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Research Article

Organizational and Technological Aspects of a Platform for Collective Food Awareness

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Can Internet-of-food technologies foster collective food awareness within a food consumer community? The paper contributes to answer this question in a fourfold aspect. Firstly, we model a cooperative process for generating and sharing reliable food information that is derived from food instrumental measurements performed by consumers via smart food things. Secondly, we outline the functional architecture of a platform capable to support such a process and to let a consumer community share reliable food information. Thirdly, we identify main entities and their attributes necessary to model the contextualized interaction between a consumer and the platform. Lastly, we review articles reviewing technologies capable of acquiring and quantifying food characteristics for food performances assessment. The purpose is to give an insight into current research directions on technologies employable in a platform for collective food awareness.

1. Introduction

Modern food consumers are ever more engaged in open discussions, comments, and feedback on characteristics, quality, and safety of food that has become a very trending topic (to give an idea, think of the many food pictures and messages that are daily posted on online social media). Also, among them, food consumers communicate and interact with food suppliers and third parties in loose, open, effective, and flexible ways in a continuous search for food information transparency and more visibility of food supply chains.

On the other hand, new technological advances, especially in food sensor miniaturization, have made possible the development of lab-on-smartphone platforms for mobile food diagnostics that allow a rapid and on-site food analysis for preliminary and meaningful food information extraction. These lab-on-smartphone platforms use hand-held and low-cost devices (e.g. food scanners or food sniffers) to capture and communicate food data (e.g., data from measures of physical, chemical, biological, and microbiological food properties) or food-related entities data (e.g., data from label, package, container, and environment) with some specialized smartphone/tablet apps. These devices are easy to use and incorporate an analytical precision and resolution almost equivalent to bench-top instruments.

These trends let envisage future scenarios where consumers and other stakeholders of the food supply chain, using their own capabilities integrated with ICT and food diagnostics technologies, could collaboratively constitute a large-scale socio-technical superorganism capable to foster collective food awareness. Here, we refer to collective food awareness (shortly, CFA) as food beliefs, knowledge and information, shared within a consumer community, that drive food consumption patterns of community members in terms of culinary preferences, and food habits and needs.

The need of sharing food information and knowledge is due to the fact that quality and safety issues about food are difficult to identify and, in the majority of cases, recognizable only after their consumption. In fact, depending on the type of attribute, food is an experience (some food attributes can be determined just after purchasing and consumption) or credence good (some food attributes that cannot be determined by consumer even after consumption). In food markets, this intrinsic nature of food facilitates the occurrence of information asymmetries that deeply affect consumers' decisions and behaviour. Main consequences of asymmetric information are moral hazard (a food producer takes more risks, e.g., false labelling or food adulteration, because consumers bear the burden of those risks) and adverse selection (producers hide some food information in a transaction, leading consumers to poor decisions making).

A broad CFA contributes to make many "problems" linked up with information asymmetries vanish and beyond that could drive consumers to greater consciousness about health, and environmental choices compatible with social goals. It can be fostered by a sociotechnical infrastructure based on a platform that empowers consumers by collectively managing (generating, verifying/validating, and distributing) information on safety and quality of food products and processes, as well as on issues around environmental, social, and ethical aspects.

In line with other works on collective awareness platforms [1–3], we view a CFA platform as an ICT system leveraging for gathering and making use of open food data, by combining social media, distributed knowledge creation and IoF (IoF (Internet of Food) is an offshoot of the Internet of things. It can be viewed as a network of smart food things, i.e., food-related objects and devices that are augmented with sensing, computing, and communication capabilities in order to provide advanced services. Smart food things include sensor-equipped information artifacts (e.g., food labels with RFID or NFC tags), time-temperature indicators, and other sensors on packages to detect spoiled foods, sensor devices that spots bacterial infection in food and water, kitchen devices that generate a record of compliance with food safety protocols, wearables to count bites and estimate calories, and so on [4]) technologies, in order to support the creation of CFA within a food consumer community.

A general research question that is crucial for sociotechnical infrastructures aimed to create a CFA is the following:

How can a CFA platform empower food consumers to have control over their own food and be responsive to their expectations of reliable food information?

In this paper, we focus on four implied questions flowing from this general question and reflecting different point of views:

(1) How can a consumer community share reliable food information derived from food properties instrumental measurements performed by consumers?

(2) What is the functional architecture of a CFA platform that supports such a process and lets a consumer community share reliable food information?

(3) What are the entities with their relevant properties characterizing the CFA platform interaction context?

(4) Which technologies can allow a CFA platform to generate food information based on scientific instrumental measurements of food properties?

The rest of the paper includes a short background discussion on the superorganism paradigm and four sections devoted to answer these questions.

2. Backgrounds

As people are increasingly becoming connected and active participants in smart environments, the convergence of "Internet of Things" and "Social Networks" worlds is gaining momentum in many researches [5], paving the way to a new generation of "user-in-the-loop" context aware systems [6]. The challenge is to harness the collaborative power of ICT networks (networks of people, of knowledge, and of sensors) to create collective and individual awareness [7].

A single "individual" is characterized by heterogeneity and limited reasoning capabilities, acting in an autonomous way within a smart environment. However, when many individuals join together they can self-organize into large-scale cooperative collectives, based on the assumption that a large number of individuals tied in a social network can provide far more accurate answers to complex problems than a single individual or a small group [8]. According to this perspective, the very large number of interconnected objects or people can be exploited to create what several researches define "superorganism" [9] or "swarm intelligence" [10], since they exhibit properties of a living organism (e.g., "collective intelligence") on their own. In fact, such approach is inspired by self-organizational behaviour of complex systems in nature [11], with particular reference to ant colonies. While a single ant has very limited sensing and actuating capabilities and little or no cognitive abilities, by and large, ants can indirectly coordinate their movements and activities, via spreading and sensing of pheromones in the environment, exhibiting, as a colony, a very powerful collective behaviour [12].

Collective intelligence and nature-inspired computing represent an extremely interesting phenomenon that has been addressed in several application fields, e.g., smart cities [13], manufacturing [14], healthcare [15], energy [16], and finance [17].

The food sector is another promising application area. The increasing demand on safe, high-quality, and healthy food, the recent food safety incidents and scandals, and the availability of new smart food technologies have led substantial changes in both food consumer's behaviour and food information user's behaviour [4, 18]. Today's consumers may have access to a wealth of mobile app-based services that provide them with food information (food traceability, nutrition advices, recipes, and purchasing support). At the same time, new digital businesses can collect and process big amount of food data through data analytics and intelligence tools for better understanding food consumers and increasing food processes effectiveness.

Moreover, the coupling of smart food technologies with social networking technologies is disclosing a world where consumers can interact, communicate, and collaborate with each other in loose, open, effective, and flexible ways for enhancing the transparency and visibility of food supply chains through collective wisdom and intelligence [19].

In a similar way we see that individual ants behave as if they were a single superorganism; we can envisage a near future where food consumers are engaged in large-scale coordinated activities for the good of everyone. In our opinion, it is advisable that some of these activities should address the creation of CFA. Although the superorganism paradigm has been employed for building collective awareness in many fields, prior research has not been explicitly focused on organizational and technological aspects in creating CFA within a consumers' community.

3. Collectively Generating and Sharing Reliable Food Information

As a first attempt to answer question 1, described in the introduction section, we introduce a process that allows a consumer community to share reliable information on food performances of some food items belonging to a same food class. In our process model, we assume that the reliability of a food performance is determined by a collective interpretation of food items' characteristics that are derived from instrumental measurements performed by some consumer community members. According to Peri [9], we refer to food characteristics as physical, chemical, biological, and microbiological food properties that are objectively attributable to food and do not change by changing the consumer (food shape, weight, size, structure, and composition, in terms of chemical or bioactive compounds). We refer to food performances as functional and subjective food properties; i.e., they relate to the consumer and do not exist except in the interaction between food products and consumers. They include sensory, nutritional, safety, and aesthetic properties.

In what follows we describe the process under a perspective that addresses its structure in terms of components and roles, and we include a process scenario.

3.1. Process Actors and Roles. Main roles, actors, and interrelationships are the following:

(i) *Recipient (R)*: he/she is a consumer community member who needs reliable information about a food item performance. He/she makes a request *r(i, p)* to a Food Information Broker, where *i* refers to some identity property values of a food item (e.g., a product batch number, production date and place, etc.) and *p* is the identifier of a performance he/she wants to know the value. In order to provide these data, he/she possibly interacts with a technological CFA platform through his/her own handheld device and Food Information Artifact (FIA) (according to [20], a FIA is a physical entity expressly created to bear food information (e.g., labels, tables, RFID chips, and NFC tags)) located in the surrounding spatial environment.

(ii) *Contributor (C)*: he/she is a consumer community member that contributes to the process by providing a Food Information Broker with some food item data. In particular:

- (a) he/she implicitly or explicitly acquires food item data through smart food things, i.e., sensor devices that capture implicit or explicit signals from a food item (e.g., food near-infrared emission, food volatile compounds) or the consumer body (e.g., blood glucose level, chewing sound, and skin temperature);
- (b) he/she explicitly acquires other descriptive identity data of a food item (e.g., batch number, production date, and provenance) from a FIA;
- (c) he/she uses his/her own handheld device to communicate acquired food item data to the Food Information Broker.

(iii) *Food Information Broker (FIB)* is an intermediate agent that plays a threefold role. Firstly, it receives a request *r(i, p)* coming from *R*, and controls if it has been already satisfied. Otherwise, it submits a new challenge question to a Collective Challenge Solver (CCS). A challenge consists in knowing to what extent food items with same values *i* share the same value of *p*, and, possibly, in finding this value. Secondly, it possibly receives challenge answers from the CCS, and makes them understandable (human-readable) to *R*. Thirdly, It receives and controls both data acquired by *C* and other interaction context data captured by environmental sensors, and passes them to a Food Analysis Manager;

(iv) *Food Analysis Manager (FAM)* is a food data analyst that is able to perform a food item diagnosis. It receives food item data and other interaction context data from FIB, and applies some intelligent methods to determine food item characteristics. Generally, these methods analyse food item data versus food characteristics specific knowledge through machine learning techniques and/or statistical analysis (such as principal components analysis, supervised pattern recognition techniques). For instance, classification-based methods match food item data against class models in order to determine a value of a single food item characteristic. Food item diagnostics and identity data are successively sent to a Food Journal Manager;

(v) *Food Journal Manager (FJM)* is a food database manager that collects and organizes data coming from FAM. It also provides results of query *q(i, c)* formulated by a Collective Challenge Solver. Query results consist in a set of values of characteristics *c* for food items having the same identity properties *i*;

(vi) *Collective Challenge Solver (CCS)* is an intelligent agent that plays the core role in the collective process for generating reliable food information. It receives from FIB a challenge question consisting in finding the value of the food performance *p* that is possibly shared by all food items with the same identity properties *i*. Leveraging on a food knowledge base, it selects food characteristics *c* that are factors of food performance *p*. It formulates the query *q(i, c)* to *FJM* and, once obtained query results, it applies collectively reliable criteria in order to possibly determine the value of the food property shared by food items with same value *i*. A Reliability Authority establishes these criteria whose application may require the CCS to use specific methods (e.g., statistical methods, machine learning, neural networks) [21, 22];

(vii) *Reliability Authority (RA)* is an organizational entity that is responsible for the process governance. It sets and manages the criteria that CCS uses to provide reliable information on food performances of some food items belonging to a same food class. These criteria consist of rules that underpin a collective interpretation of food items' characteristics and determine reliability of information on food performances derived from those characteristics.

3.2. The Process Flow. In what follows, we give a description of the process flow that is also visually represented in Figure 1. The process flow consists of two streams, say 1 and 2, which are started by *R* and *C*, respectively.

In stream 1, *R* needs reliable information about a food item performance *p*. He/she provides *FIB* with some identity property value *i* and asks *FIB* for the value of *p* on the food item. *FIB* controls if the request can be immediately satisfied by consulting a solved challenge database that collects answers given to previous requests. Otherwise, *FIB* submits a new challenge question to *CCS*. *CCS* identifies food characteristics necessary to determine the value of *p* and asks *FJM* for their values on all food journal items with the same value *i*. *CCS* controls these data and decides if the value of *p* can be computed and collectively reliable criteria (established by a *RA*) are applicable. In positive case, *CCS* determines the value of *p*, and it both inserts the new record in the solved challenge database and sends the challenge answer to *FIB* that makes it understandable to *R*.

In stream 2, *C* examines a food item through his/her own devices (smart food things) in order to acquire measurement data of food item properties. He/she provides *FIB* with these data and descriptive identity data, say *id*, of that food item. *FIB* collects and controls them as well as other interaction context data captured by environmental sensors, and it passes the whole data to *FAM* that determines some food characteristic values, say *c*, by performing a food item diagnosis. The pair (*id*, *c*) is sent to *FJM* that stores it a Food Journal.

3.3. Exemplification Scenario. In what follows, we present a scenario to clarify the collective process described above.

A consumer community faces the problem of knowing relevant water performance (e.g., safety) of a branded bottled water. A community member can act as contributor (*C*) and/or recipient (*R*).

Cs are community members that are equipped with lab-on-smartphones (taste-analysis based devices connected to a smartphone), capable to acquire data on electrical impedance of water. Each of them examines a sample of water, acquires electrical impedance data, and transmits them to the *FIB* with some descriptive identity data (e.g., "product batch number"). *FIB* collects and controls these data coming from many *Cs*, and it sends them to the *FAM* that makes a diagnosis of the sampled water. *FAM* applies some methods, e.g., multiple regression analysis or principal component analysis to identify chemical compounds (e.g. "magnesium," "calcium," "sodium," poisoning elements as "cyanide," heavy metal pollutants as "copper," and "arsenic") [23] and microbial properties (e.g., pathogenic bacteria as "coliform group" and "escherichia coli") [24]. These water characteristic values of the water sample are permanently stored in the Food Journal.

R is a community member that needs to know performance values (e.g., safety) of a branded bottled water *b*. He/she uses his/her smartphone to scan the label of *b* to acquire the product number of the batch that *b* belongs to, and he/she queries the *FIB* about the safety of the water contained in *b*. *FIB* acquires the *R*'s request and determines if it is well formed (e.g., "batch number" correctness, water performance checkability). If this request had not been previously solved, the *FIB* submits the following challenge to the *CCS:* "determine if all bottles in the batch of *b* are safe." The *CCS* selects water characteristics (e.g. cyanide, heavy metal pollutants) that it needs to know in order to solve the challenge. Successively, it queries the *FJM* to obtain characteristic values referring to previously analysed bottles belonging to the batch of *b*. Once obtained these values, it solves the challenge by applying some methods based on some collectively reliable criteria (established by the *RA*). In carrying out its activity, the *CCS* could apply some machine learning or statistical methods to establish:

(i) What is the set of water characteristics (e.g., escherichia coli, cyanide, copper, and arsenic)?

(ii) How they combine in order to obtain category inspect indicators (e.g., pathogenic bacteria, heavy metal pollutants, and chemical contaminants)

(iii) How to use these indicators to determine the water safety performance.

Lastly, the *CCS* sends the challenge answer to the *FIB* that could possibly generate a hazard warning for collective awareness of a safety risk related to the water bottles' batch which *b* belongs to.

4. Functional Architecture of a CFA Platform

In what follows we describe a high-level architecture for a CFA platform, as it can support the collective process for sharing reliable food information. The architecture, illustrated in Figure 2, is structured as a classic three-tier architecture commonly found in today's software applications:

(i) An interface layer that enables the user to submit, retrieve, and manipulate data

(ii) An application layer that performs data processing and analysis

(iii) A storage layer where information is stored and retrieved from a persistent database.

In our platform architecture, the interface layer is the front-end interface between the user/consumer and the CFA platform back-end, and it is responsible for interactions with the external environment (user's request formulation, sensor data acquisition, and information presentation/visualization

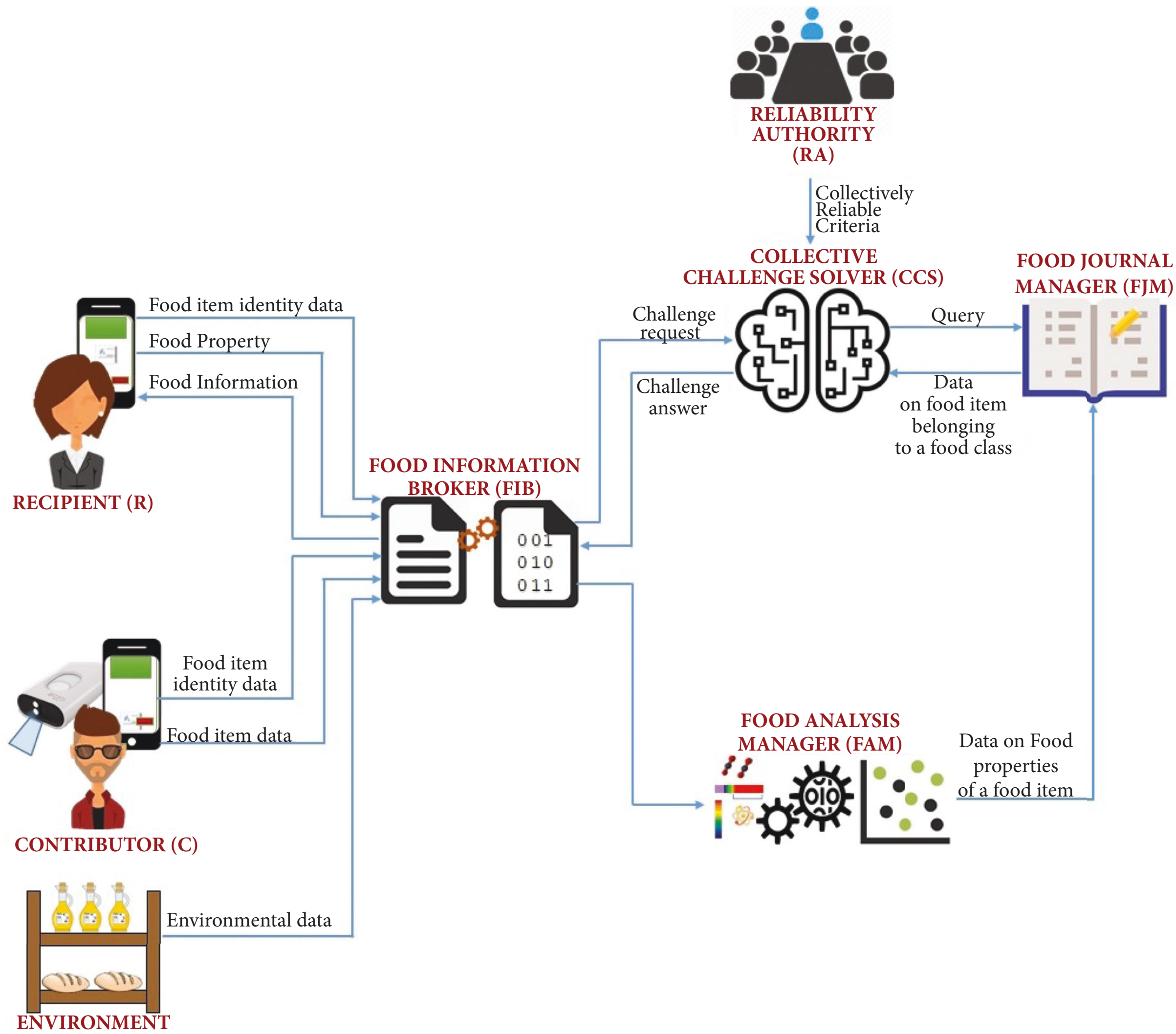

Figure 1: A representation of the Collective process for generating reliable food information.

to the user). In particular, the interface layer comprises simple and empowered nodes that are used by the CFA platform to interact with the user, food items and the surrounding environment. A simple node comprises user interface devices while an empowered node include also smart food things, environment sensors and wearable devices, where

(i) *user interface devices* are input-output devices (e.g. smartphone, tablet) that take input from and deliver output to the user in his/hers foreground attention. These devices are able to manage users' requests, manual data entry and acquire data from FIA (e.g. from labels, tables, RFID chips, and NFC tags) and provide human readable food information to users.

(ii) *smart food things* are sensing devices, owned by contributor users that are able to capture implicit signals from food (e.g. food near-infrared emission, food volatile compounds) with or without requiring user's action or attention. Smart food things can be connected and synchronized to users' interface devices.

(iii) *environmental sensors* are networked sensors that take environment data without requiring user's action or attention. These devices include sensor devices embedded in food packaging, containers, and food appliances and small tools (e.g., kitchen or cooking utensils), as well as ambient sensors;

(iv) *wearable devices* are devices that take input from the user in the background of user's attention (also called, peripheral attention), while he/she is involved in food consumption activities, such as many wearables for food intake monitoring.

The application layer comprises the following:

(i) *Food Information Broker*: this module has the following main functionalities:

(a) It receives unformatted digital data from an empowered node and translates them in a proper

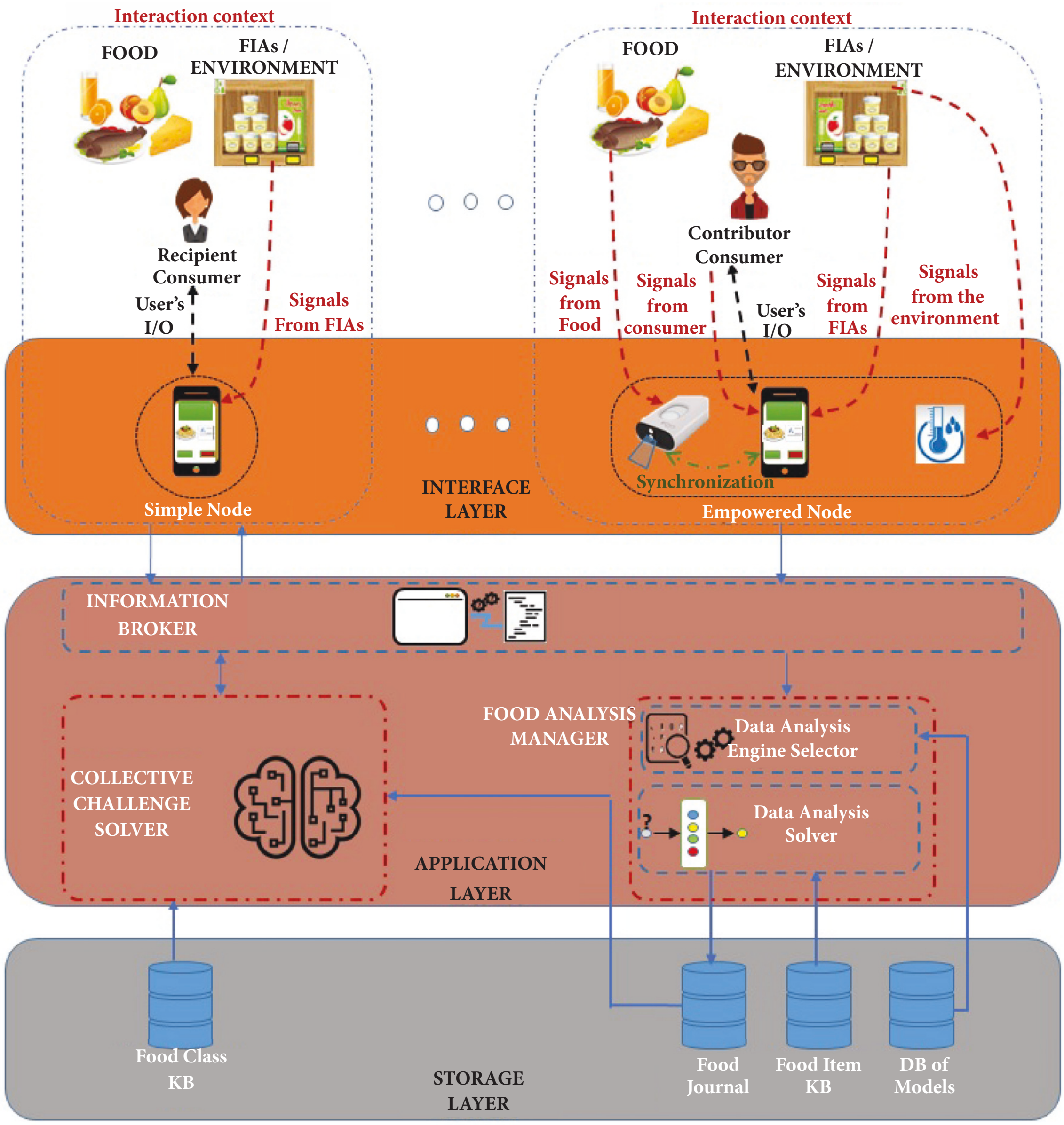

FIGURE 2: A three-tier architecture for the CFA platform.

schema or grammar in order to generate a well-formed digital document (e.g., XML) representing a diagnostic data model and then send it to the FAM so that it can be processed;

(b) It receives data from a simple node and generates a formatted digital document to properly define the challenge to be solved by the CCS;

(c) It verifies if a challenge has been already solved, by querying the *Solved Challenges DB*.

(d) It returns to a simple node challenge results in a formatted document that can be easily processed and converted in human-readable views.

(ii) *FAM Data analysis engine selector:* this submodule receives the formatted diagnostic document from FIB. By analyzing document entities, it automatically at run-time selects, from the *Model DB*, library software modules for the FAM data analysis solver. They are the implementation of some model/method (statistical, deep learning) for determining food characteristics from sensing data. The selection can be driven by empowered node features contained in the diagnostic document.

(iii) *FAM Data Analysis Solver*: this submodule receives the selected software modules that complete a food diagnosis process engine. By leveraging on an auxiliary database (e.g., a food item training set), the engine produces characteristic values of a single food item and it stores them in the Food Journal.

(iv) *Collective Challenge Solver:* It receives a formatted challenge question from FIB. It leverages on a *Food Class DB* to analyze data coming from Food Journal, in order to determine the challenge results according to some collectively reliable criteria. To perform its analysis it may use complex software libraries such as extreme/deep learning machines, neural networks, classifier algorithms, clustering algorithms, and statistical/regression algorithms.

The storage layer contains persistent food data. In particular, it comprises the following:

(i) *Food Item Training Set*: a database containing data and inference rules to determine food characteristics of a food item.

(ii) *Model DB*: a set of library software modules that can complete a diagnosis process engine.

(iii) *Food Journal*: a public ledger containing data on food characteristics of analyzed food items.

(iv) *Food Class DB*: a set of library software modules that are the systematic representation of collective reliable criteria established by the *RA* and used, on a case by case basis, to determine a class food performance.

(v) *Solved Challenges DB*: a database containing challenge questions already solved by the *CCS*.

5. Entities of the User-CFA Platform Interaction Context

In order to support the collective process, described in Section 2, the CFA platform needs to acquire data from

(a) a user in foreground attention. The user explicitly interacts with platform interface devices that are in the foreground of his/hers attention, i.e. he/she is intentional conscious of interacting with the CFA platform. For instance, he/she could use handheld devices to get data from some food information artifacts, such as labels, RFID, and NFC tags, and, in the place where the artifacts are located, transmits them to the platform. He/she could also interact with smart food things in order to capture and communicate data on some property of a food item.

(b) a user in background attention. The user implicitly interacts with platform interface devices that are in the background of his/hers attention, i.e. they escape the user's observation. For instance, wearable sensors could provide the CFA platform with data for real-time food intake monitoring [25].

(c) a food item or the environment, without requiring any user's action or attention. Some smart things automatically detect food properties and environment conditions, and transmit related data to the platform. They include sensor devices embedded in food packaging, containers, and food appliances and small tools (e.g., kitchen or cooking utensils), as well as environmental sensors.

In what follows we summarize the main entities with their properties (attributes) that are relevant for the CFA process and characterize the CFA platform interaction context.

Context entities:

(i) **user**: a consumer who interacts with the platform through interface devices (including his/her own handheld devices) located in the environment, as he/she participates to the CFA process as recipient or contributor. In the recipient role, he/she asks the platform to give him/her validated information about a food attribute. In the contributor role, he/she can also contribute to the validation process by communicating food item (a class identifier and a food attribute value) and other interaction context information to the platform.

(ii) **food**: it refers to a food item which the user and the platform can interact with. Food related stimuli are perceived by the user and, possibly, smart food things detect signals coming from the food item. Attribute values of the food item can be exchanged during the interaction between the user and the platform;

(iii) **environment**: it is the physical and organizational environment where interactions take place (e.g., a home kitchen, a restaurant, and a food shop). Environmental conditions have direct or indirect influence on the behaviour of both consumer and interface devices during the interaction. Physical properties, like light, humidity, temperature, localization, and spatial layout of the environment, may affect both consumers' perception and instrumental measurements of food item properties. Organizational aspects, like rules, shop opening hours, and working time, may drive the provision of information from the platform.

Context entities attributes are

(i) **Identity**. It refers to properties that identify a context entity or a class the entity belongs to. In particular, the CCS of the platform can build a food class identity by inferring class properties from food item data coming from instrumental evaluations of food item qualities;

(ii) **Time**. It comprises temporal aspects that may range from a current time representation to a complete time history of context entity properties. When referred to a food item, values of this attribute allow the CFA platform to recognize or predict over time qualities of food items in a certain class. For instance, a time series of values of properties, like temperature, pH, or microbial growth, could be used to generate and, share, within a consumer community, information on when food items of a certain class are at their nutritional best and are safe to eat, or on when they should be disposed of to avoid ill health;

(iii) **Location**. Values of this attribute may be quantitative or qualitative. They represent current and previous positions of context entities in absolute or relative terms. When referred to food, location is a fundamental attribute when creating a CFA based on geographical traceability or geographic-based origin determination of food products.

(iv) **Activity**. It refers to fundamental changes of entity attributes that occur when a food activity is performed by a consumer. In particular, changes of food item characteristics, like surface conditions, temperature or size, could be used by the CFA platform to drive a collective awareness on consumption activities (e.g., cooking, or eating) on a certain class of food items.

6. Food Analysis Technologies for a CFA Platform: A Review of Reviews

Food analysis technologies are based on a plethora of quantitative/qualitative food analysis techniques and methodologies investigated by many researchers of various scientific fields. These methods are addressed to automatically acquire food item information (e.g., food quality traits) by using sensor devices, and they can be employed in technical approaches to the development of a CFA platform. Here, we refer to a technical approach as a collection of techniques, tools, devices, and knowledge, that is applied to measure a certain food characteristic (i.e., physical, chemical, biological, and microbiological attributes) in order to determine a certain set of food performances.

In this section, we present a review of review articles that were published from 2012 to 2017 and explicitly referred to technologies capable of nondestructively acquiring and quantifying food characteristics (external and internal quality attributes) for fast, real-time food performance assessment. The intent is to answer the following questions:

(i) Which technical approaches to food-data capture and analysis are investigated in scientific research literature?

(ii) Which food characteristics could be detected by these approaches?

(iii) Which information on food performances could be provided?

According to Kitchenham [26] we have been undertaken a systematic literature review of reviews, in order to provide a complete, exhaustive summary of current literature relevant to our research questions. The steps of the methodology we followed are below described, while Figure 3 shows the workflow we adopted:

(i) *Step 0. Initialization*: we selected Scopus as scientific database where to perform our search. Scopus delivers a comprehensive overview of the world's research output in our domain of reference and it has the ability to handle advanced queries. We initialized a list L of search keywords with English terms related to technologies capable of nondestructively acquiring and quantifying food characteristics (e.g., "spectroscopy," "camera photo," "e-nose," "e-tongue,"and "machine vision," as well as synonymous, and other broader/wider terms).

(ii) *Step 1. Search process*: We performed a search on Scopus database by using keywords in the list L coupled with term "food" and other terms used for major food groups; then, we filtered retrieved papers by choosing only those indexed as reviews and published since January 2012.

(iii) *Step 2. Screening relevant papers*: We manually analysed metadata (authors, title, source, and year) in order to detect and remove duplicated items. Moreover, we analysed the abstract of each paper in order to determine whether it matched our inclusion criterion:

(a) the paper is classifiable as a research paper review;

(b) the review specifically focuses on research applications for detection and classification of food properties;

Moreover, the list L was possibly extended by adjoining new terms found among the author keywords of each paper.

Steps 1 and 2 were iteratively performed until no newer keywords or new papers were found. At the end of this cycle we obtained the final set R of review papers to be analysed.

(iv) *Step 3. Review papers analysis*. For each review paper $r \in R$ we identified the set *TRP(r)* of technology research patterns that the paper focuses on. An element of *TRP(r)* is represented by a triple (t_i, C_i,and P_i), where t_i is a technical approach, C_i is the set of food characteristics measured by t_i, and P_i is the set of food performance determined by t_i from the values of the food characteristics of C_i.

6.1. Results and Discussion. The resulting set R is constituted by 67 review papers whose references are listed in the Appendix. In what follows we present and discuss results with respect to the research question we posed at the beginning of this section. Table 1 shows the set T of technical approaches reported in the literature, Table 2 describes food characteristics that can be detected by these approaches, and Table 3 shows the set of information on food performances that can be determined.

In Table 4, for each technical approach t_i, we summarize the set of technological patterns that comprise t_i, and we indicate the review papers focusing on it.

From these results, it emerges that five class of technologies are promising to be a valued addition to the development of CFA platforms:

(i) **Spectroscopy**. These technologies are mostly based on vibrational spectroscopic data acquisitions and statistical analyses (e.g., principal components analysis, supervised pattern recognition techniques). The first ones collect spectroscopic data (e.g., mid- and near-infrared reflectance or transflectance data) as they measure molecular vibrations either by the

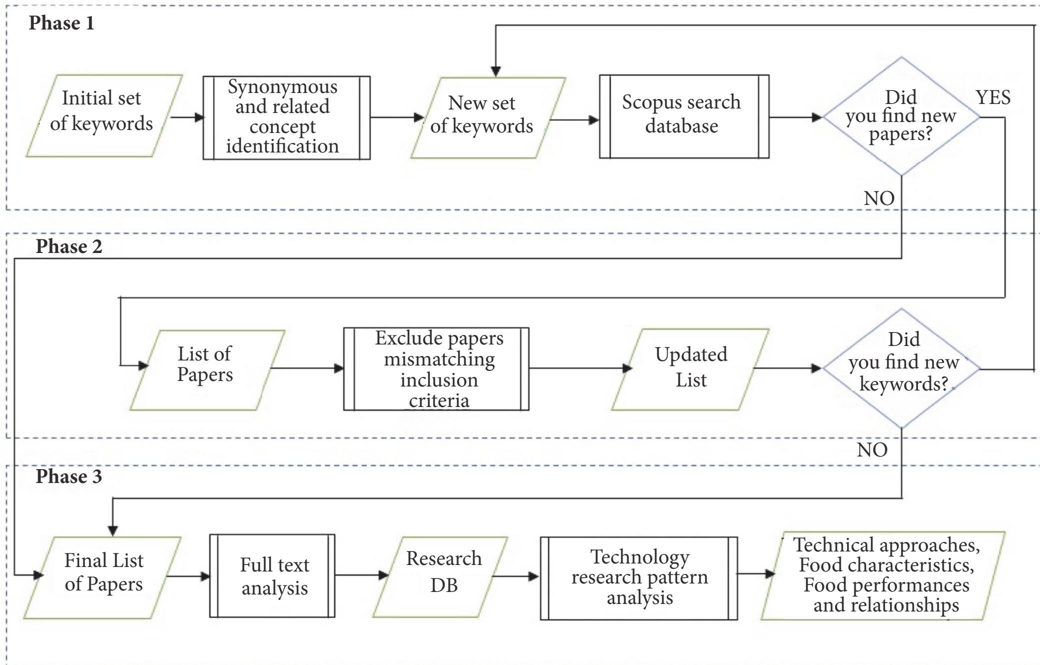

Figure 3: Systematic literature review workflow.

Table 1: The set T of technical approaches.

Technical Approaches	
t_1: near infrared spectroscopy	t_8: Gas Biosensors
t_2: mid infrared spectroscopy	t_9: Gas Electrochem sensors
t_3: raman spectroscopy	t_{10}: Gas Optical sensors
t_4: fluorescence spectroscopy	t_{11}: Solids and Liquids Gravimetric sensors
t_5: camera image sensors	t_{12}: Solids and Liquids biosensors
t_6: hyperspectral imaging	t_{13}: Solids and Liquids Electrochem sensors
t_7: Gas Gravimetric sensors	t_{14}: Solids and Liquids Optical sensors

Table 2: The set C of food characteristics.

Food Characteristics		
Index	**Name**	**Description**
c_1	microbial properties	food kinetic properties that can be measured by microbial detection (e.g., the total count of microorganism in a sample of food)
c_2	chemical properties	food kinetic properties that can be chemically detected (e.g., pH value and total volatile basic nitrogen);
c_3	chemical compounds	chemical compounds' properties (e.g., concentration level);
c_4	surface conditions	visible attributes describing the physical outer aspect of a food item (such as colour, shape);
c_5	mass-volume related properties	physical properties of a food sample (e.g., weight and the volume);
c_6	volatile organic compounds	compounds of organic vapours or gases released into the air by solid or liquid foods.

Table 3: The set P of food performances.

Food Performances		
Index	**Name**	**Description**
p_1	freshness/spoilage	spoilage/edible level of a food product
p_2	hazard	degree of hazard, e.g., presence of illegal ingredients or treatments contaminating or poisoning a food product
p_3	ingredients	edible substances in a dish or a food product
p_4	category	food group (e.g. fruits, dairy, meat, fish) or food type (e.g. apple, orange, apricot) which a food sample belongs to
p_5	variety	variety of a food sample belonging to a food type (e.g. sunstar orange, belladonna orange, tarocco orange)
p_6	nutrients	nutrients (protein, carbs, fat, calories, vitamins, minerals) and their quantities in a food sample
p_7	taste perception	level of tastes (e.g., sourness, saltiness, umami, bitterness, and sweetness)
p_8	quality grade	quality assessment a food sample according to some standardised grading system
p_9	geographical origin	geographical area where a food sample has been originate, according to some geographical classification
p_{10}	adulteration	presence and quantities of improper substances in a food product

Table 4: Technological research patterns and related works.

Technical Approach	*Food Characteristics*	*Food Performances*	*Review Papers*
t_1	c_1, c_2, c_3	$p_1, p_2, p_6, p_8, p_{10}$	[r1] [r2] [r3] [r6] [r7] [r8] [r9] [r10] [r11] [r12] [r13] [r14] [r15] [r16] [r17] [r18] [r19] [r20] [r22] [r23] [r24] [r26] [r25] [r28] [r31] [r32] [r55] [r67]
t_2	c_2, c_3	$p_1, p_2, p_3, p_4, p_8, p_9, p_{10}$	[r2] [r10] [r11] [r12] [r13] [r14] [r17] [r19] [r21] [r23] [r31] [r32]
t_3	c_1, c_2, c_3	p_1, p_3, p_8, p_{10}	[r5] [r8] [r9] [r11] [r12] [r13] [r14] [r21] [r23] [r25] [r32]
t_4	c_1, c_2	p_1, p_{10}	[r8] [r11] [r12]
t_5	c_4, c_5	p_1, p_5, p_6, p_8	[r4] [r27] [r35] [r36] [r37] [r39] [r40] [r42] [r44] [r41] [r43] [r45] [r67]
t_6	c_1, c_3, c_4, c_5	$p_1, p_5, p_6, p_8, p_{10}$	[r9] [r12] [r13] [r14] [r15] [r16] [r18] [r21] [r23] [r27] [r28] [r29] [r30] [r33] [r34] [r38]
t_7	c_6	p_1, p_{10}	[r46]
t_8	c_6	p_1, p_{10}	[r46]
t_9	c_1, c_6	$p_1, p_4, p_8, p_9, p_{10}$	[r46] [r47] [r48] [r49] [r50] [r51] [r52] [r53] [r54] [r55] [r56]
t_{10}	c_6	p_1, p_{10}	[r47] [r48] [r49]
t_{11}	c_3	p_1, p_7	[r53] [r62] [r63] [r65]
t_{12}	c_3	p_1, p_5, p_7	[r62] [r63] [r65]
t_{13}	c_1, c_3	$p_1, p_2, p_4, p_7, p_9, p_{10}$	[r54] [r55] [r56] [r57] [r58] [r60] [r61] [r62] [r63] [r64] [r66]
t_{14}	c_1, c_3	p_1, p_7, p_9, p_{10}	[r46] [r53] [r58] [r62][r63] [r64] [r65]

absorption of light quanta or the inelastic scattering of photons; the second ones are suited to perform targeted and nontargeted screening of ingredients using spectral profiles [27, 28]. They are at the core of food knowledge-based approaches aimed to analyze foods at the molecular level. In most laboratory researches, they are used to collect spectroscopic data coming from scanned training food samples, to build a classification or cluster model according to known values of a certain property, and to determine the property value of a new food sample by matching sample's spectroscopic data against class models [29]. For example, spectroscopic analysis has been successfully applied in food safety analysis and prediction for several food categories, such as meat, fish, fruits and vegetables. In particular, the verification through spectroscopy of the freshness and the presence of any adulterants (or improper substances) in food can be based both on the chemical compounds of food and on the analysis of some properties (such as pH, TVB-N, and K1.), as well as on analytical techniques based on microbial count. Reviews highlight that several methods to assess food freshness have been developed. Such methods are based on the measurement of food deteriorative changes associated with microbial growth and chemical changes.

(ii) **Machine vision**. Recognition methods embedded in computer vision systems can detect visible characteristics by analyzing food images captured with a camera-enabled device (e.g., a smartphone camera photo). They can be employed to determine data relating to the mass, weight and volume of a food product and to identify its food category and subcategory. However, several reviews highlight the existence of substantial obstacles to recognize food in complex cases, such as a home cooked meal or a composite plate [30]. Combinations of these methods in conjunction with databases of food knowledge (e.g., nutritional facts tables) and consumers' profiles can be applied to provide quantitative analysis of various food aspects (e.g., amount of calorie and nutrition in the food), even in a personalized manner. Furthermore, other contextual clues, such as restaurant location and menus, can be also utilized to augment or improve the information provided by the combination of these methods [31–33];

(iii) **Hyperspectral imaging**. Hyperspectral imaging (HSI) is an approach that integrates conventional imaging and spectroscopy to attain both spatial and spectral information from a food object. "The spatial features of HSI enable characterization of complex heterogeneous samples, whereas the spectral features allow a vast range of multiconstituent surface and subsurface features to be identified" [34]. Applications of this technology make it possible to analyze food quality, freshness, and safety, especially for fruits and vegetables Pu et al. [35];

(iv) **Odour analysis (e-noses)**. These technologies mimic the human sense of smell, by identifying and analyzing some food properties on the basis of its odour. The employed methods are based on an array of sensors for chemical detection of analysis of volatile organic compounds (VOCs) and a pattern recognition unit [36]. The sensing system consists of broadly tuned sensors (optical, electrochemical, and gravimetric) that are able to infer a variation of concentration a gas. Optical sensors work by detecting a shift in the emission or absorption of different types of electromagnetic radiation on binding with a desired analyte [37]; electrochemical sensors detect a variation of electrical conductivity of a gas while gravimetric sensors detect a variation of mass of a gas [38]. These technologies are mainly used to discriminate different food varieties for food authenticity and adulteration assessment [39];

(v) **Taste analysis (e-tongues)**. These technologies are based on analytical tools mimicking the functions of human gustatory receptors. Liquid samples are directly analysed without any preparation, while solids require a preliminary dissolution before measurement [40]. Like odour analysis systems, taste analysis tools include an array of nonspecific sensors and a set of appropriate methods for pattern recognition [41]. They are employed to identify variety or geographical origin, to detect adulteration, and to assess authenticity of many food products [42].

7. Conclusions

Today's consumers have more and more need of reliable food information for their food consumption activities to become aware of the wider consequences of decisions they make. Recent cases of adulterations, allegations of fraud and subterfuges that have invested food sector have increased this trend. Current conventional ways of providing food information (e.g., labelling, mass media) have limited chance to satisfy this need, as they are usually product/producer centered and driven by food producers and distributors that tend to reveal only information that suit their marketing approach.

As opposed to that, we have introduced a democratic and bottom-up approach that lets consumers be more food aware as helping them to make more informed decisions in their food related activities. This approach leverages on the superorganism and the capabilities of smart food technologies in determining physical, biochemical, and microbiological properties of food and beverages. At its core, there is a cooperative process that is aimed to foster collective food awareness, as letting a consumers' community share reliable information derived from scientific instrument measurement of food properties.

The main contribution of this paper is to envisage the organization of such a process, as well as a technological platform capable to support it. Moreover, in order to point out significant research outcomes potentially useful for developing the platform, we have conducted a survey of academic papers reviewing technical approaches for determining food characteristics and performances.

We conclude by addressing what we view as limitations and areas for further development of this article.

Firstly, we have presented only a framework in which details of the cooperative process remain unspecified. For instance, how to define a criterion for deriving a food class performance? When do we consider "collectively reliable" such a criterion? How do we empirically assess the cooperative process effectiveness? These are relevant questions when it comes to translating our framework into concrete guidelines for the platform design.

Secondly, all the reviews in our survey have been conducted by scholars and, thus, they have been concerned with research findings oriented to clarify or discover conceptual state of a technology. A more relevant contribution would be given by investigating current gaps between technology research and mobile food diagnostics tools already available. Identifying and understanding knowledge and application gaps is vital for researchers so they can recognize technical challenge, missing insight or pieces of complementary technology in order to move forward from research to development and viability of a platform for collective food awareness.

For us, the above considerations suggest a clear direction for future research. Together with a more extensive exploration of our process model, we need empirical work that reflects both technological and food consumer behaviour perspectives.

Appendix

See Table 5.

Table 5

Review Paper	*Reference*
r1	Qu, J. H., Liu, D., Cheng, J. H., Sun, D. W., Ma, J., Pu, H., & Zeng, X. A. (2015). Applications of near-infrared spectroscopy in food safety evaluation and control: A review of recent research advances. Critical reviews in food science and nutrition, 55(13), 1939-1954.
r2	Barbin, D. F., Felicio, A. L. D. S. M., Sun, D. W., Nixdorf, S. L., & Hirooka, E. Y. (2014). Application of infrared spectral techniques on quality and compositional attributes of coffee: An overview. Food Research International, 61, 23-32.
r3	Wang, L., Sun, D. W., Pu, H., & Cheng, J. H. (2017). Quality analysis, classification, and authentication of liquid foods by near-infrared spectroscopy: A review of recent research developments. Critical reviews in food science and nutrition, 57(7), 1524-1538.
r4	Wu, D., & Sun, D. W. (2013). Colour measurements by computer vision for food quality control–A review. Trends in Food Science & Technology, 29(1), 5-20.
r5	Li, J. L., Sun, D. W., & Cheng, J. H. (2016). Recent advances in nondestructive analytical techniques for determining the total soluble solids in fruits: a review. Comprehensive Reviews in Food Science and Food Safety, 15(5), 897-911.
r6	Fu, X., & Ying, Y. (2016). Food safety evaluation based on near infrared spectroscopy and imaging: a review. *Critical reviews in food science and nutrition*, *56*(11), 1913-1924.
r7	Porep, J. U., Kammerer, D. R., & Carle, R. (2015). On-line application of near infrared (NIR) spectroscopy in food production. Trends in Food Science & Technology, 46(2), 211-230.
r8	He, H. J., & Sun, D. W. (2015). Microbial evaluation of raw and processed food products by Visible/Infrared, Raman and Fluorescence spectroscopy. Trends in Food Science & Technology, 46(2), 199-210.
r9	Magwaza, L. S., & Tesfay, S. Z. (2015). A review of destructive and non-destructive methods for determining Avocado fruit maturity. Food and bioprocess technology, 8(10), 1995-2011.
r10	Uríčková, V., & Sádecká, J. (2015). Determination of geographical origin of alcoholic beverages using ultraviolet, visible and infrared spectroscopy: A review. Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy, 148, 131-137.
r11	Dai, Q., Cheng, J. H., Sun, D. W., & Zeng, X. A. (2015). Advances in feature selection methods for hyperspectral image processing in food industry applications: a review. Critical reviews in food science and nutrition, 55(10), 1368-1382.
r12	Gowen, A. A., Feng, Y., Gaston, E., & Valdramidis, V. (2015). Recent applications of hyperspectral imaging in microbiology. Talanta, 137, 43-54.
r13	Lohumi, S., Lee, S., Lee, H., & Cho, B. K. (2015). A review of vibrational spectroscopic techniques for the detection of food authenticity and adulteration. Trends in Food Science & Technology, 46(1), 85-98.
r14	Cheng, J. H., & Sun, D. W. (2015). Recent applications of spectroscopic and hyperspectral imaging techniques with chemometric analysis for rapid inspection of microbial spoilage in muscle foods. Comprehensive Reviews in Food Science and Food Safety, 14(4), 478-490.
r15	Xiong, Z., Xie, A., Sun, D. W., Zeng, X. A., & Liu, D. (2015). Applications of hyperspectral imaging in chicken meat safety and quality detection and evaluation: a review. Critical reviews in food science and nutrition, 55(9), 1287-1301.
r16	He, H. J., Wu, D., & Sun, D. W. (2015). Nondestructive spectroscopic and imaging techniques for quality evaluation and assessment of fish and fish products. Critical reviews in food science and nutrition, 55(6), 864-886.
r17	Schmitt, S., Garrigues, S., & de la Guardia, M. (2014). Determination of the mineral composition of foods by infrared spectroscopy: A review of a green alternative. Critical reviews in analytical chemistry, 44(2), 186-197.
r18	Fox, G., & Manley, M. (2014). Applications of single kernel conventional and hyperspectral imaging near infrared spectroscopy in cereals. Journal of the Science of Food and Agriculture, 94(2), 174-179.
r19	Hossain, M. Z., & Goto, T. (2014). Near-and mid-infrared spectroscopy as efficient tools for detection of fungal and mycotoxin contamination in agricultural commodities. World Mycotoxin Journal, 7(4), 507-515.
r20	Chen, G. Y., Huang, Y. P., & Chen, K. J. (2014). Recent advances and applications of near infrared spectroscopy for honey quality assessment. Advance Journal of Food Science and Technology, 6(4), 461-467.
r21	Damez, J. L., & Clerjon, S. (2013). Quantifying and predicting meat and meat products quality attributes using electromagnetic waves: An overview. Meat science, 95(4), 879-896.

Table 5: Continued.

Review Paper	*Reference*
r22	Cattaneo, T. M., & Holroyd, S. E. (2013). The use of near infrared spectroscopy for determination of adulteration and contamination in milk and milk powder: updating knowledge. Journal of Near Infrared Spectroscopy, 21(5), 341-349.
r23	Cheng, J. H., Dai, Q., Sun, D. W., Zeng, X. A., Liu, D., & Pu, H. B. (2013). Applications of non-destructive spectroscopic techniques for fish quality and safety evaluation and inspection. *Trends in Food Science & Technology*, *34*(1), 18-31.
r24	Zhang, X. (2013). Application of near infrared reflectance spectroscopy to predict meat chemical compositions: A review. *Spectroscopy and Spectral Analysis*, *33*(11), 3002-3009.
r25	Yibin, F. X. Y. (2013). Application of NIR and Raman Spectroscopy for Quality and Safety Inspection of Fruits and Vegetables: A Review [J]. *Transactions of the Chinese Society for Agricultural Machinery*, *8*, 027.
r26	López, A., Arazuri, S., García, I., Mangado, J., & Jarén, C. (2013). A review of the application of near-infrared spectroscopy for the analysis of potatoes. Journal of agricultural and food chemistry, 61(23), 5413-5424.
r27	Chen, L., & Opara, U. L. (2013). Texture measurement approaches in fresh and processed foods—A review. *Food Research International*, *51*(2), 823-835.
r28	Dale, L. M., Thewis, A., Boudry, C., Rotar, I., Dardenne, P., Baeten, V., & Pierna, J. A. F. (2013). Hyperspectral imaging applications in agriculture and agro-food product quality and safety control: a review. *Applied Spectroscopy Reviews*, *48*(2), 142-159.
r29	Feng, Y. Z., & Sun, D. W. (2012). Application of hyperspectral imaging in food safety inspection and control: a review. Critical reviews in food science and nutrition, 52(11), 1039-1058.
r30	ElMasry, G., Kamruzzaman, M., Sun, D. W., & Allen, P. (2012). Principles and applications of hyperspectral imaging in quality evaluation of agro-food products: a review. *Critical reviews in food science and nutrition*, *52*(11), 999-1023.
r31	Cozzolino, D. (2012). Recent trends on the use of infrared spectroscopy to trace and authenticate natural and agricultural food products. Applied Spectroscopy Reviews, 47(7), 518-530.
r32	Ellis, D. I., Brewster, V. L., Dunn, W. B., Allwood, J. W., Golovanov, A. P., & Goodacre, R. (2012). Fingerprinting food: current technologies for the detection of food adulteration and contamination. *Chemical Society Reviews*, *41*(17), 5706-5727.
r33	Zhang, R., Ying, Y., Rao, X., & Li, J. (2012). Quality and safety assessment of food and agricultural products by hyperspectral fluorescence imaging. *Journal of the Science of Food and Agriculture*, *92*(12), 2397-2408.
r34	ElMasry, G., Barbin, D. F., Sun, D. W., & Allen, P. (2012). Meat quality evaluation by hyperspectral imaging technique: an overview. *Critical Reviews in Food Science and Nutrition*, *52*(8), 689-711.
r35	Martin, C. K., Nicklas, T., Gunturk, B., Correa, J. B., Allen, H. R., & Champagne, C. (2014). Measuring food intake with digital photography. Journal of Human Nutrition and Dietetics, 27, 72-81.
r36	Sharp, D. B., & Allman-Farinelli, M. (2014). Feasibility and validity of mobile phones to assess dietary intake. *Nutrition*, *30*(11-12), 1257-1266.
r37	Ma, J., Sun, D. W., Qu, J. H., Liu, D., Pu, H., Gao, W. H., & Zeng, X. A. (2016). Applications of computer vision for assessing quality of agri-food products: a review of recent research advances. *Critical reviews in food science and nutrition*, *56*(1), 113-127.
r38	Pu, Y. Y., Feng, Y. Z., & Sun, D. W. (2015). Recent progress of hyperspectral imaging on quality and safety inspection of fruits and vegetables: a review. *Comprehensive Reviews in Food Science and Food Safety*, *14*(2), 176-188.
r39	Devi, P. V., & Vijayarekha, K. (2014). Machine vision applications to locate fruits, detect defects and remove noise: a review. *Rasayan J. Chem*, *7*(1), 104-113.
r40	Zhang, B., Huang, W., Li, J., Zhao, C., Fan, S., Wu, J., & Liu, C. (2014). Principles, developments and applications of computer vision for external quality inspection of fruits and vegetables: A review. *Food Research International*, *62*, 326-343.
r41	Dowlati, M., de la Guardia, M., & Mohtasebi, S. S. (2012). Application of machine-vision techniques to fish-quality assessment. *TrAC Trends in Analytical Chemistry*, *40*, 168-179.
r42	Rady, A. M., & Guyer, D. E. (2015). Rapid and/or nondestructive quality evaluation methods for potatoes: A review. *Computers and electronics in agriculture*, *117*, 31-48.
r43	Steele, R. (2015). An overview of the state of the art of automated capture of dietary intake information. *Critical reviews in food science and nutrition*, *55*(13), 1929-1938.
r44	Mahajan, S., Das, A., & Sardana, H. K. (2015). Image acquisition techniques for assessment of legume quality. *Trends in Food Science & Technology*, *42*(2), 116-133.

Table 5: Continued.

Review Paper	*Reference*
r45	Zhang, B., Huang, W., Li, J., Zhao, C., Fan, S., Wu, J., & Liu, C. (2014). Principles, developments and applications of computer vision for external quality inspection of fruits and vegetables: A review. *Food Research International*, *62*, 326-343.
r46	Banerjee, R., Tudu, B., Bandyopadhyay, R., & Bhattacharyya, N. (2016). A review on combined odor and taste sensor systems. *Journal of Food Engineering*, *190*, 10-21.
r47	Beltran Ortega, J., Martinez Gila, D. M., Aguilera Puerto, D., Gamez Garcia, J., & Gomez Ortega, J. (2016). Novel technologies for monitoring the in-line quality of virgin olive oil during manufacturing and storage. *Journal of the Science of Food and Agriculture*, *96*(14), 4644-4662.
r48	Jha, S. N., Jaiswal, P., Grewal, M. K., Gupta, M., & Bhardwaj, R. (2016). Detection of adulterants and contaminants in liquid foods—a review. *Critical reviews in food science and nutrition*, *56*(10), 1662-1684.
r49	Wang, Y., Li, Y., Yang, J., Ruan, J., & Sun, C. (2016). Microbial volatile organic compounds and their application in microorganism identification in foodstuff. *TrAC Trends in Analytical Chemistry*, *78*, 1-16.
r50	Balasubramanian, S., Amamcharla, J., & Shin, J. E. (2016). Possible application of electronic nose systems for meat safety: An overview. In *Electronic Noses and Tongues in Food Science*(pp. 59-71).
r51	Wiśniewska, P., Dymerski, T., Wardencki, W., & Namieśnik, J. (2015). Chemical composition analysis and authentication of whisky. *Journal of the Science of Food and Agriculture*, *95*(11), 2159-2166.
r52	Loutfi, A., Coradeschi, S., Mani, G. K., Shankar, P., & Rayappan, J. B. B. (2015). Electronic noses for food quality: A review. *Journal of Food Engineering*, *144*, 103-111.
r53	Sliwinska, M., Wisniewska, P., Dymerski, T., Namiesnik, J., & Wardencki, W. (2014). Food analysis using artificial senses. *Journal of agricultural and food chemistry*, *62*(7), 1423-1448.
r54	Peris, M., & Escuder-Gilabert, L. (2013). On-line monitoring of food fermentation processes using electronic noses and electronic tongues: a review. *Analytica chimica acta*, *804*, 29-36.
r55	Smyth, H., & Cozzolino, D. (2012). Instrumental methods (spectroscopy, electronic nose, and tongue) as tools to predict taste and aroma in beverages: advantages and limitations. *Chemical reviews*, *113*(3), 1429-1440.
r56	Ponzoni, A., Comini, E., Concina, I., Ferroni, M., Falasconi, M., Gobbi, E., Sberveglieri, V., Sberveglieri, G. (2012). Nanostructured metal oxide gas sensors, a survey of applications carried out at sensor lab, Brescia (Italy) in the security and food quality fields. Sensors, 12(12), 17023-17045.
r57	Cetó, X., Voelcker, N. H., & Prieto-Simón, B. (2016). Bioelectronic tongues: New trends and applications in water and food analysis. *Biosensors and bioelectronics*, *79*, 608-626.
r58	Wadehra, A., & Patil, P. S. (2016). Application of electronic tongues in food processing. *Analytical Methods*, *8*(3), 474-480.
r59	Alessio, P., Constantino, C. J. L., Daikuzono, C. M., Riul, A., & de Oliveira, O. N. (2016). Analysis of Coffees Using Electronic Tongues. In *Electronic Noses and Tongues in Food Science* (pp. 171-177).
r60	Jiménez-Jorquera, C., & Gutiérrez-Capitán, M. (2016). Electronic Tongues Applied to Grape and Fruit Juice Analysis. In *Electronic Noses and Tongues in Food Science* (pp. 189-198).
r61	Ha, D., Sun, Q., Su, K., Wan, H., Li, H., Xu, N., Sun, F., Zhuang, L., Hu, N., Wang, P. (2015). Recent achievements in electronic tongue and bioelectronic tongue as taste sensors. *Sensors and Actuators B: Chemical*, *207*, 1136-1146.
r62	Tahara, Y., & Toko, K. (2013). Electronic tongues–a review. *IEEE Sensors Journal*, *13*(8), 3001-3011.
r63	Yasuura, M., & Toko, K. (2015). Review of development of sweetness sensor. *IEEJ Transactions on Sensors and Micromachines*, *135*(2), 51-56.
r64	Gutiérrez-Capitán, M., Capdevila, F., Vila-Planas, J., Domingo, C., Büttgenbach, S., Llobera, A., Puig-Pujol, A., Jiménez-Jorquera, C. (2014). Hybrid electronic tongues applied to the quality control of wines. *Journal of Sensors*, *2014*.
r65	Chen, Z., Wu, J., Zhao, Y., Xu, F., & Hu, Y. (2012). Recent advances in bitterness evaluation methods. *Analytical Methods*, *4*(3), 599-608.
r66	Latha, R. S., & Lakshmi, P. K. (2012). Electronic tongue: an analytical gustatory tool. *Journal of advanced pharmaceutical technology & research*, *3*(1), 3.
r67	Rateni, G., Dario, P., & Cavallo, F. (2017). Smartphone-based food diagnostic technologies: a review. *Sensors*, 17(6), 1453.

Data Availability

All data generated or analysed during this study are included in this article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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