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WHAT'S IN MY DISH? – EXTRACTING FOOD INFORMATION THROUGH MOBILE CROWDSOURCING

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ABSTRACT

This paper presents the results of research work performed at the Luxembourg Institute of Science and Technology (LIST) evaluating crowdsourcing approaches for the acquisition of nutrition-related information. In particular, using an online crowdsourcing survey, we aimed at assessing the usability and user acceptance of a set of interaction options applied in different user-supported tasks in the context of semi-automated acquisition of food-related information with smartphones. In this context, the survey also explored the participants' attitudes towards food-related information and corresponding mobile applications.

KEYWORDS

Food information, ingredient lists, interaction options, online survey, semi-automated information acquisition, crowdsourcing.

1. INTRODUCTION

Food-related diseases like food allergies, food intolerances, diabetes and obesity are major public health burdens in EU countries. According to a World Health Organization (WHO) report from 2004 (Robertson et al., 2004), diseases with major nutritional determinants make up 41% of disability-adjusted life years among all diagnosed diseases. As an example of western population, food allergy sufferers make up 4% of German nationals (Zuberbier et al., 2004), and Rösch et al. show that most additional costs for sufferers of food allergies or food intolerances are related to the purchase of food (Rösch et al., 2011).

In parallel with the growing spread of smartphones, tablet PCs and other mobile computing devices, the m-health sector is gaining increasing relevance. The British National Health Service (NHS) has encouraged their general practitioners to "prescribe" medical apps to patients choosing from a list of well-proven applications, which for example support patients in managing chronic diseases, monitor certain bodily functions or give an overview of medical services in the patient's vicinity (http://mediacentre.dh.gov.uk/2012/02/22/gps-to-‘prescribe’-apps-for-patients). Food-related conditions – such as food allergies and intolerances, obesity, diabetes, etc. – are of special interest for use in these applications, as the number of affected people has been rising in the last decades and m-health approaches seem to be promising in this context. Patients affected by food-related diseases can be supported in their everyday lives based on monitored food intake data, e.g., as described by (Wald et al., 2004) or (Halamka et al., 2007). Given that in this case patients normally experience immediate benefits through the use of such health application use, they are expected to be more motivated to continue using them and to provide more complete and accurate information, which results in a higher degree of sustainability of the corresponding systems. A survey concerning the relationship between people's nutrition awareness and their BMIs has shown that “the more aware a participant was of nutrition, the more likely he or she was to be healthy” (Mankoff et al., 2002). Another review of consumer health informatics systems carried out by Gibbons et al. has demonstrated that applications providing personalized and adaptive user interfaces and functionalities as well as appropriate behavioral feedback based on the collected data have the most significant impact concerning the improvement of patients' health (Gibbons et al., 2009). In the medical context, there is also a high number of mobile applications being developed to support users in making food-related decisions or keeping food diaries, such as the Personal Allergy Assistant (PAA) (Arens et al., 2008). Commercial food-related mobile apps, such as MealSnap (http://mealsnap.com), DailyBurn (http://dailyburn.com), DietPicture (http://dietpicture.com), FoodCheck (http://www.lebensmittelampel.com), and many more, indicate the growing need for food- and health-related assistance, especially in mobile scenarios.

It is quite obvious that the quality of food-related assistance applications substantially depends on the quality and comprehensiveness of the corresponding food databases that these applications can access. Due to the fact that there are currently no official regulations concerning the electronic availability of food-related data, such as ingredient lists, none of the commonly used food product databases, like FDDB.info (http://www.fddb.info), Open Product Data (http://product.okfn.org) or EAN Search (http://www.decept.co.uk/ean-lookup) is actually complete, and therefore many service providers have developed their own custom food product databases (CalorieKing (http://www.calorieking.com), MyFitnessPal (https://www.myfitnesspal.com), MyNetDiary (http://www.mynetdiary.com)). Two types of food information can be distinguished: 1) product identifying data (e.g. product name, EAN number, brand or company name) and 2) food content information (e.g. ingredient lists, nutritional values, health claims, nutrition claims and logos) that characterizes certain attributes of the food items. One can further distinguish between food-related information concerning archetypical food (e.g. chocolate) and information concerning specific food products (e.g. Ritter Sport milk chocolate).

One popular approach to updating and extending a food-related database is to offer application users the opportunity to fill in missing information and thus to complete the database using crowdsourcing. The manual input of food-related data can, however, be a tedious task and users might refuse to do it if it is too laborious and they don’t see any direct incentives. To mitigate this burden, tools using optical character recognition (OCR) can be applied to automatically extract food ingredient lists from pictures of the corresponding product packaging. Such vision-based approaches are, however, error-prone, so that some manual steps are still required to be performed by the crowd users in order to achieve a correct final result.

In the present survey, we have focused on crowdsourcing of user-generated content, specifically concerning the extraction of ingredients and other (descriptive) food-related information specified as text or symbols on food packaging. In our previous work, we have developed a first prototype of a mobile user interface for semi-automatic extraction of food product ingredient lists (Leidinger et al., 2013). This mobile app was designed to allow interested users not only to retrieve information from a publically available food database (WikiFood: http://www.wikifood.eu) but also to provide new food product data to this database on voluntary basis. The data provision process was implemented in a semi-automated manner based on optical character recognition (OCR) (Leidinger et al. 2012), so that it still requires some manual input by the user. In the survey presented in this article, we explored different options for the implementation of these manual input steps with the aim to find an appropriate interaction design for the mobile WikiFood app that is most accepted by the users.

In the next section, we describe crowdsourcing approaches in the field of health and food. Following this, an experiment on interaction modes for the mobile acquisition of food-related information is described and its results are presented. Section 4 presents a mobile game approach for food information crowdsourcing, before summarizing the performed work and drawing conclusions in section 5.

2. CROWDSOURCING APPROACHES FOR HEALTH AND FOOD APPLICATIONS

The described research work explored the potentials of crowdsourcing for food data acquisition in the context of mobile food-related assistance. The work focused especially on possible incentives and convenient user interfaces aiming at motivating users to participate in providing valuable food information, resulting in both design guidelines as well as practical implementations of appropriate interfaces for food-related crowdsourcing. In the food-related assistance context, the tasks that deal with nutrition-related crowdsourcing encompass a) food identification, b) food ingredient recognition, and c) food amount estimation for both packed and unpacked food. The work presented in this article concentrated mainly on the crowdsourcing of user-generated content, especially the extraction of ingredient and other (descriptive) food-related information specified as text or symbols on food packaging.

The term "crowdsourcing" has initially been coined by Howe in 2006 (Howe, 2006), who defines it in his blog as *"the act of a company or institution taking a function once performed by employees and outsourcing it to an undefined (and generally large) network of people in the form of an open call*" (http://crowdsourcing.typepad.com/cs/2006/06/crowdsourcing_a.html). After having identified and analyzed 40 different definitions of crowdsourcing, Estellés and González have proposed a new integrating definition:

> *"Crowdsourcing is a type of participative online activity in which an individual, an institution, a non-profit organization, or company proposes to a group of individuals of varying knowledge, heterogeneity, and number, via a*

> *flexible open call, the voluntary undertaking of a task. The undertaking of the task, of variable complexity and modularity, and in which the crowd should participate bringing their work, money, knowledge and/or experience, always entails mutual benefit. The user will receive the satisfaction of a given type of need, be it economic, social recognition, self-esteem, or the development of individual skills, while the crowdsourcer will obtain and utilize to their advantage that what the user has brought to the venture, whose form will depend on the type of activity undertaken."* (Estellés and Gonzáles, 2012)

Noronha et al. (Noronha et al., 2011), present a system that performs nutrition analysis of food based on crowdsourcing approaches. The PlateMate system allows users to take photographs of their meals (packed as well as unpacked food) and exploits the human intelligence provided by Amazon Mechanical Turk (https://www.mturk.com/mturk/welcome) to estimate the nutritional values of the food present in these images. The goal of this application is to support people in logging and monitoring their daily food intake in order to increase their nutrition awareness. The PlateMate system comprises a management framework facilitating the crowdsourcing of complex tasks by decomposing them into manageable and verifiable Human Interactive Tasks (HITs), such as food item localization, food identification and estimation of portions. The evaluation of PlateMate has shown that it can estimate the calorie content of food items nearly as accurate as trained dietitians do. Moreover, most study participants considered PlateMate to be a more comfortable approach for maintaining food diaries compared to a manual food logging application as the PlateMate interface required fewer manual entries. In spite of its sophisticated task decomposition approach, however, the PlateMate system has the drawback that it does not provide any kind of task automation to support the crowdsourcers' work. The authors themselves state in their article that the application accuracy could be improved by combining crowdsourcing with machine learning, computer vision, personalization, and location information.

Another commercial crowdsourcing solution in the healthcare area has been launched in 2011 in the US. HealthTap (https://www.healthtap.com) is a web platform, which offers, personalized health advice to individuals based on health information crowdsourced by health experts. The relevant health information is derived from data entered by approved physicians and from information published in peer-reviewed medical journals. Apart from the provision of medical information, the health experts are also given the opportunity to rate the information provided by their colleagues. For end users, the application offers an easy-to-understand data visualization, which represents complex medical content by means of simple visual elements. In addition, the HealthTap platform also enables the building of a community of special interest groups encompassing both physicians and patients. In this context, HealthTap allows individuals to follow the physicians whose advice they find helpful and connect to individuals with similar medical conditions. In this way, both physicians and patients can benefit from participating in HealthTap: the patients by receiving valuable medical advice and the health experts by raising their own medical reputation and thus winning new patients.

Several research projects have pursued different approaches on the issue of automatically recognizing unpacked food items and the ingredients and amount of cooked dishes from images in order to enable appropriate recommendations. DietCam is a system for automatic dietary assessment for mobile phones, which takes as input three photos of the food item captured with the phone camera and estimates the type of food present in the pictures (based on previously trained SIFT features) and its amount (based on 3D reconstruction) (Kong and

Tan, 2012). At startup, the user has to take three pictures of a checkerboard pattern in order to calibrate the intrinsic camera parameters. Moreover, in order to enable food amount estimation, a credit card has to be present in all food images as a size reference object. This research project focuses rather on the image processing techniques for food recognition and does not involve any user input, except for the image taking process. Consequently, in cases of misinterpretation of the food images, it does not offer any error handling strategies. Similar approaches making use of color and texture features for food recognition without allowing the user to support the recognition process through additional input for disambiguation or error correction are proposed by (Arivazhagan et al., 2010), (Joutou and Yanai, 2009) and (Bosch et al., 2011). All these food recognition systems need a preliminary training phase with a set of appropriate food images, and most of them further require camera calibration and specific reference objects (e.g., checker board pattern, color and size reference objects) to be present in the analyzed food images in order to accomplish the recognition tasks. As they are fully automated and purely image based, the recognition accuracy of these applications highly depends on the lighting conditions during image acquisition and on the number and type of trained food items.

Maruyama et al. propose an approach to improving the classification process of food images taking into account the user feedback on the automatically detected results (Maruyama et al., 2010). The classification in this case is rather simple as it only discriminates between images containing food items and such that do not contain any food. However, the incremental personalization of the classification algorithm to the user's input seems to be a promising approach, which could be adapted for a more sophisticated food item classification or ingredient recognition.

Finally, Puri et al. propose an approach to refining the results of an image-based food recognizer by allowing the user to list out each of the food items present in a picture using spoken utterances (Puri et al., 2009). However, like in most previously introduced related work, the system by Puri et al. does not offer any further opportunity for error handling through the user.

Concerning the incentives influencing people's crowdsourcing behavior, Huberman et al. have empirically shown that, in crowdsourcing, productivity exhibits a strong positive dependence on attention (Huberman et al., 2009). By analyzing data from YouTube participants, they could demonstrate, among others, that the more attention a contributor experiences in a certain time period (measured as the number of views on the uploaded content), the more active this person becomes during the following time period (more videos uploaded). Based on their findings, Huberman et al. reason that the problem of having only a few digital content providers while the majority of others are only beneficiaries – which they refer to as the "tragedy of the digital commons" – can be overcome by *"making the uploading of digital content a private good paid for by attention"*, i.e., the motivation to participate in crowdsourcing can be increased through increasing attention on the provided content. This conclusion implies that attention could be used as a motivating factor also in the food-related data acquisition process.

Fundamental research on motivation has been carried out by (Ryan and Deci, 2000), who distinguish between two basic types of motivation, namely intrinsic and extrinsic one. They define intrinsic motivation as *"the doing of an activity for its inherent satisfactions rather than for some separable consequence"*. In this sense, enjoyment, curiosity or challenge are regarded as possible incentives, which motivate people intrinsically. In contrast to that, extrinsic motivation is "a construct that pertains whenever an activity is done in order to attain some separable outcome", i.e., extrinsically motivated behavior expects a certain kind of reward. The latter can be monetary, but it can also consist, e.g., in an improved social status or in the absence of certain sanctions. According to (Kaufmann et al., 2011), who explored motivation factors in the crowdsourcing context, intrinsic motivation can be either *enjoyment-based* (e.g. skill variety, task identity, task autonomy, direct feedback and pastime) or *community-based* (e.g. community identification and social contact), and extrinsic motivation can be classified as *immediate payoffs* (e.g. payment), *delayed payoffs* (e.g. human capital advancement) or *social motivation* (e.g. social obligation). These different motivation aspects can be considered when exploring possible incentives for motivating users to participate in mobile food-related data acquisition.

Considering the described related work, it can be observed that the problem of recognizing food items, their ingredients and further nutrition information (such as nutrition values, health claims, claims like "vegetarian", "vegan", "organic", "kosher", "halal", etc., which can be specified in textual or symbolic form) in a practical application is a demanding task which cannot be solved by merely applying image recognition techniques. The crowdsourcing approach, on the other hand, has shown to be efficient for obtaining food information from images. Thus, it was intended to combine optical data acquisition with crowdsourcing approaches for a more extensive food information acquisition.

Different input and output modalities and interaction paradigms for mobile devices have been explored. One possible approach was the incorporation of Optical Character Recognition (OCR) for a semi-automatic extraction of information printed on the food product packaging. The goal in this case was to explore how human-assisted computing in the context of food data acquisition can be realized to be simple and effective, in order to not discourage users from participating. In an ideal case, data acquisition would be smoothly and seamlessly integrated into existing food assistance processes requiring only minimal user interaction.

The research work focused on the following research questions concerning user interface design and crowdsourcing-based data acquisition in the context of food-related assistance on mobile devices:

- Which incentives could intrinsically and / or extrinsically motivate users to contribute to the mobile crowdsourcing of food-related data?
- How can mobile crowdsourcing be realized in specific contexts in order to obtain reliable and sound data?
- How can user interfaces for mobile food-related crowdsourcing be realized in an effortless and effective way in order to motivate user participation?
- How can techniques for error prevention, detection and correction be used to support user interaction and simplify the crowdsourcing process with the aim to increase motivation and data quality?

3. SURVEY ON INTERACTION MODES FOR MOBILE ACQUISITION OF FOOD-RELATED INFORMATION

In order to approach a large number of potential participants, we designed the study as an online survey, using the LimeSurvey framework (https://www.limesurvey.org). The interactive tasks described later in this article were implemented using JavaScript. The survey was provided in German. Potential survey participants were approached through nutrition-related mailing lists and forums.

At the beginning of the survey, the general context was briefly described and participants were asked a number of questions concerning their smartphone usage and their interest in and experience with nutrition-related apps. In the second phase of the survey, the participants were asked to perform three tasks representing the manual pre- and post-processing steps of the semi-automated product ingredient acquisition process, namely *text selection*, *result analysis* and *error correction*. For each task, three different interaction options were offered. These different interaction modes were illustrated with the aid of corresponding example videos. The participants were given the opportunity to test each interaction option as often as they liked, and finally, they were asked to rate the ease of use of each individual option on a scale from 1 (cumbersome) to 5 (effortless). Additionally, at the end of each task block, the participants were asked to compare the three previously tested interaction modes for this particular task and to rank them in order of their personal preferences. The order in which the different interaction options for each task were offered was randomized throughout the study in order to compensate for potential order-effect bias.

3.1 Text Selection Task

In a first step, the users are asked to select the area of an image containing the product ingredient list, so that it can be further analyzed by the embedded OCR system. The offered interaction options for completing this *text selection* task, illustrated in Figure 1, were as follows:

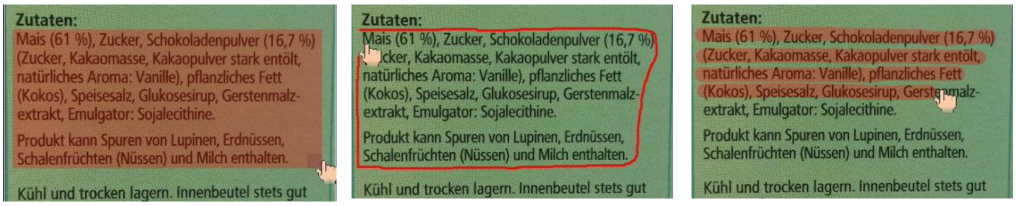

Figure 1. Interaction options for the text selection task: a) Rectangle; b) Circling; c) Highlighter

- *Rectangle*: By clicking on the upper left corner of the text region and dragging to the lower right corner, the user can draw a semitransparent rectangle overlaying the selected area. If needed, the size and position of this rectangle can be subsequently adjusted by the user by dragging the lower right corner of the rectangle (resize) or by dragging the entire rectangle (move).
- *Circling*: The user can define the region of interest by circling the text as if drawing with a pen.
- *Highlighter*: Each individual line of the relevant text can be marked as if using a highlighter.

3.2 Result Analysis Task

After the selected text is automatically analyzed by the system, i.e., the marked image section is translated into text through the embedded OCR engine, the corresponding result needs to be manually verified. Thus, in a first analysis step, the user is asked to classify each text item identified by the system as either "correct" (part of the ingredient list; marked in green), "misspelled" (part of the ingredient list, but not recognized correctly; marked in yellow) or "wrong" (not part of the ingredient list; marked in red). In this context, in the task definition, quantity statements (e.g. 20%, 15g) were explicitly declared as not being part of the ingredient list.

The three interaction options for the *result analysis* task are illustrated in Figure 2. In all three cases, the recognized text strings are displayed in a white box at the bottom of the screen, while the corresponding original text part is marked with a white frame in the image. The user can now decide if this text string is correct, misspelled or wrong, and perform the corresponding action to classify the string accordingly by applying the following interaction alternatives:

- *Click on symbols*: The user can click on one of three symbols (✓: correct; **?**: misspelled; **X**: wrong), which are displayed below the string.
- *Draw symbols*: The user can draw one of three symbols (✓, **?** or **X**) anywhere on the screen.
- *Swiping gesture*: The user can drag the box containing the text string to the right (correct), down (misspelled) or to the left (wrong). To indicate the appropriate swiping direction, each side of the text box is labeled with an arrow in the corresponding color.

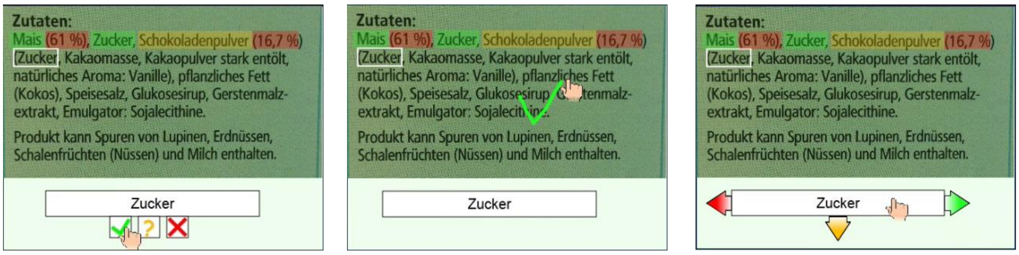

Figure 2. Interaction options for the result analysis task: a) Click on symbols; b) Draw symbols; c) Swiping gesture

3.3 Error Correction Task

Finally, the items which have been classified as misspelled in the previous step need to be fixed. To complete this *error correction* task, the users in our study were offered the following interaction options (see Figure 3).

Figure 3. Interaction options for the error correction task: a) Select option; b) Adjust text; c) Input text

- *Select option*: The users are presented a list of items from which they can chose the one that corresponds to the text marked in the image above by clicking on the corresponding text box.
- *Adjust text*: The misspelled string provided by the OCR system can be manually corrected by the user by means of a virtual keyboard.
- *Input text*: The user needs to manually enter the complete text item marked in the image by means of a virtual keyboard.

3.4 Results

In total, 54 subjects (25 male, 46%) completed the described online survey. The subjects can be classified in the following age groups:

- 18 – 29: 14 subjects (26%), 6 of which were male (43%);
- 30 – 49: 35 subjects (65%), 16 of which were male (46%);
- 50 and older: 5 subjects (9%), 3 of which were male (60%).

This gives a uniform distribution of male and female participants among the different age groups. The average time that the participants took to complete the survey was 18 minutes.

3.4.1 Questions on Smartphone Usage and Nutrition-Related Apps

Most survey participants (93%) claimed to have at least some experience with smartphones ("some experience": 27 (50%); "a lot of experience": 23 (43%)). Only 4 subjects (7%) stated to have no experience with smartphones.

Almost half (24, 48%) of the 50 subjects who stated to have experience with smartphones declared not using their smartphones in a supermarket environment. The others stated using smartphones in the following supermarket contexts: shopping list: 22 (44%), price comparison: 11 (22%), product comparison: 4 (8%), food product information: 9 (18%), mobile discount coupons: 3 (6%), games: 1 (2%), other: 4 (8%), e.g. recipes, customer reviews, product information. This question accepted multiple answers. Only 20% (10 subjects) stated to be using any kind of nutrition-related apps.

On the other hand, the interest in food product-related information was very high among the respondents. Ingredient-related facts, such as allergens, additives or preferred ingredients, turned out to be the type of information the study participants were most interested in (74%, 40 subjects). The country of origin of food products was important for 34 subjects (63%). About 44% (24 subjects) declared to be interested in information about nutritive values, such as calories, fats, sugar, carbohydrates, proteins, vitamins etc. The same number of respondents

(44%, 24 subjects) were interested in certification labels, such as “organic”, “fair trade”, “regional”, “animal welfare” or “GM-free”. Finally, 37% (20 subjects) expressed to be interested in food product-related information concerning a special diet, e.g. diabetic food, low fat, gluten-free, lactose-free, vegetarian, vegan, kosher or halal. A summary of these question results is presented in Figure **4**

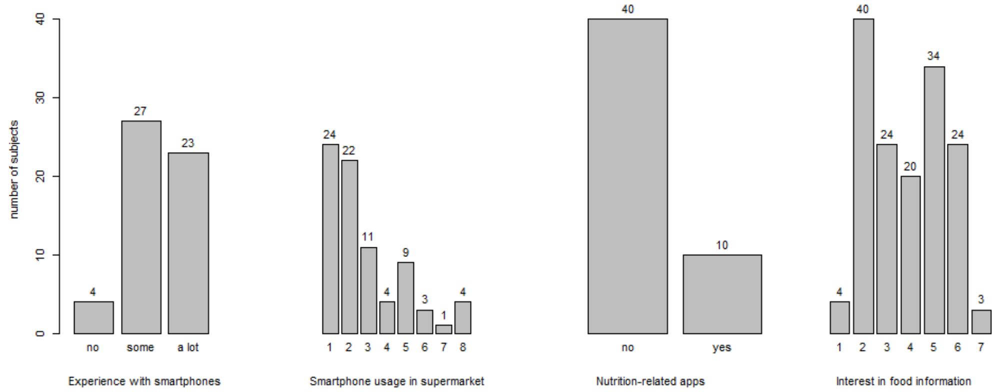

Figure 4. Results of questionnaire on smartphone usage and nutrition-related apps:

- Smartphone usage in supermarket: 1: No usage; 2: Shopping list; 3: Price comparison; 4: Product comparison; 5: Food information; 6: Mobile discount coupons; 7: Games; 8: Other;
- Interest in food information: 1: No interest; 2: Ingredients; 3: Nutritive values; 4: Special diet; 5: Country of origin; 6: Certification labels; 7: Other.

3.4.2 Evaluation of Interaction Modes for the pre- and post-processing Tasks

The results of the evaluation regarding the ease of use of the different interaction modes proposed for the three tasks concerning the acquisition of food product information are summarized in Table 1 (1: cumbersome – 5: effortless). This table also presents the results of the ranking order questions, with the figures representing the proportions (and numbers) of respondents who have placed the corresponding options first, second or third respectively.

Table 1. Individual ratings and preference ranking results for the interaction options for the pre- and post-processing tasks

	Mean	SD	Median	1st	2nd	3rd
Text selection task						
Rectangle	4.09	1.29	5	**72% (37)**	6% (3)	22% (11)
Circling	2.98	1.41	3	14% (7)	**67% (34)**	19% (10)
Highlighter	2.41	1.46	2	14% (7)	27% (14)	**59% (30)**
Result analysis task						
Click on symbols	4.04	0.97	4	**72% (36)**	28% (14)	0% (0)
Draw symbols	2.17	1.30	2	26% (13)	**52% (26)**	22% (11)
Swiping gesture	3.52	1.38	4	2% (1)	20% (10)	**78% (39)**
Error correction task						
Select option	4.67	0.78	5	**92% (45)**	6% (3)	2% (1)
Adjust text	3.37	1.26	4	8% (4)	**67% (33)**	25% (12)
Input text	2.87	1.36	3	0% (0)	27% (13)	**73% (36)**

The analysis of the rating results for the *text selection* task shows that there is a clear preference for the option *rectangle*, which is also supported by the corresponding ranking order results. For the same task, *circling* is only slightly more preferred than *highlighter*. However, both these options are clearly outperformed by the top-ranked one. This is also emphasized by the median value of 5 for *rectangle*, which shows that at least half of the respondents assigned this option the best possible rating.

In contrast, the results are less clear for the *result analysis* task. According to the individual ratings, *click on symbols* is the best-rated option, closely followed by the *swiping gesture* option, and *draw symbols* having a much lower rating. The comparative ranking, however, reflects a slightly different preference order, where *click on symbols* is still the top-ranked option, but *draw symbols* scored better than *swiping gesture*, which is at odds with the individual rating results. These to some extent contradicting results indicate that the respondents' opinion about these two interaction options was rather unsteady and they probably disliked both options.

Then again, in the *error correction* task, the results are quite unambiguous, showing a clear preference for the *select option* and a clear dislike of the *input text* option. In this context, it should be mentioned that an implementation of the *select option* is only feasible if the previously performed OCR-based text recognition and post-processing provide appropriate results, i.e., a list of terms retrieved from an ingredients dictionary that to a certain extent match the analyzed text chunk. However, the recognition rates of current OCR systems are not sufficiently high to guarantee that the correct term will always be present in the list of candidates, so that the user could simply choose it. Thus, in cases of poor OCR results, the *adjust text* or *input text* option has to be available as a fallback solution, i.e., there must be an opportunity for the user to specify that the correct term is not in the list of options proposed by the system and then to either adjust one of the optional terms, which might contain only minor errors, or to type in the correct term.

4. MOBILE GAME APPROACHES FOR FOOD INFORMATION CROWDSOURCING

In order to increase people's motivation to provide food-related information, individual tasks of the information acquisition process can be incorporated into some kind of simple game. In order to achieve appropriate user motivation, videogames often use elements such as skill scores, high scores, progress bars but as well virtual goods or awards. One of the most prominent mobile game-based crowdsourcing approach is Google's Ingress augmented reality game (http://www.ingress.com): While players strive to capture so-called portals which resemble specific landmarks in the real world, the game advises the player to take certain routes in order to reach those real world objects or places. Sometimes, the users are asked to take pictures on their way. Google uses the uploaded pictures as well as the accelerometer and GPS data of the device to improve services like Google Maps and Street View. Another successful example of such crowdsourcing games is the Digitalkoot (http://www.digitalkoot.fi) system, using the power of human computation for fixing errors in the Optical Character Recognition (OCR) process of old texts by integrating single error correction tasks as part of simple mini-games (Chrons & Sundell, 2011). The system was developed for the National Library of Finland in order to digitize papers more efficiently. It allows to crop individual words out of a scanned text and to hand them out to volunteers in the form of micro-tasks embedded in games. In this context, the authors developed two game approaches: “Mole Hunt” is used for the verification of the recognized words, while “Mole Bridge” allows capturing new words that the OCR was not able to detect. In “Mole Hunt”, moles appear holding signs that show pictures of scanned text chunks as well as the words recognized by OCR system. The player must then compare these word pairs and decide whether they match or not. If they match, the mole disappears. Correct answers grow a flower, wrong answers let the moles eat a portion of the flower. In “Mole Bridge”, players must build a bridge so that the moles can cross a river. To build such a bridge, the players are shown pictures of scanned text chunks that they have to type in correctly. As a result, small blocks are generated and placed side by side, which eventually create a bridge that enables the moles to cross the river. The offered text chunks represent words that have not been correctly recognized by the OCR system in the digitization process. The aim of the game is to get as many moles as possible to the other side.

Inspired through the Digitalkoot system and its gaming approaches, we have designed a prototype of a mobile game for capturing and verifying food product information in digital form. For this, the player can capture products using the mobile phone camera and answer questions that are generated by the game server. In order to motivate the players to always create new products, also a reward system has been implemented. The gaming idea is realized as a collectable card game in which playing cards are generated corresponding to food product records available in the database, where product attributes, such as nutrition values or ingredients, are used to compute certain card attributes (offensive and defensive points). Special cards can be applied to amplify attributes of an own card or to weaken attributes of an opponent’s card. In the course of the game, players are motivated to earn points either by capturing food product information (taking photos of ingredient lists or nutrient tables on product packagings) or by verifying (potentially erroneous) information from the food product database. For example, if a captured product is not yet present in the database, the user is asked to take pictures of specific food product elements (Figure 5). Figure 6 shows a verification dialog allowing the player to gain extra points through verifying specific product facts. Players can then apply these points to extend their own card decks by purchasing new playing or special cards. In this way, the process of providing food product-related information is coupled with the incentive of enhancing and upgrading one’s own card deck, which increases the chance of winning. More details on the game concept and its implementation have been documented in (Joerg, 2014).

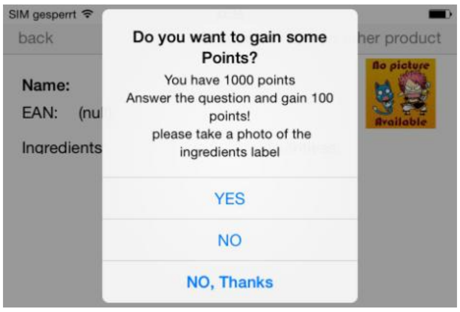

Figure 5. A new product has been captured. The user is asked to take a photo of the ingredients list.

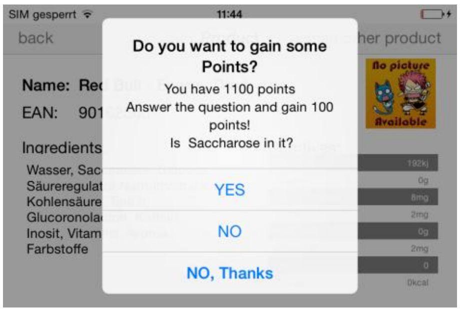

Figure 6. As soon as a product has been captured, verification questions are asked

This mobile game approach has been tested in a small-scale proof-of-concept trial. In a future work, we plan to test and improve the mobile game within a field study.

5. CONCLUSION

In this paper, we presented the results of research work performed at the Luxembourg Institute of Science and Technology (LIST) evaluating crowdsourcing approaches for the acquisition of nutrition-related information. Based on surveys and user studies, food- related crowdsourcing tasks have been identified and assessed concerning their need and suitability for human assistance. We described in detail the design and evaluation of an online survey exploring people's attitude towards food-related information and corresponding mobile applications. Additionally, the survey aimed at assessing a set of interaction options concerning different user-supported tasks in the context of semi-automated acquisition of food-related information with smartphones.

The evaluation of the results collected in the first part of the survey reveal that the vast majority of the respondents (more than 90%) are using smartphones, but only less than half of these persons are using their smartphones in a supermarket context. Moreover, although more than 90% of the respondents are interested in different types of food product-related information, the majority (80%) stated not to use any nutrition-related mobile apps. These findings – especially the large discrepancy in terms of the numerous participants interested in nutrition-related information and the small proportion of participants actually using nutrition-related apps – clearly indicate that nutrition-related assistance on smartphones is a domain of high interest, which nonetheless still requires considerable enhancement and further innovation in order to offer useful solutions for affected groups and the general public.

The interactive part of the study revealed that certain user interface interaction options were clearly preferred by the majority of the participants, indicating that it is these options that should be used in a future commercial mobile food acquisition application. However, the fact that the participants were performing the study tasks in a web browser instead of using a more realistic mobile app is to some extent a limitation of this study, which might have biased the study results. Therefore, in a next step, the preferred interaction modes can be combined in a prototypical implementation of a mobile app for semi-automated acquisition of food product ingredient lists, so that this mobile app can be tested in a more realistic setup to verify the results of our preliminary survey.

In a future work, the individual information acquisition and verification steps evaluated in the study and presented in this paper will be integrated in the described gamified approach of gathering and verifying food product-related information.

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