Food | Consumer | Health

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Deliverable D7.1

Inventory of types of consumption data and data collection methodologies for consumer-generated food consumption data

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Executive summary

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 behavior and associated lifestyle activities. An important part of the RICHFIELDS design will center on the evaluation of the scientific, technical, legal and ethical aspects related to integration and governance of consumer-generated data on food behavior. The tasks related to Deliverables 5.1 to 7.1 are to implement the provided quality framework and operationalization of Deliverables 5.3-7.3 and to collect the necessary data for the creation of an inventory of data and data collection tools. The aim of the inventory is to provide a list of data collection tools which is representative for the variety of tools used by and accessible to the general public, the methodologies they implement, the health and lifestyle parameters they collect and integrate. The tools and data collected in this inventory provide the basis for the identification of possible scientific, legal, technical and ethical gaps and needs regarding the use and integration of the consumer generated food behavior data and to capture developments to improve or simplify current practices in the collection and integration of food consumption data. The Deliverables 5.1-7.1 share a common framework and tool for data collection, but the tools and scientific data collected for the inventory are specific for the domains purchase (D5.1), preparation (D6.1) and consumption (D7.1)). Also, domain specific search strategies for the generation of their respective part of the inventory have been applied. The present report is based on the inventory of tools related to food consumption and lifestyle data (Deliverable 7.1). The result of this deliverable are 1) the inventory in the form of a database of food consumption tools and methodologies (mainly smart phone apps) including the associated quality information related to the dimensions of scientific relevance, legal governance and data management, which was collected based on the quality framework and operationalizations developed and described in Deliverable 7.3, 2) a description of the methodology underlying the generation of this inventory including the tool selection and data collection process and 3) aggregations of relevant descriptive data about the tools listed in the inventory. Aggregations, analyses and evaluations of the collected information related to the quality criteria developed in Deliverable 7.3 will be part of Deliverable 7.4 and 7.5.

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1. Introduction

1.1 BACKGROUND

There is a strong tendency of a large group of people to incorporate technology into their lives for the purpose of quantifying and monitoring certain aspects of their behaviors (Choe, Lee, Lee, Pratt, & Kientz, 2014; Lupton, 2016; Wolf, 2009, 2010; Yau & Schneider, 2009). With the rise of mobile phones and tablets, there has been an increase in the number of software applications especially geared towards recording and improving people's food consumption and lifestyle behavior (e.g., Chen, Bauman, & Allman-Farinelli, 2016; Franco, Fallaize, Lovegrove, & Hwang, 2016). These apps allow their users to record what they eat and drink on a daily basis, within the actual behavioural context and close in time to the users' experiences. They allow inputs from various sources such as food databases, favorite or frequently consumed dishes, barcode scanners, restaurant menus, or diet plans. They offer management solutions for their users' recipes and shopping lists and provide personalized nutrition and lifestyle recommendations and coaching based on their user's progress, needs and goals. People basically became a special type of "citizen scientists" with the improvement of their own lives, health and wellbeing as the main subject. In addition to monitoring and evaluating vital nutritional intakes and food consumption behaviors such as food preparation and purchase, providers of especially mHealth services show an increased tendency to support the exchange and integration of services and data from other vendors (Research2Guidance, 2016). An application that monitors how much calories a user consumes each day, might connect to a heart rate monitoring belt of a third party vendor, to a step tracking bracelet of another vendor, and a sleep monitoring kit from yet another vendor. The application might also connect to social network applications such as Twitter, Facebook and Instagram in order to provide status updates to the social network about a user's personal goals and progresses (Park, Weber, Cha, & Lee, 2015; Vickey, Ginis, & Dabrowski, 2013). There seem to be a similar strong interest by users of mHealth services to combine various services. Chen et. al (2016) reported that the majority of participants in their sample who have used a lifestyle app or wearable have combined that service with one to nine other services. Interestingly, the most popular combination of health topics was

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reported to be physical activity and nutrition, followed by the combination physical activity, nutrition, and weight (Chen et al., 2016).

This increasing connectedness of health applications is accompanied and fueled by a new type of applications, the aggregator apps or central health data hubs such as Apple's HealthKit or Google-Fit (Curtis, 2014; Mandl, Mandel, & Kohane, 2015; Menaspa, 2015; Williams, 2015). HealthKit for instance is a framework designed to integrate healthcare and fitness apps, allowing them to work together and collate their data. For instance, an exercise monitoring app and dietary tracking app that do not offer the option of exchanging data and services through their own infrastructure could still exchange data from within an aggregator application and integrate and visualize that data on a single user dashboard. Such application ecosystems of centralized storage and sharing of health and fitness data from various sources might ultimately become a standard interface for eHealth services (Mandl et al., 2015).

Researchers on food consumption behavior and its determinants (e.g., physical activity, mood, sleep etc.) argue that relevant data is often fragmented with limited possibilities to link different types of data from different sources, and is collected outside the behavioral context and often with a large time gap between the actual performance and the time of recording (DEDIPAC Final Report, 2016; Glanz & Murphy, 2007; Shim, Oh, & Kim, 2014; Snoek et al., under review). A suitable method for understanding the determinants of food related behaviors, however, needs to be capable of capturing the behavioral influences which act on a shorter time frame and within specific physical and social contexts (see also van den Puttelar, Verain, & Onwezen, 2016). The consumer generated stream of in situ and real time food related behavioral data generated by the users of mHealth apps and services seems to provide a promising opportunity for researchers who want to do research on consumer generated food consumption data and link this data to other relevant lifestyle data such as where and how people purchase and prepare what they consume, the activities, exercises, and social networks they engage in, their overall wellbeing and other vital fitness and health data.

1.2 AIM

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An important part of the RICHFIELDS design will center on the evaluation of the scientific, technical, legal and ethical aspects related to integration and governance of this dynamically and innovatively generated stream of in situ and real-time consumer-generated food behavior and lifestyle data (Phase 1). The three main topics related to food behavior covered within the first Phase of RICHFIELDS are consumer generated food purchase data (Working Package 5), food preparation data (Working Package 6), and food consumption data (Working Package 7). The common focus of the three working packages is 1) the type and quality of data collection and 2) the possibility for integration of food purchase, preparation and consumption data. A quality framework and operationalizations for data collection regarding the relevant areas of quality (scientific, legal, technical) have been developed in Deliverable 5.3 - 7.3. The aim of Deliverable 5.1, 6.1 and 7.1 is to implement the provided operationalizations and collect the necessary data for the creation of the inventory of data and data collection tools. Considering the sheer number of potentially relevant data collection tools on the market, the inventory created in the current Deliverable will not be a complete list of tools available. The challenge of this inventory is to provide a list of data collection tools which is able to capture the variety of data collection tools out there, the methodologies they implement, the health and lifestyle parameters they collect and integrate and to capture developments to improve or simplify current practices in the collection and integration of food consumption data. In general, tools and data collected in this inventory should provide a solid basis for the identification of possible scientific, legal, technical and ethical gaps and needs regarding the use and integration of the data generated by users of these tools. The aims of this deliverable (D7.1) are hence to provide 1) the inventory in the form of a dataset of food consumption tools and methodologies including the associated quality information, which was collected based on the quality framework developed and described in Deliverable 7.3, 2) a description of methodology underlying the generation of this list including the tool selection and data collection process and 3) aggregations of descriptive (meta) data regarding tools in the inventory and 4) an initial characterization (or typology) of the type of food consumption apps in the inventory based on the intended purpose of the applications and the type of dietary assessment methodology they implement.

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Although the work packages WP5-7 share a common framework for data collection developed in Deliverable 5.3-7.3, the three WPs collect domain specific information and adopted domain specific search strategies for the generation of their respective part of the inventory. The following report is based on the generation of the inventory of tools related to food consumption and lifestyle data (D7.1). Aggregations, analyses and evaluations of the dataset produced in this deliverable will be part of Deliverable 7.4 and 7.5 respectively. The accompanying reports for the generation of the inventories of tools related to food purchase and preparation data will be delivered by WP5 and WP6 respectively.

2. Methodology

2.1 TOOL TYPES

After initial searches through the relevant literature and explorations of the available tools online we decided that the main area of innovation, dynamics and relevance regarding in situ and real-time consumer-generated data collection is the mobile (health) app market. According to a recent report, almost 100,000 mHealth apps have been added since the beginning of last year (2015), amounting to 259,000 mHealth apps currently available on major app stores (Research2Guidance, 2016), of which around 7% (ca. 18,100 apps) of these mHealth applications is related to the category food and nutrition apps (IMS Institute for Healthcare Informatics, 2015). In addition, mobile devices running Apple's IOS and mobile devices running Android together have a market share of close to 99% (see International Data Corporation, 2016). As a result, in our search we focused exclusively on mobile applications supporting the Android and IOS operating systems. We also included existing platforms and infrastructures which collect and aggregate relevant consumer generated food consumption and lifestyle data from third party mobile applications. Overall in the Phase 1 inventory for RICHFIELDS (Deliverable 5.1-7.1) we differentiated between the following tool types: 1) Food purchase apps, 2) Food preparation apps, 3) Food consumption apps, 4) Activity, health and fitness trackers and 5) Health and wellness data aggregators. In this Deliverable 7.1 we focus only on the collection of data related to food consumption apps, activity, health and fitness trackers and health and wellness data aggregators. Data related to the tool types 'food purchase apps' and 'food preparation apps' are collected and

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described by Deliverables 5.1 and 6.1 respectively. The applied search strategies for locating relevant tool types for the inventory varied depending on the tool type and specific purpose of the tool for the inventory (see 2.2 for more detail).

2.1.1 FOOD CONSUMPTION APPS

Food consumption apps are computer programs designed to run on mobile devices such as smartphones and tablets, with a clear focus on the collection of dietary consumption data, such as tracking foods, consumed energy, water consumption, macro- or micronutrients, by the means of for instance food diaries, 24-hour recalls or food frequency questionnaires. Modern nutrition related apps combine a multitude of features such as diet and meal planning in the form of recipe and shopping list management, personal assistance in the form of dietary feedback and diet recommendations and advices and some form of lifestyle data tracking including activity, energy expenditure, weight and body composition (see Franco et al., 2016). Note that these types of additional features are only logged for each tool in the inventory if they were offered as an integral part of the system. That is, in order to prevent redundancy, all lifestyle data and services related features which depend on data imported from third party systems such as partner apps (e.g., Research2Guidance, 2016) have been collected only for the systems or partner apps included in the inventory. What has been logged for the data receiving system is the connection with the third party system and data origin. Within the vast array of features and services contemporary nutrition related mobile apps provide, the single feature which determined whether an app fell into the category of food consumption app and hence be considered for possible inclusions in this collection of tools, was whether the app collected behavioral and measurable food intake data (as opposed to intentional or inferential). This pool of apps will form the largest group in the inventory and will provide the basis for the identification of possible scientific, legal, technical and ethical gaps and needs regarding the use and integration of the data collected by these tools.

2.1.2 ACTIVITY, HEALTH AND FITNESS SENSOR APPS

Activity, health and fitness sensors are wireless-enabled technology devices such as accelerometers, pedometers, or location sensors, including supporting (mobile) software

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applications (applications with gadgets) for monitoring and tracking fitness and health-related metrics such as activity levels, heart rate, distance walked or run, or quality of sleep. The aim of this pool of apps is mainly to investigate the possible technical integration and linkage of this data with the data collected by food consumption apps included in this inventory. Hence, this pool of apps is important for getting a better understanding of the scientific relevance of the food consumption data such as for instance regarding the determinants of the food consumption behavior. In addition, this pool of apps can help to better understand the nature of existing data networks, their access points and the types of data they exchange.

2.1.3 DATA AGGREGATORS

Data aggregators are platforms that allow for the integration of data collected from various mHealth apps and sensors such as health data, exercise data, and dietary consumption data and access and visualize these various streams of data on a single dashboard. Similar to the pool of lifestyle and health sensor apps aim of this pool of apps is mainly to investigate the possible technical integration and linkage of this data with the data collected by the pool of food consumption apps. In addition, this pool of apps is important for investigating developments to improve or simplify current practices in the collection and integration of food consumption data and associated lifestyle data.

2.2 SEARCH STRATEGIES

The search strategies applied for finding the relevant tools depended on the type of the tool searched for as well as on the specific purpose of the tool for the inventory. In general, little is known about the quality of health apps only that within the domain of mHealth applications the quality can vary greatly. There are applications for instance that claim they can help users to select the sex of their unborn babies, offer cellphone light therapy against acne, or help reduce weight by listening to isochronic tones radiated by the application. Both the iTunes store and the Google Play store are filled with health apps that experts say do not work and in some cases could even endanger people (Sharp, 2012). The following search strategies were implemented with two important aims in mind 1) reduce the enormous amount of food consumption apps in the app stores to a more workable list of

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approximately 200 apps. 2) generate a good representation of relevant apps used by the general public and 3) decrease the chances of including the kind of low quality applications just described. Next we will describe the search strategies we implemented based on the tool types collected.

2.2.1 FOOD CONSUMPTION APPS

Our aim was to get an overview of the variety of food consumption apps, which includes more popular apps which are used in larger numbers by the general public as well as more new and innovative apps, or apps that have not been released to the general public yet. For that reason, we implemented two complementary search strategies: 1) a more systematic search strategy in which we searched the iTunes and Google Play stores for more popular apps with a predefined set of search terms and 2) a more open search strategy in which we included a variety of sources outside the app stores such as app reviews, blogposts or newsletters. In the following two paragraphs we describe these two search strategies in more detail.

2.2.1.1 SYSTEMATIC SEARCH

In order to find more popular and widely used food consumption apps we searched the iTunes and Google Play store. For the search terms we relied on the set of search terms created by Franco et al. in their recent review of popular nutrition apps (see Franco et al., 2016). The set of search terms included: calorie(s), diet, diet tracker, dietician, dietitian, eating, fit, fitness, food, food diary, food tracker, health, lose weight, nutrition, nutritionist, weight, weight loss, weight management, weight watcher, and ww calculator. For both app stores we implemented an automated web crawling technique using either the public iTunes Search application programming interface (Apple Inc. Search API) or a web data extraction procedure for the collection of the relevant Google Play Store data (see also Xu & Liu, 2015). For interacting with the iTunes search API we implemented the open source Nodejs module itunes-search[1] (version 1.0.1) and for extracting data from the Google Play

[1] iTunes-search module version 1.0.1. Nodejs module to search application data on the iTunes search api. Url: https://github.com/connor/itunes-node

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Store we implemented the open source Nodejs module google-play-scraper[2] (version 0.2.1). Both modules have been installed in- and used from within the Richfields Inventory Management System (RIMS; see below), and have been configured to retrieve only the first 100 applications for each search term. In addition, since each member of the work packages within phase 1 should be able to extract the relevant data from the search results, we were only interested in apps which provided their content in English. For that reason, we only searched for apps available in the United Kingdom (UK) app storefronts. No affiliate account or token has been used for identifying at the iTunes Search API. The initial search resulted in a list of 1185 IOS apps and a list of 1248 Android apps. The lists of apps were further reduced by only including apps with a minimum user rating of 3 (range 1 to 5) and a minimum user rating count of 20. This resulted in a more feasible size of 433 IOS apps and 854 Android apps for further investigation, and also ensured an already established user base and a certain degree of app quality. Next we excluded 19 apps that were not available in the English language and 2 paid versions of apps that were present as free and paid version and the upgrade did not extend the available features but simply eliminated the display of in-app advertisements. Finally, we excluded all apps that did not collect food consumption data or collected only intentional food consumption data (e.g., purchases, preparations). Eventually 102 food consumption apps were included from iTunes and 152 food consumption apps from Google Play. 57 of the apps appeared in searches of both app stores which resulted in a total of 197 popular food consumption apps (see 3.1.1 for more details).

2.2.1.1 OPEN SEARCH

Our aim is to get an overview of the variety of apps, which also includes new and innovative apps. Since such apps might not be found in a systematic search based on popularity or app store relevance, we complemented our systematic search for food-consumption apps by an open-search strategy which included sources such as app reviews, blogposts, newsletters, conference contributions, workshops, as well as recommendations by colleagues and friends. The aim of this search was to include food consumption applications which could

[2] Google-play-scraper module version 0.2.1. Nodejs module to search application data on the Google Play store. Url: https://github.com/facundoolano/google-play-scraper

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add to the variability of already collected applications in terms of dietary assessment methodology and types of data collected and integrated. Using this loose and open search strategy we added another 59 food consumption applications of which 11 systems had not yet been released to the general public at the time of collection. Of those 11 systems it was unclear which mobile platforms they will support. Of the remaining 48 published apps found in this open search strategy 20 apps supported Android devices, 46 apps supported IOS devices and both types of devices supported 18 of the included apps.

2.2.2 ACTIVITY, HEALTH AND FITNESS TRACKERS

In our search for activity, health and fitness sensors we entirely relied on application reviews published online. Our aim was to capture the most popular and widely used systems capable of integrating with other data collection systems. The search was conducted using the google search engine using the following search phrases: “Best fitness trackers 2016”, “Best activity trackers 2016”, “Best health trackers 2016”. We included only reviews which contained a ranking of “best tools” in order to prevent inclusions of negative reviews. In total we looked at the first 30 google search results and included a total of 12 “best of” reviews. From each of the reviews we included the top 5 apps mentioned in the review which resulted in a list of 16 popular health and fitness trackers. Since we were interested in the extent to which the data of these apps can be integrated with the apps in the food consumption data pool, we excluded 3 apps from the initial list which did not implement a public API for possible data exchanges with other systems. This resulted in the final list of 13 popular activity health and fitness trackers.

2.2.3 DATA AGGREGATORS

For aggregators we did a nonsystematic search on Google using several combinations of the following search terms: “wellness”, “fitness” or “health” combined with “data integration”, “data hub”, “data aggregator” or “data platform”. We also included aggregators mentioned in the app descriptions of our included food consumption apps. We again applied a more open search strategy which included sources such as app reviews, blogposts, newsletters, conference contributions, workshops, as well as recommendations by colleagues and

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friends. We only included those aggregators that integrated food consumption data. This resulted in a list of 12 data aggregators.

2.3 DATA COLLECTION AND MANAGEMENT

2.3.1 THE RICHFIELDS INVENTORY MANAGEMENT SYSTEM (RIMS)

The RICHFIELDS Inventory Management System (RIMS) was created in response to Tasks 5.1, 6.1 and 7.1 which required the creation of an inventory of types of purchase, preparation, consumption and lifestyle associated data, and data collection methodologies. RIMS was created for the management of the inventory and in order to ensure a data collection procedure that was transparent to all parties and standardized across the three work packages of phase 1 (WP5-WP7). The open source Nodejs content management system Keystonejs (version 0.3.17) has been used as application framework for the development of RIMS. RIMS is structured into two main areas, a backend and a frontend. The purpose of the backend was to support data collection and data management about the tools identified by the three work packages of phase 1. The backend consists of a set of branched web forms for data input and data editing. The content of the web form was based on the operationalization of the quality framework developed in task 5.1, 6.1 and 7.1. The purpose of the frontend was to support data aggregations and visualizations.

2.3.2 DATA INPUTS

The web form in RIMS allowed the collection of the data types, numbers and text, by the use of more open single text or text array input fields, and more closed single selection and multiple selection fields. RIMS was also designed to allow for the management of input options used for the single and multiple selection fields (except for yes-no-no information answering formats). This had the advantage of standardizing provided inputs and making them reusable. For instance, at the start, the field which was used to collect data about the tools' implemented method for dietary assessment contained an empty multiple selection widget in form of a drop down menu. If the first collected tool used for instance "barcode scanning" as a method; the method was logged in a separate collection and a definition about the methods was provided. By linking that collection to the input widget, the option "barcode scanning" became available as an alternative option within the multiple selection widgets of the dietary assessment method field, and consequently could be assigned and reused for the current and future tools collected by various researchers and work packages. This way we ensured the explorative nature of our data extraction and collection procedure and at the same time developed a qualitative framework for a standardized categorization and labeling of extracted information.

2.3.3 TOOL TYPES

RIMS allows for the collection of different tool types in separate collections, which are aggregators, food consumption apps (as well as purchase WP5 and preparation WP6 apps) and activity, health and fitness sensors (and apps). The extent and type of data collected for the tools differs depending on tool type. We collected the complete set of scientific, legal and technical data as defined in Deliverable 7.3 for the group of food consumption apps only (popular as well as new and innovative apps). For the group of aggregators and activity health and fitness sensors, the set scientific relevance criteria were modified and we collected only data regarding the possibility for integration with the pool of food consumption apps and data aggregators. For activity, health and fitness sensors we additionally collected information about implemented sensor types and the type of activity, health and fitness parameters collected. Since we were not interested in accessing activity, health and fitness data directly from those platforms, but rather as integrational part of dietary assessment data we did not collect criteria related to technical data management from those types of tools. Since we intend to use and integrate data from all these tool types we collected data related to the legal governance of data regardless of tool type.

2.3.4 DATA TYPES

The composition of the web form for the app collections depended on whether the purchase, preparation and/or consumption apps were entered. Specifically, each data type was associated with a different set of input fields regarding scientific relevance of the data, which corresponded to the different sets of quality criteria identified for the three data types in deliverables 5.3, 6.3 and 7.3 respectively.

2.3.5 DATA COLLECTION SOURCES

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For tools available in the app stores we investigated the platform specific data provided by the app stores including descriptive app data such as supported devices, user ratings, company information, number of installs etc. We also investigated the application features and collected data about the apps based on the descriptions and screenshots provided by the app vendors. In addition, for all tools which provided references to a website or homepage we also investigated the information provided on those sources including features and service descriptions, frequently asked questions, tutorials, terms and conditions, privacy statements etc. The aim of this data collection process was to use all of the mentioned sources for the extraction of information relevant to the operationalizations of the framework of quality criteria (Deliverable 7.3). The extraction and coding of data from the included sources was structured by the dynamically generated list of reusable input categories collected in RIMS (see 2.3.2). Once an input was logged (e.g., food diary) and defined, each future occurrence of information fitting that qualitative description was coded by linking the input to the investigated quality criteria of an app (e.g., dietary assessment methods).

2.3.6 AVAILABILITY OF DATA SOURCES

The extent to which we were able to collect the relevant application data depended on the availability of the sources of data (see 2.3.5). Unfortunately for a large part of the included apps crucial sources of information were lacking. Of all food consumption apps included by the two implemented search strategies (n = 256), 21% (n = 54) did not have a reference to a working home page. In addition, for those apps that had a reference to a working website (n = 202), 48% (n = 97) did not provide a terms and conditions document and 42% (n = 85) did not provide a privacy policy document. 41% (n = 83) of the included apps did neither provide a terms and conditions document nor a privacy policy document. For those apps, if the app had already been published, only app store descriptions were investigated for extracting the relevant information, which were for the most part related to information relevant for the scientific quality criteria and data accessibility. Four applications provided a reference to a working webpage that did not support the English language and 1 application which did reference a webpage with an English language version did not provide an English version of their terms and privacy policy documents. In case an application either did not

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provide the necessary sources for extracting the relevant application data or the provided sources did not contain the relevant information the data input option "no information" was assigned to the quality criteria investigated.

3. The inventory datasets

All data which have been extracted from the tools app store and online resources and collected in RIMS have been fetched from the database and converted into three Excel files corresponding to the three tool type collections. These files contain all the data collected for the respective tool types (see 2.3.3). In addition, a data file with a collection of all generated RIMS data inputs (see 2.4.2) and their respective definitions has been produced and grouped by the dimension of the quality framework and criteria they refer to. The following descriptive summaries should provide the reader with an overview of the types of tools listed in this inventory datasets. An overview of the types of data collected in this datasets has been provided in Deliverable 7.3 and more detailed summaries and aggregations regarding these criteria will be presented and evaluated in Deliverable 7.4 and 7.5. The following aggregations are based on the descriptive app (meta) data which has been collected in addition to data related to the quality framework as specified in Deliverable 7.3.

3.1 THE FOOD CONSUMPTION APP DATASET

The food consumption app dataset (FCAD; Appendix 1: FoodConsumptionAppDataset.xlsx) includes a total of 256 food consumption apps of which 197 apps included by a more systematic search for popular and widely used food consumption applications and 59 applications included by a more open unsystematic search for capturing more new and innovative food consumption apps (see Table 1). The collected data is relevant for providing input to the scientific, legal and technical quality criteria as defined in Deliverable 7.3. The initial lists for the group of popular Android and IOS food consumption apps have been compiled and cached on 15th of October 2016 and 18th of October 2016 respectively. The collection of the new and innovative apps took place between March and December 2016. Of the 59 new and innovative food consumption apps, 11 have not yet been released to the general public. In the FCAD all apps collected support the English language. Since information of the complete set of languages an app supports was only provided by the

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iTunes store, the following percentages of supported languages are only based on apps found in the iTunes store: Spanish (40%), German (36%) and French (34%). The most supported platform of the collected apps in FCAD is Android with 70% (n = 179). IOS devices are supported by 68% (n = 175) of the apps. Apps which also supported Windows and Blackberry devices added up to 2% of the total number of apps included in the FCAD. 74% of collected food consumption apps were free of charge in the iTunes store and the price for the paid apps varied from £7.99 (1 app) to £0.79 (5%). In the android store the percentage of free apps were 86% with the paid apps ranging from £7.61 (1 app) to £0.55 (1 app). 43% of all apps offered additional paid services or in app purchases. For IOS apps 54% of the apps required a minimum IOS version of 8.0 and for Android apps 46% required an Android OS version of 4.0 and higher. For 15% of the Android apps the minimum Android OS version varied with device. Only 2 of the applications collected were registered as a medical device (mySugar Scanner and mySugr Diabetes Diary). The IOS apps in FCAD had a user rating between 3 and 5 in 82% of the cases and for android devices 87%.

3.1.1 APP POPULARITY

We investigated the popularity of the collected apps based on the scores of provided user ratings and the number of users who rated an application (see Table 2). IOS apps that have been included by the systematic search strategy showed a mean user rating of M = 3.68 (SD = 0.82) and an average number of users who provided a rating of M = 2725 (SD = 14707). IOS apps included by the open search strategy showed a mean user rating of M = 3.46 (SD = 1.06) and an average number of users who provided a rating of M = 123 (SD = 178). Android apps that have been included by the systematic search strategy showed a mean user rating of M = 4.03 (SD = 0.44) and an average number of users who provided a rating of M = 249,20 (SD = 124,869). Android apps included by the open search strategy showed a mean user rating of M = 3.37 (SD = 1.04) and an average number of users who provided a rating of M = 3685.44 (SD = 124,869). Since apps that have been included by the systematic search have been selected based on user rating (>= 3) and user rating count (n >= 20) we expected a difference in ratings and rating counts with apps collected in the systematic search having a higher rating and rating counts compared to apps collected in the open search. The number of rating counts of IOS apps included from the systematic search appears to be

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much larger compared to rating counts of apps included from the open search. Since the number of times an app has been installed is only provided for Android apps the following analysis is only based on android application.

Table 1: The food consumption app dataset (FCAD) descriptive summaries.

Descriptive	Summaries	Values
Data file		FoodConsumptionAppDataset.xlsx
Collected data	Quality criteria:	Scientific relevance, legal governance, data management
Creation dates	Popular iTunes apps: Popular Android apps: New and innovative apps:	15th of October, 2016 18th of October, 2016 March - December, 2016
Number of apps	Total: Popular apps: New and innovative apps: Unreleased (new and innovative): Medical (popular):	256 197 59 11 1
Supported Platforms	Android: IOS: Android & IOS: Windows: Blackberry:	70% 69% 43% 1% 1%
Language support (IOS only)	English: Spanish: German: French:	100% 40% 36% 34%
Price	iTunes free: iTunes paid: Android free: Android paid: Paid services:	74% £0.79 - £7.99 86% £0.55 - £7.61 43%
Minimum OS	IOS 8.0: Android 4.0:	54% 46%
Android installs	1000 - 5000: 5000 - 10000 10000 - 50000: 50000 - 100000: 100000 - 500000:	12% 10% 20% 15% 16%

In general, 16% of the Android apps have been installed 100,000 – 500,000 times, 12 % have been installed 50,000 – 100,000 times, 20% have been installed 10,000 – 50,000 times, 10% have been installed 5,000 – 10,000 times and 15% have been installed 1,000 – 5,000 times (see Table 1). The minimum number of installs was lower for Android apps that have been included by the open search strategy (M = 122,867, SD = 316,863) than for Android apps that have been included by the systematic search strategy (M = 162,0271, SD = 920,3835).

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This implies that overall the popularity of the apps is higher for the apps that have been included by the systematic search strategy compared to apps that have been included by the open search strategy.

Table 2: Mean user ratings and rating counts by supported app platform and search strategy.

	Systematic search				Open search			
	Rating		Count		Rating		Count	
	M	SD	M	SD	M	SD	M	SD
IOS	3.68	0.82	2725	147,06	3.46	1.06	123	178
Android	4.00	0.44	249,20	124,869	3.37	1.04	3658	123,86

Table 3: Mean minimum number of installs of Android apps by search strategy.

	Systematic search		Open search	
	M	SD	M	SD
Mean min installs	162,0271	920,3835	122,867	316,863

3.2 THE ACTIVITY, HEALTH AND FITNESS TRACKER DATASET

The activity, health and fitness tracker dataset (AHFTD; Appendix 2: HealthFitnessTrackersDataset.xlsx) includes a total of 13 activity, health and fitness trackers which have been collected in the period between March and December 2016 (see Table 4). The dataset contains the collected data regarding legal quality criteria as defined in Deliverable 7.3 and in addition the tool type specific information regarding the data integration with apps in the food consumption app dataset and with the data aggregators. The types of data parameters the tool collects and the type of sensors implemented for data collection can also be found in this dataset. 11 of the trackers support the IOS operating system and 12 support the Android operating system. 10 trackers support both platforms.

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Table 4: The activity, health and fitness tracker dataset (AHFTD) descriptive summaries.

Descriptive	Summaries	Values
Data file		HealthFitnessTrackersDataset.xlsx
Collected data	Quality criteria: Tool type specific:	Legal governance Integrated food consumption apps in FCAD, Implemented sensor type
Creation date	All:	March - December, 2016
Number of aggregators	Total:	16
Supported platforms	IOS: Android: IOS & Android:	13 15 13
User rating range	Android: IOS:	2.4 - 4.2 1.5 - 4.5
Price	Free:	16

3.3 THE AGGREGATOR DATASET

The aggregator dataset (AD; Appendix 3: AggretatorDataset.xlsx) includes a total of 12 aggregator systems and have been collected in the period of March and December 2016 (see Table 5). The dataset contains data concerning the legal quality criteria as defined in Deliverable 7.3 and in addition collects the tool type specific information with respect to the integration with apps in the food consumption app dataset.

Table 5: Aggregator dataset (AD) descriptive summaries.

Descriptive	Summaries	Values
Data file		AggretatorDataset.xlsx
Collected data	Quality criteria: Tool type specific:	Legal governance Integrated food consumption apps in FCAD
Creation date	March - December, 2016	
Number of aggregators	Total:	12
Supported platforms	IOS: Android: HTML5:	1 2 9

3.4 THE DATA INPUTS DATASETS

The data inputs datasets (DID; Appendix 4-7: DescriptiveDataInputs.xlsx, LegalDataInputs.xlsx, ScientificDataInputs.xlsx, TechnicalDataInputs.xlsx) contain the collection of all generated RIMS data inputs (see 2.4.2), their respective definitions and the

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numbers and names of apps the inputs have been assigned to. The data inputs collected in this datasets are grouped by the dimension of the quality framework and criteria they refer to. In sum, these datasets contain the set of categories and labels as they have been generated and assigned for our qualitative analysis and labeling of the collected data.

4. Typology of food consumption apps

We created an initial characterization (or typology) of the type of food consumption apps in the inventory. This initial characterization was based on two sets of generated inputs: 1) the purpose of the apps and 2) the implemented dietary assessment methodologies.

4.1 APP PURPOSE

The categorization of apps according to their intended purpose was extracted from the description of the application in the app stores. Some apps might only have a single purpose (e.g., diabetes management) whereas other apps can be assigned more than one purpose. For instance, and app can be aimed at helping their users in managing weight by monitoring the calories consumed and burned, as well as supporting a healthy diet such as monitoring the consumption of recommended amount of minerals and vitamins. As can be seen in Table 6 the most prominent purpose of the collected food consumption apps was “Weight management” (see also Franco et al., 2016), with a percentage of 51%. This implies that the majority of apps will most likely involve some sort of behavioral change interventions such as nutrition advices and recommendations, coaching or social support (e.g., Pellegrini, Pfammatter, Conroy, & Spring, 2015). In fact, apps labeled as weight management apps provided at least one of the following behavioral change elements: nutrition recommendations (count 41, percentage: 31%), eating reminders (count 26, percentage: 20%), coaching (count 18, percentage: 13%), social support (count 18, percentage: 13%), personal feedback (count 15, percentage: 11%) and challenges (count 15, percentage: 11%). The second most prominent app purpose category which has been assigned was “Healthy diet” and similar to weight management apps these apps are also aiming at changing people’s behaviors using various types of behavioral change techniques. The category of “Intake recording” refers to apps that do not described any means or motivations for

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behavioral change, but solely provide an interface for food consumption tracking. Such apps were identified 25 times in the present inventory (9%).

Table 6: Overview and frequencies of the described purpose of the applications

Purpose	Count	Percentage
Weight management	131	51
Diabetes	12	4
Hydration	13	5
Healthy diet	65	25
Special diet	13	5
Food intolerance	12	4
Alcohol / Coffee consumption	6	2
Memory / Sharing experience	17	6
Intake recording (productivity)	25	9
Nutritional disease	4	1
Muscle gain	8	3
Eating disorders	2	0
Food safety	1	0

4.2 DIETARY ASSESSMENT METHODOLOGY

Similar to app purpose, apps can and often do implement more than a single method for dietary assessments. In fact, two of the apps included in the inventory implemented 7 different dietary assessment techniques including variations of the same methodology. The most prominent dietary assessment methodology implemented by the included food consumption apps was a food diary (see also Franco et al., 2016). We also differentiated food diary techniques based on their inputs. 104 apps (40%) implemented a food diary where users were allowed to input self-generated food items and 95 apps (37%) allowed for food inputs from precompiled food item database. Other forms of food diary input sources were recipes (count 18, percentage: 7%), users self-generated lists of favorite foods (count 18, percentage: 7%), recently consumed foods (count 10, percentage: 3%), and restaurant dishes (count 21, percentage: 8%). We also found a set of apps which implemented specific types of food diaries which allow users to directly enter the nutrient values of their

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consumed foods such as calories (count 9, percentage: 3%) or macronutrients (count 4, percentage: 1%). Finally, a few of the collected apps implemented another type of food diary which also allowed for or were specialized in the collection of specific food types such as alcoholic beverages (count 4, percentage: 1%), cheese (count: 1, percentage: 0%), or water (count 29, percentage: 11%).

Food product identification by barcode scanning is another prominent feature of the food consumption apps and has been found in 46 of the apps (18%). Finally, a few more innovative apps implemented external sensor inputs for dietary assessment such as impedance sensing, audio spectrogram and light spectrum analysis or food image recognition (by software as well as by humans). In sum, the collected apps implement a multitude of dietary assessment techniques mostly based on the food diary methodology, allowing for inputs from various sources and a wide range of foods. The advantage of combining several variations of dietary assessment methodologies seems to be the coverage of a wider and more complete dietary pattern. The data collected by these techniques and its quality with respect to scientific relevance, legal governance and data management will be discussed in more detail in Deliverable 7.4 and 7.5 respectively.

Table 7: Overview and frequencies of implemented dietary assessment methods of food consumption apps

Dietary assessment method	Count	Percentage
Food diary (Custom input)	104	40
Food diary (Food database input)	95	37
Food diary (Products database input)	13	5
Food diary (Recipe input)	18	7
Food diary (Menu input)	2	0
Food diary (Favourites input)	18	7
Food diary (Restaurant input)	21	8
Food diary (Fast food restaurants input)	4	1
Food diary (Recently consumed input)	10	3
Food diary (Frequently consumed input)	9	3
Food diary (Diet plan input)	5	1
Food diary (voice input)	6	2

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Food photo diary	36	14
Food score diary	2	0
Alcohol diary	4	1
Calorie diary	9	3
Protein diary	1	0
Macro diary	4	1
Water diary	29	11
Beverage record	6	2
Food record	2	0
Food photo record	5	1
Food log reminder	2	0
Future food log	1	0
Barcode scanning	46	18
Recurring food method	1	0
Impedance sensing	1	0
Audio Spectrogram analysis	1	0
Spectrometer analysis	2	0

5. Discussion

The aim of this deliverable (D7.1) was to create an inventory in the form of a dataset of food consumption tools and methodologies based on the quality framework developed and described in Deliverable 7.3. In addition, we provided a description of the methodology underlying the generation of this inventory including the tool selection and data collection process. Finally, this Deliverable includes aggregations of descriptive (meta) data regarding tools in the inventory and an initial characterization of the type of collected food consumption apps based on the intended purpose of the applications and the type of dietary assessment methodology they implement.

The most prominent dietary assessment methodology implemented by the included food consumption apps was a food diary (see also Franco et al., 2016). The different types of food diaries found allowed for dietary assessment inputs from various sources such as self-generated food items, precompiled food item database, recipes, favorites or restaurant menus. We also found apps which support food product identification by barcode scanning and other external sensor supported dietary assessment methods including impedance

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sensing, audio spectrogram, light spectrum analysis or image recognition. In sum, the collected apps implement a multitude of dietary assessment techniques allowing for the collection of data in real-time and within the context of food consumption. The quality of the data collected by these techniques with respect to scientific relevance, legal governance and data management needs to be further investigated in Deliverable 7.4 and 7.5 respectively.

Due to the number of apps included in the inventory, we considered it not feasible to download each app for further inspections and testing. Consequently, the content of the inventory might lack important information which has not been provided by the vendors of the tools or might contain misleading information based on the vendors' goals and strategies. It has been noticed that a large proportion of the included food consumption apps was developed by small independent app developers, who didn't provide the same level of information as those provided by larger companies. In addition, in order to increase user-friendliness, it is important that apps provide assistance for individuals having technical problems or questions regarding the use of an app and access to its data. Such support includes availability of a home page, contact information, and concise and comprehensive documentation of the app and data access protocols. For apps in the current inventory, however, a large number (21%) did not provide a reference to a working home page. For those apps that provided a reference to a working home page almost 50% of the applications did not provide a terms and conditions document or a privacy policy document (in 41% of the cases both were missing). Only to the extent that information was provided by the app manufacturers, we were able to complete the quality criteria related to the scientific, legal and technical nature of the app.

In the field of Personal Informatics (or Quantified Self) the common strategy is that through the collection of and reflection on personal data, people are enabled and encouraged to discover themselves, and to use that knowledge to alter vital aspects of their behaviors and habits. However, self-tracking technologies also have a long list of barriers toward their adoption such as unsuitable visualizations and analytics tools, poor skills for analyzing data, and fragmented data scattered across multiple platforms (Choe et al., 2014; Li et al., 2010). The majority of popular health apps does not seem to allow individuals

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access to their data beyond what is presented through the commercial interfaces. As a result, people are unable to investigate their data or share their data with others (Chen et al., 2016). By solely investigating the available online information, the current strategy for data collection was not able to generate a clear picture about some of the potential issues related to the integration of consumer generated data. For instance, it remains unclear which data is actually accessible by the app users. That is, users might be able to collect a set of frequently consumed or favorite foods, however, for the most part we were not able to determine whether such valuable indications of people's food preferences were actually represented in the set of accessible data.

For a large amount of apps in the inventory, users are required to grant a worldwide, non-exclusive, and royalty-free right to the vendors or manufacturers of the app to use and exploit the data. However, the available of data storage options (e.g., servers and/or mobile devices) and which data is accessible and exploited by the app vendors or manufacturers was often uncertain. We were repeatedly not able to determine whether and how an app was syncing data to a server, which is for instance automatically in the background by default or initiated by the user. Also what type of information is shared and used by the app vendors was often not explicitly mentioned. The shared data was often referred to as "user generated content", however that can include blog posts, feedback, comments as well as vital health and food consumption data. Since the transparency of the purpose of data collection and usage is a vital characteristic of ethically responsible scientific research, the legal rights of app vendors regarding user generated content, in particular how and which data is collected and exploited needs further clarification.

Hence, we believe that it is crucial to examine a smaller selection of apps in our inventory more closely before the data they collect should be used and recommended for scientific research. We believe that such a more elaborate investigation and validation procedure cannot be accomplished by relying solely on the data provided by the manufacturers without downloading and testing specific apps. Especially the evaluation of the dietary assessment procedure and its underlying calculations, the type, format and accessibility of data and the possibilities and procedures for data integration from other systems, requires a more direct investigation strategy based on actual data collection and

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data retrieval.

For the assessment of the quality of apps it is important that the owner or manufacturer of the app discloses the intended purpose of the app (Kim et al., 1999). Different kinds of apps have different purposes depending on who the intended user is. The intended purpose can also determine its status as medical device such as intended for use in the diagnosis, cure, mitigation, treatment, or prevention of diseases (FDA, 2015; KNMG, 2016). The inventory created for the present deliverable contains apps with a variety of purposes (across as well as within apps). Only 1 app had the status of a medical device and the majority of apps were aimed at supporting their users' weight management efforts (see also Franco et al., 2016). Hence the majority of apps collected do not only collect consumer generated food consumption data but they also try to support behavioral change in the form of coaching, social support and nutrition recommendations. Due to these potentially confounding contextual influences on people's food consumption behavior, the interpretation of the collected data by these apps and the effects of usual food intake on people's wellness and health status might be problematic.

In sum, by profiling a relatively large and heterogeneous sample of food consumption apps according to certain quality criteria, the aim of the present deliverable was to generate an inventory which captures the diversity of consumer generated food consumption data and data collection methodologies used by and accessible to the general public (or will be available in the near future). The inventory contains several types of tools such as, food consumption apps, health and fitness sensors and health data aggregators. The collected data regarding these tools includes scientific relevance information such as the apps' implemented dietary assessment methodologies, the types of data they generate, share and integrate. The dataset also includes technical information about the tools, such as supported platforms, data accessibility and data format as well as legal information regarding ownership and privacy of the data. We are confident that this set of data is able to provide the RICHFIELDS design process with the necessary overview of existing food consumption data collection tools and methodologies, and in forming a knowledge base for the identification of possible scientific, legal, technical and ethical gaps and needs regarding the use and integration of the data collected by these tools.

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