextual influences on users’ purchase behaviour. These data have the potential to be used for key research questions (i.e., What/Who/Why/How).

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### 2.1.1 DATA COLLECTION PURPOSE

We identified 4 overarching purposes of tools as they were propagated and marketed through the descriptions of the tools (see Table 1 and Appendix 1): 1) tools that were aimed at supporting the purchase decision through increasing **knowledge and understanding** of products 2) **planning and organization** of a purchase (e.g., shopping list, budgets and booking services), 3) tools through which a **purchase is made** and 4) tools that focus on the **financial understanding** or penalties of the purchase. However, many tools in the inventory were described as serving more than one purpose. For instance, a tool could be described as supporting increased knowledge and understanding through searching for offers and searching for stores, as well as providing help with planning and organisation by creating shopping lists or increase the financial understanding showing tracked transactions (e.g. 'ASDA'). By this, keep in mind that the categories presented are not mutually exclusive and the numbers in tables thereby does not add up to the total number of tools collected (one tool can be included more than once). In the current sample we identified several tools that supported the user by increased knowledge and understanding, planning and organisation as well as making a purchase (e.g. 'ASDA', 'Tesco' and 'my Supermarket'). However, we did not identify any tool that supported the user in all phases of the purchase process (i.e. four categories), or tools that provided financial understanding in combination with making a purchase. Some tools that provided financial understanding did also provide support with planning and organisation (e.g. budgeting) (e.g. 'Goodbudget', 'Money Manager Pro', 'On Trees', 'Personal Banking', and 'Pocket Expense').



**Table 1.** The 4 identified categories of “the purpose of the tools” (named *user motivation* in the typology, see Appendix 1) and the sub-groups which explain the behaviours of each purpose. The subgroups are further explained in the following sections.

<b>Knowledge &amp; understanding N=42</b>		<b>Planning &amp; organization N=26</b>		<b>Making a purchase N=19</b>		<b>Financial understanding N=7</b>	
Store/restaurant search/locator	26	Creating a shopping list	14	Placing an order	19	Transactions	7
Searching for offers	22	Budgeting	7				
Searching for experiences	19	Booking services	5				
Comparing products and price	13						

#### 2.1.1.1 KNOWLEDGE & UNDERSTANDING

The group of tools propagating knowledge & understanding represented the largest category in the inventory of purchase tools. Within the category “searching for stores/restaurants” was the most prominent aim described by the tool vendors followed by “searching for offers”, “searching for experiences” and “comparing products and prices”. Important characteristics of the tools in “searching for stores/restaurants” were that they had a search function in which the consumer could search for specific stores or restaurants in a certain area via GPS function – resulting in generated GPS data and also often the venue names. Intentional data is generated by consumers’ search history (by manual search or input), voice input and/or barcode scanning. Several tools in this category had also a feature where the users’ could place an order which generate actual purchase data (e.g. order confirmations, financial transactions, and purchase history and loyalty cards). There is an interesting research potential of data from these apps to combine intentional purchase behaviour with actual purchase behaviour – what does the consumer search for and what is actual being purchased.

The majority of these tools provided product information like pictures (visual properties) and price. Depending on the tool – data about food, food group, product, cuisine, dish, ingredients, product volume and/or weight was available. There is a challenge to build and manage a research infrastructure (RI) since the level of details is different – meaning it may

be difficult and challenging to compare data from different data sources (e.g. tools). Also the method, with which the data is collected, differs between tools and this may result in potential discrepancies. For example barcode scanning, where consumers scan the barcode of a product and e.g. receives data about ingredients and allergens might have errors if ingredients are not correctly logged into the system however might also instead result in a more accurate data compared to what is written on a website where new ingredients might not been added to a list, while a food packaging and its barcode is more reliable.

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#### 2.1.1.2 PLANNING & ORGANIZATION

Tools aimed for planning and organization were represented as the second largest category in the inventory and generate mainly intentional purchase data. Creating shopping lists was found to be the most prominent purpose described within the group of planning tools followed by budgeting booking services.

Manual input<sup>1</sup> was the most common method that was used to collect *what* was purchased followed by barcode scanning and manual search<sup>2</sup>. Only 5-10% of the tools had features like transaction, order confirmation, purchase history and/or loyalty card; meaning that actual data was poorly generated from these tools.

The majority of these tools provided product characteristics information as pictures (visual properties), price, product volume, weight and type of food. Information about food group, ingredients, product, cuisine, cooking advice/instructions and energy content was also available for at least 1/5 of the tools.

Important personal generated data from many of these apps were; GPS data, food preferences, posts and notes since this kind of data can explain actual food purchase behaviour.

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<sup>1</sup> *Manual input* by the consumer; e.g. creating grocery shopping list by manually typing/selecting, manual uploading of photos, comments or manual reporting of spending.

<sup>2</sup> The user can *search manually*; e.g. by product categories, specific product, typing in product/brand names etc.

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### 2.1.1.3 MAKING A PURCHASE

Making a purchase refers to the actual point of sale where the consumer places an order. This category of data gives data on actual purchases (and sometimes also intentional when using the tool for planning of purchases), money has been spent and food items have been purchased. The category includes e.g. take away, online shopping and subscription services.

These tools generate GPS data in nearly half of the collected tools and 8 out of 19 tools have the possibility to register food preferences (i.e. save food/ products as favourites). Most tools provide data with product information; the most common information is price and pictures (visual properties) and ingredients. Data on product volume, weight, origin, allergen information and so forth is only collected by approximately one third of the tools. The method for *what* was purchased is in 14 of 19 tools an order confirmation of the purchase and in 11 tools a financial transaction. 3 of 19 tools have a loyalty card program for customers.

Because the generated data in most cases end up in an order confirmation and/or financial transaction, money is the measured unit for all tools. Since it is only data on total purchases, there is no information about consumer unit, even though there is data on *how much* was purchased (measured in money).

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### 2.1.1.4 FINANCIAL UNDERSTANDING

For this category 7 tools were collected in the inventory. The tools include e.g. data showing a summary of spending and transaction history. In 5 out of 7 tools, the user could make a financial planning and budget (these are thereby included in the planning & organisation category).

The only product information collected for this category is price. However, price per product is considered only when one product is purchased, since the tools show total amount of money and not per product/food item. By this; data from this category of tools does not result in any data about *what* was purchased (meaning no information about food, product, calories etc.) only *how much* was purchased (measured in money).

The time of the purchase occasion is collected in 5 tools and can be shown in terms of the date, weeks and months, for 2 tools also purchases per year, meaning separated purchases

as well as series of purchases can be shown. Data from different time periods could be very useful when analysing potential changes over time.

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#### 2.1.2 PURCHASE METHOD – HOW MUCH WAS PURCHASED

The most used method for collecting *how much* was purchased among the collected apps (where the method/s were known, n=49) was manual input, see table 2. Manual input means that the consumer for example creates grocery shopping list by manually typing/selecting or manual reporting of a spending. 18 apps collected data by “manual search” i.e. the user can search manually, for example by categories, product, typing in product/brand names. These two methods collect in most cases intentional data meaning that data about what was purchased refers to intentions to purchases. The methods “order confirmation”, “financial transactions”, “purchase history”, “loyalty card” and “scanned receipt” generate actual data of purchases. Apps with several collecting methods generate both intentional and actual purchase data; one example is the app ‘mySupermarket’ where the user can create shopping lists manually but the user can also shop online from several supermarkets. Barcode scanning will not generate actual data on its own. It is used for adding an item to a shopping list or look up product information (e.g. the apps ‘SnipSnap’ coupon app and ‘Quick Scan’). The apps for which the method was not clearly stated were mainly the financial apps.

**Table 2.** Methods used to collect **what** was purchased, presented divided into the 4 categories and also summarized all tools together. Keep in mind; one tool might have more than one method for the collection on **what** was purchased, the table present the methods in the same order and the most common method is not always placed at the top.

	Knowledge & understanding N=42	Planning & organization N=26	Making a purchase N=19	Financial understanding <sup>3</sup> N=7	All tools summarized N=62
Manual input	17	17	8	0	29
Manual search	16	5	9	0	18
Order confirmation	13	2	14	0	15
Financial transaction	10	2	11	0	13
Barcode scanning	9	6	5	0	12
Purchase history	9	2	9	0	11
Loyalty card	4	1	3	0	4
Voice input	1	2	1	0	2
Scanned receipt	1	0	0	0	1
Spectroscopic analysis	1	0	0	0	1

### 2.1.1.3 PRODUCT CHARACTERISTIC – WHAT UNIT

“Product” (i.e. the specific food product which has been purchased such as Dunkin Donuts, Coca Cola or a Quaker Oats cereal) as a measure for *what* have been purchased was found in 30 of the collected apps (where the purchase method/s were known, n=49), see table 3. However, one must take into consideration that a unit like product, dish, and food etc. on its own does not say anything about if it actually has been purchased or just was intended to being purchased. Only apps with the unit “money” can state an actual purchase being made.

<sup>3</sup> No method used for what was purchased in the category of financial understanding since no information about the product is shown in the tool.

Examples of apps with at least “money” as unit are ‘Tesco’, ‘Domino’s pizza’, ‘Taste Card’ and ‘Hello Fresh’. The unit “dish” was almost only used for restaurant apps.

**Table 3. The units** which the purchases have been measured, presented divided into the 4 categories and also summarized all tools together at the end. Keep in mind; one tool might have more than one unit in which the purchase has been measured, the table show the units in the same order the whole time and the most common unit is not always placed at the top.

	Knowledge & understanding N=42	Planning & organization N=26	Making a purchase N=19	Financial understanding <sup>4</sup> N=7	All tools summarized N=62
Product	21	11	12	0	30
Money	20	9	19	0	28
Food	13	12	4	0	18
Dish	9	1	6	0	9
Beverage	12	3	7	0	6
Food group	4	2	1	0	4
Food box	2	0	3	0	3
Calorie	2	0	0	0	0
Macro nutrients	2	0	0	0	0
Glycemic index	1	0	0	0	0
Ingredients	1	2	0	0	2

#### 2.1.4 HOW MUCH

“Spending”<sup>5</sup>, as referring to expenses of a purchase, was the most common unit or method for collecting *how much* was purchased; among the collected apps where “how much was purchased” was known (n=39), see table 4. Both financial/ budget apps, restaurant and groceries apps use “spending” (money) for *how much* was purchased. Product weight and volume were used for shopping list apps and grocery apps as a measurable unit. Serving size was found as a unit for several restaurant apps like ‘Domino’s pizza’ and ‘Starbucks’, for some coupons apps, as well as when ordering coffee capsules from ‘Nespresso’. Data on

<sup>4</sup> No unit which the purchase has been measured in the category of financial understanding since no information about the product is collected.

<sup>5</sup> Spending (money) refers to the expenses of a purchase and is collected primary for finance apps: Money that you spent or plan to spend on activities you enjoy, entertainment, personal things, food etc.

*how much* is about the quantity purchased or intended to be purchased. For example shopping lists can have a function that summaries the costs for all items – however if the products are being purchased or not, is not proven based on only this data.

**Table 4.** Methods used to collect *how much* was purchased, presented divided into the 4 categories and also summarized all tools together at the end. Keep in mind; one tool might have more than one method in which the data was collected, the table show the methods in the same order the whole time and the most common method is not always placed at the top.

	Knowledge & understanding N=42	Planning & organization N=26	Making a purchase N=19	Financial understanding <sup>6</sup> N=7	All tools summarized N=62
Spending (money)	20	14	19	7	35
Product weight	10	9	8	0	17
Product volume	10	9	8	0	17
Serving size	8	0	6	0	8
Portion size	1	0	1	0	1

#### 2.1.5 DATA ACCESSIBILITY

*Data accessibility criteria:* For almost all apps “no information” was available regarding whether data collected by the tools was accessible directly via the tools technical infrastructure or not. Only for 5 apps an API was found and only 5 apps provided additional information about the type of data access. Information about whether accessing the data requires prior authentication was mentioned for only 1 app.

#### 2.1.6 DATA OWNERSHIP

Only 1 out of 4 of the collected tools in the inventory provided information about the ownership of the user-generated data; either the user or the vendor. In most cases it was not clearly stated in the privacy documents. However in most privacy documents it was clear that the tool vendor had the right to access and exploit the user generated data meaning publish and distribute.

<sup>6</sup> No unit which the purchase has been measured in the category of financial understanding since no information about the product is collected.

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### 2.1.7 DATA PRIVACY

Almost all of the investigated tools that had available privacy documents (n=48) that provided information about that personal identifiable information (PII) was collected. The most common collected information was name, email and phone number and this information was collected for a majority of those tools. Information with respect to sharing PII with affiliated parties, which are parties that by contract need to adhere to the privacy policy of the tool vendor, was offered for a majority of the tools, n=32/72%. Information regarding the sharing of data with unaffiliated parties, which are parties that are not bound to the privacy policy of the tool vendor, was offered for about 50% of those tools that collected PII. However, in many cases, privacy policy documents were not distinctly formulated and information was not sufficient enough for some of the tools whereby “no information” was recorded in the data collection.

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### 2.1.8 CONTEXTUAL DATA

In this chapter we will discuss types of contextual data that was connected to generated purchase data. Contextual data refers to factors that influence human eating behaviour from circumstances and settings in different situations, social contexts and the framing of our environment. This contextual data will be mapped onto the determinants described in the DONE (Determinants Of Nutrition and Eating) framework (Stok et al., 2017, Symmank et al., 2016). Human nutrition and human food and eating behaviour is a key issue in many branches of science and the DONE framework, created by an interdisciplinary workgroup, and present determinants related to nutrition and eating behaviours in an evolving process as it continuously improves by the contributing experts. The DONE framework is meant to enable a common language across disciplines and thereby encourage inter/transdisciplinary collaboration (Symmank et al., 2016). The framework has a socio-ecological structure with four main levels; individual, interpersonal, environment, and policy, these main levels are further divided in *stem categories* which in turn are divided down into *leaf categories*. The sorting layers called steam category and leaf category is used as a framework and making the structure into a fine-grained three layer structure.



The categories identified in the DONE framework regarding the data collected from purchase tools are listed below; to the far right of the table you find the number of tools that collected that type of data. Further down in the text; these numbers of tools will be more explained by examples of tools.

Main level	Stem- category	Leaf- category	N of tools	
Individual;	Biological	Food- Related Physiology	18	
		Sensory Perception		
	Demographic	Biological Demographics Cultural Characteristics	2-9	
Interpersonal;	Social	Psychological	Food Habits	17
		Family Food Culture	9-19	
		Household Socio-Economic Status		
		Social Influence Social Support		
Environmental;	Product	Intrinsic Product Attributes <sup>7</sup>	1-36	
		Extrinsic Product Attributes <sup>8</sup>		
Environmental;	Micro	Portion Size	1	
		Home Food Availability And Accessibility		
Environmental;	Meso-Macro	Characteristics Of Living Area	11-30	
		Exposure To Food Promotion		
		Market price		

#### INDIVIDUAL PREDICTORS

*Biological factors:* The majority of the identified individual predictor's data was related to diverse biological factors. We identified 18 apps that allowed users to save/indicate food or

<sup>7</sup> Intrinsic product attributes: Appearance, odour, taste/flavour and texture.

<sup>8</sup> Extrinsic product attributes: Price, packaging, branding etc.

food products as favourites (*leaf category Sensory perception*). Supermarket apps (e.g. 'Tesco', 'my Supermarket') and shopping list apps (e.g. 'Shoppinglist3' and 'IntelliList') as well as restaurant apps (e.g. 'Frankie & Benny's', 'Just Eat') let the user to save favourites. Food preferences have the potential to provide relevant contextual insights in the reasons for people's food choices (e.g. Mela, 1996) and have furthermore been identified by the DONE framework as an important determinant of food consumption behaviour. Furthermore, data that is generated by comments, posts and evaluations may also contain relevant information regarding users' sensory perception (e.g. taste) of food. See more in section 2.1.2.2.

*Demographic factors:* Several apps collect data related to demographic factors - like age (n=9), gender (n=7), nationality and ethnicity (n=2). Apps collecting this kind of data were mainly those tools where an actual purchase is made/a point of sale; e.g. 'Whole Foods Market', 'ASDA', and 'Nespresso'. However, the app 'SurveyMini UK' belongs to the category "knowledge & understanding" did also collect the demographic factors such as gender and date of birth.

*Psychological factors:* The only identified psychological factor in the framework, for purchase tools, is food habits which is an important determinant of food consumption behaviours (Stok et al, 2017) and could potentially be inferred in the purchase tools which generate order confirmations (n=15), store purchase history (n=11) or have a loyalty card connected (n=4). Apps collecting this kind of data are apps in the subcategory "making a purchase" and refer to the actual point of sale as mentioned before.

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#### INTERPERSONAL PREDICTORS

*Social factors:* In our inventory, apps were identified as generating several types of social data e.g. Family food culture – meaning that data generated is telling us which food culture that exists in the family/household from what they purchase or intend to purchase. This data is generated from tools where the user can save "favourites" and from generated order confirmations, data from loyalty cards and purchase history. Socio-economic status in a household can also be analysed by data generated in the subcategories "Transactions" and

“Budgeting” (e.g. apps like ‘Goodbudget’, ‘Personal Banking’ and ‘Pocket Expense Personal Finance’).

Social influences/support is explained as diet- and eating-related influences/support from others in the environment. The DONE framework identified social influences as an important determinant (Stok et al, 2017). We identified 9 tools that allowed the user to express their opinions by posting comments about products/foods. These tools were at least logged in the category “Knowledge & understanding”, for example the apps ‘Find me a coffee’, ‘Taste Card’ and ‘Just Eat’. In these tools, one of the purposes is to search for, and share, experiences and knowledge. Nine tools allowed the user to evaluate foods/products for example a restaurant (e.g. ‘Taste Card’, ‘Open Table’, ‘Just Eat’). These functions generate interesting sources for unstructured contextual data related to users’ food purchase behaviours but also consumption behaviour. 19 apps allowed their user to share data and interact with each other on public forums like Facebook and 13 tools had data integration with Twitter.

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#### ENVIRONMENTAL PREDICTORS

*Product factors:* our result showed that data on attributes related to the intrinsic (characteristics like taste/flavour, texture, and smell) and extrinsic characteristics of a product price and appearance (visual properties), weight, volume, ingredients, energy content, nutrient content, allergen information, origin and brand name could be generated by purchase apps.

*Micro factors:* Data in this part refers to the size of a portion and visual cues to portion size. We identified only one purchase app that generated data about the size of the portion. Many tools provided however visual properties of a food.

*Meso-Macro factors:* The majority of the identified environmental predictor’s data was related to some type of Meso-Macro factor. We identified apps that collected data about a users’ living environment like post code (n=11) and home address (n=22). Exposure to food promotion is another factor related to Meso-Macro predictor. Apps in the subcategory

“Searching for offers” (e.g. ‘ASDA’, ‘Domino’s pizza’ and ‘Voucher codes.co.uk’) as well as in “Comparing products and prices” (e.g. ‘SnipSnap’ coupon app, ‘Quick scan’, ‘my Supermarket’) allow users to search for food adverts.

Market prices, e.g. the cost of food, were recorded as a product characteristic for 30 apps. However, that data say nothing about if a purchase was made (actual purchase data) since that data was generated by several categories of apps (both the apps in pre- purchase phase and actual point of sale). It might be expected that GPS functions in tools also should be seen as environmental predictors and useful for the RICHFILED infrastructure.

### 3. DISCUSSION & CONCLUSIONS

The aim of deliverable D5.5 was to define gaps and needs and identify potentials and limitations with the tools collected in the WP 5 inventory. The data collection process of the purchase tools was investigated; what/who/why/how of the purchase was covered by investigation of the purpose of the tools, the method/s used for data collection, contextual influences on the purchase and intentional or actual eating behaviour. The largest limitation with purchase data is that it does not say anything about if the purchased food is or will be consumed or not, at least not by the individual person who made the purchase. The purchase could very well be products to me and/or my family but could likewise be intended for my friends only. In comparison with for instance consumption data in WP 7, this is a large difference, where the majority of consumption tools instead focus on primary individual consumer data.

Neither do we know if a search for information is an intentional purchase for the individual or for someone else who asked us to look something up for them. The data thereby might give us weak information and connections to actual eating behaviour of the app-user. By this, strong connections to public health are limited on an individual level as there are many potential errors when it comes to energy intake and nutrient content. But, it still gives us a pointer regarding what foods and restaurants that is “on your mind” in a certain area or at a specific time. Regarding GPS functions in tools, location can be very informative; where people live and also where they purchase their food. The data also communicates how much money you spend on food per week, month or year; even though you might waste some of the food and also have friends over for dinner sometimes (meaning that you probably not consume every food you purchased).

The access to data is another large identified limitation. Legal documents, such as term of use and privacy policy documents come with insufficient information about the rules as well as what users must accept in order to use the tools and services. Also, insufficient information, or no information at all, was found regarding what the collected data is used for by the vendor and its affiliated partners. Documentations that users must accept in order to use a service and the ways a vendor gathers, uses, discloses, and manages their

data is important for the understanding of the potentials with the data generated by the tools. As a consequence of this insufficient legal information; important indicators relevant for data governance such as ownership, usage licences and sharing of personal information with unaffiliated parties were overall relatively under-documented. The limitations about e.g. the tools' documentation of options and methods for accessing and extracting data, technical infrastructure for data assess as well as what format the generated data has are connected to large challenges in the continuation of the RICHFIELDS project.

Because of the research field and the complexity with food and eating behaviours, the various types of contextual data, that most probably influence the users' food purchase behaviour (and potential consumption), might be very useful to take into consideration in the research about determinants of food purchase behaviour. It might be an interesting opportunity for researchers to integrate food purchase data with relevant contextual data, also beyond professional boundaries in the aim of more reliable pictures of consumer behaviour, not least for the continuation and future work for the improvement and creation of public health initiatives. Intentional data from searching and planning purchases gives an overview about potential purchases which show what is on the consumers' mind. Concerning some of the contextual data (for example interpersonal; social) there is however still a limitation as the data is unstructured and non-evidence based information. Comments, evaluations and pictures published in social networks (Facebook and Twitter) do not reveal if a real purchase has been made or not.

Next is a summarizing list of gaps and needs identified in the inventory. These gaps and further needs rest on the criteria set up for the inventory in phase 1. Due to time constraints, the inventory had to focus on showing a large diversity including a variety of tools and data collection methods rather than the most common used tools, this in order to show potentials in collection methods. Also there is a limitation since the inventory only included UK storefronts. A more comprehensive inventory is needed to fully embrace the field. Because of that, the potentials with this qualitative review in general are many and in line with the RICHFIELDS project, however, there are limitations at this point to summarize any specific potential only based on what was found in the qualitative work done.

### Summarizing gaps and needs

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- (1) The inventory includes a wide variety of tools; however therefore result in a restricted number of tools in total where one category of tools sometimes is only represented by one or two tools and might not be representative for all tools in that category.

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- (2) Focus has been on showing the diversity in data collection methods, meaning this report has to be seen as a qualitative review of tools and collection methods.

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- (3) Tools use different methods of collecting data and generate both intentional and actual behavioral data which gives different but complementary information about consumer behavior.

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- (4) The availability of publicly accessible information about the tools is limited.

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- (5) There is a lack of documentation about the procedures for data access.

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- (6) Insufficient information about the technical infrastructure for data access.

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- (7) There were no interconnected tools and platforms identified.

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### Summarizing potentials

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- (1) Purchase data together with data from preparation and consumption generate a more complete picture of behavior where food activities are complex and is influenced by many factors.

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- (2) Integration of food purchase data with relevant contextual data has the potential to give a more reliable picture of consumer purchase and eating behavior.

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## REFERENCES

Mela, D. J. (1996). Eating behaviour, food preferences and dietary intake in relation to obesity and body-weight status. *Proc Nutr Soc*, 55(3), 803-816.

Stok, F. M., Hoffmann, S., Volkert, D., Boeing, H., Ensenauer, R., Stelmach-Mardas, M., Kiesswetter, E., Weber, A., Rohm, H., Lien, N., Brug, J, Holdsworth, M. & Renner, B. (2017). The DONE framework: Creation, evaluation, and updating of an interdisciplinary, dynamic framework 2.0 of determinants of nutrition and eating. *PLoS One*, 12(2), e0171077. doi:10.1371/journal.pone.0171077

Symmank, C., Mai, R., Hoffmann, S., Stok, F. M., Renner, B., Lien, N., & Rohm, H. (2017). Predictors of food decision making: A systematic interdisciplinary mapping (SIM) review. *Appetite*, 110, 25-35. doi:10.1016/j.appet.2016.11.023



## APPENDIX 1 TYPOLOGY

