Augmented Shopping Experience for Sustainable Consumption using the Internet of Things

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Abstract—The digital world offers ample availability of data, both historic and real-time. While this capability has the potential for a better decision-making, the contrary can be the case for a human actuator. Information overflow causes mental overload rather than empowerment of choice. In the context of the traditional supermarket shopping for example, customers are exposed to unstructured and complex product information including ingredients, nutrition facts, product labels, and more. Processing all this information in the context of multiple sustainability aspects requires expert knowledge. On the other hand, the rise of digitalization and the Internet of Things can be used to assist and empower customers during this shopping process. However, an integrated solution is required to provide a high grade of usability and the crucial complexity reduction for customers. Therefore, we outline an IoT decision-support system which assists customers on the sales floor and enables a better decision-making according to personal preferences and sustainable consumption. It integrates an indoor localization system, a product information database and a ranking system considering the individual shopping preferences, where the latter is specified by the customer within an interactive smartphone application. The discussed IoT decision support system was deployed and tested in two retail stores. Its interaction with non-expert test participants was observed over months and the results are summarized in this contribution.

1 Introduction

With the rise of the Internet of Things (IoT), sensors are becoming ubiquitous. They provide real-time information and allow an "instant" overview of the state of a complex system. Actuators can automatically respond to input and consequently translate digital data into decisions and physical actions. While at the initial hype of IoT and cyber-physical systems, the smart fridge was a prominent example for automating in grocery shopping, this example never really took off. Currently, most grocery shopping is still happening in physical stores with limited digital support.

In physical stores, customers are overloaded with unstructured product information including ingredients, nutrition facts, product labels and more. The customers would need to filter out the best product regarding their personal preferences, which is a complex task and would require expert knowledge. The process of information gathering, evaluation and decision-making for each purchase is often rather simplified or totally neglected by customers. Complexity reduction is achieved through habitual buying decisions, which often results in purchasing behavior with a low awareness of sustainability. A more augmented shopping experience is required to shift towards a more personalized and potentially sustainable consumption behavior as we have earlier presented [1], [2].

Hence, herein we demonstrate how an IoT decision support system for shopping builds upon human actuation and vice versa. The presented IoT system (developed in the EU-funded project ASSET [3]) supports customers on the sales floor. It harnesses a sensor system for indoor localization, combines the output with the map and planogram of the retail stores, the retailers' product database, external product information, a customer's smartphone and the customer's individual preferences. The derived service comprises an individual product matching and rating that provides complexity reduction by (i) a structured overview of available products via sensor systems, (ii) by vertical integration into the retailer database and (iii) by applying a content-based personalized rating system for product short lists. In the following, we describe an example of the new augmented shopping process: The customer has to select a product group in which she or he is interested. Here, the first part of the complexity reduction happens by self-localization of the customer's smartphone and by providing a ranked list of product groups depending on their current distance to the customer's smartphone. Then, the customer has to select the product group of interest. This selection triggers the second and third part of complexity reduction. Product data corresponding to the selected product group are retrieved from a database, and a rating system ranks the products according to the customer's personal preferences and product data. The result is shown on the customer's smartphone by a list of rated products. Which of these products ends up in the shopping cart is the subject of human actuation.

The innovation of the presented solution is the establish-

- *This work has been supported by the European Union's Horizon 2020 research and innovation program under grant agreement No 688364, and by the LCM K2 Center within the framework of the Austrian COMET-K2 program.*
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ment of a complete service ecosystem that utilizes both IoT hardware via sensors as well as IoT software via interfaces, various available product data and supermarket maps, and in its reasoning based on the data linking product and preference information. As a complete practical IoT solution, the added value comes by smart and novel interconnection of several complex components. Within the outlined field tests we demonstrate and validate the solution and outline the user's responses. The IoT decision support system comes with an ontology to structure complex product information and provide a personalized aggregated view on-demand to customers, seamlessly integrated in the shopping process. The following sections contain an introduction of the proposed IoT decision support system, the field test results of the deployment in two retail stores, one in Estonia, one in Austria, and the customer feedback aggregated during the field tests. Finally, we present lessons learned and future direction concerning the IoT decision support system.

2 IoT Decision Support System

The implemented IoT system basically aims to reduce complexity by providing only relevant product information at the point of sale. It is built as a smartphone application (app). The app relates the customer's current position with nearby products, retrieves all available product information and matches the data with the customer's preferences. The latter covers Likert-type scale questions [4] on sustainability aspects such as health, environment, quality and social aspects. An overview of the system is shown in Fig. 1. The augmented retail store environment mainly consists of the product range provided to customers, the localization infrastructure and the customer's usual purchasing behavior. These facts have to be captured to provide input data to the rating system. The physical product range is supplemented by a virtual representation including digitalized product information. Furthermore, the retail store is supplemented by an infrastructure consisting of signal-emitting Bluetooth Low Energy (BLE) beacons. The localization algorithm uses measurements of the signals of these BLE beacons to determine the current position of the customer and the surrounding product groups. The customer's purchasing behavior is inserted into the app by preference scores. This information and an additional input from experts, crowd-based and related project data are used by the rating. The output is visualized to the customer by a ranked product list. The customer can use this list to choose a product that fits best to his or her needs. Furthermore, a behavioral analysis of the customer's individual-preference-driven choice of products can be used for potential actions: First, customers are encouraged to give feedback, which can be used to optimize the rating or remove data inconsistencies. Second, the customers may change their usual purchasing behavior because of an improved awareness on certain aspects of their needs. And third, the change of the purchasing behavior may cause a change of the product range of the retail store. Continuously applied, this control process creates a system which is able to adapt on changing needs of customers. This change can ultimately lead to more sustainable consumption.

From the implementation point of view, the presented IoT decision support system consists of four major elements

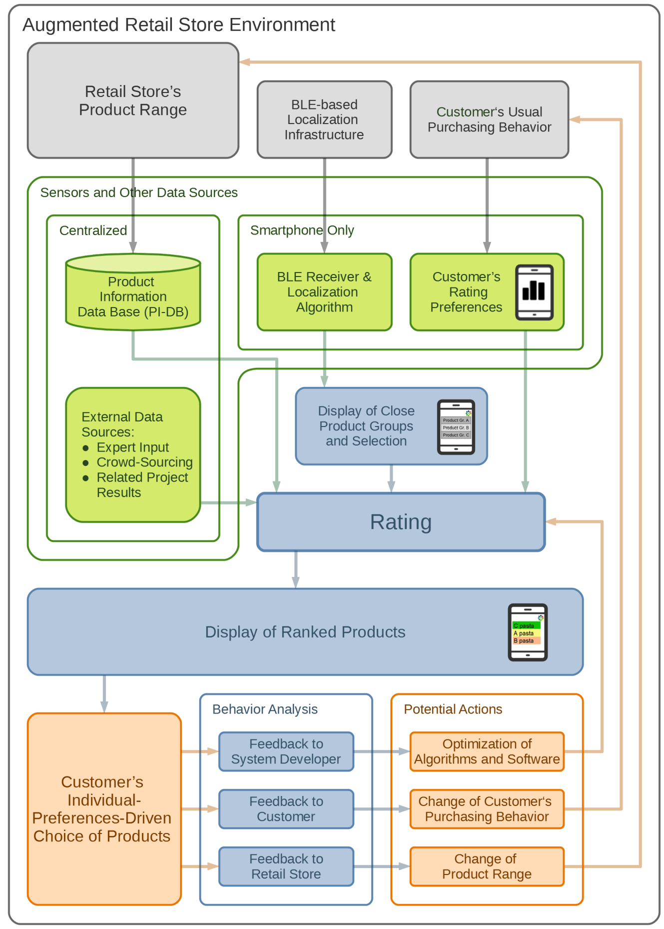

Fig. 1. System overview of the complete IoT decision support system which can be seen as a control process. The gray blocks represent the control path, the green blocks represent the sensors, the blue blocks form the controller itself and the red blocks represent the actuators. The set point of the control system is provided by the individual preferences of the customers.

which are: a localization system, a smartphone application, a product information database, and a personalized rating system. The technical realization of these elements is summarized in the following.

2.1 Localization System (LocSys)

The requirements on the LocSys were determined from a questionnaire with the involved stakeholders, which are retailers, customers and their customer representatives as well as the technology providers. As a result of this questionnaire, the LocSys ought to be transparent and easy to use for the customer as well as easy to install and cost-efficient for the retailer. This reduces the range of possible technical solutions [5]. Considerations of applicability, cost efficiency and privacy resulted in the choice of Bluetooth Low Energy (BLE) over other location sensing technologies: First, it can be used by most smartphones without any additional hardware, second, the installation costs are manageable, and third, it preserves the privacy since the position can directly be calculated on the customer's smartphone. The LocSys consists of two separated parts, as depicted in Fig. 1: First, a certain number of distributed BLE beacons compose the localization infrastructure and second, the BLE receiver

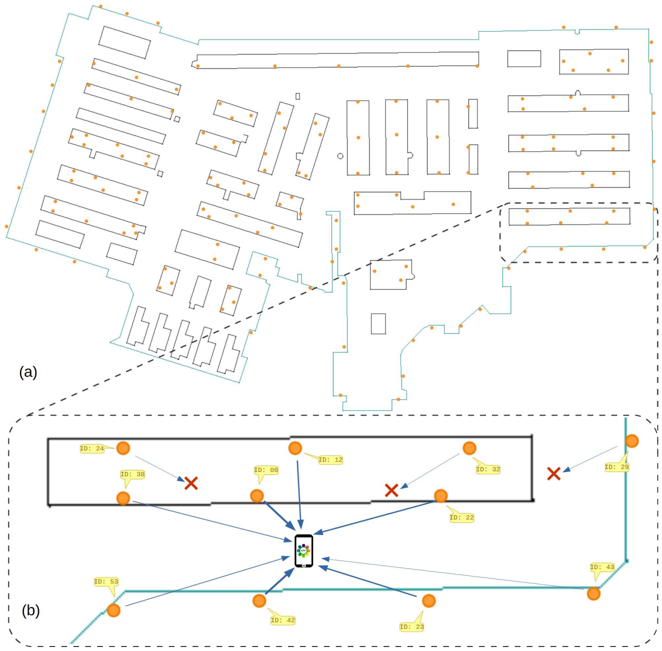

Fig. 2. Overview of the LocSys infrastructure in a retail store showing (a) a 2D map with the installed BLE beacons as orange dots and (b) a receiving example of RF packets by the smartphone to determine the current location. Each RF packet contains the unique ID of the respective BLE beacon.

that is part of the smartphones' hardware together with the localization algorithm which is integrated in the smartphone application. The BLE beacons are placed along the product shelves as shown in Fig. 2(a) for an Austrian retail store.

Each beacon can be seen as an IoT sensor node, which can be accessed by any smartphone supporting BLE. The main challenge is to aggregate a large number of signal measurements and to derive the location of the smartphone. Therefore, the beacon broadcasts radio frequency (RF) packets containing its unique ID, which can be received by each smartphone within a receiving range (see Fig. 2(b)). The smartphone measures the signal strength indication (RSSI) of each received RF packet. Based on one RSSI value, the localization algorithm can estimate the distance of the receiver to the corresponding beacon. Using the measured RSSI values from all beacons in range along with their corresponding IDs and known positions, the localization algorithm estimates the position of the smartphone inside the retail store considering geometric restrictions, respectively the two-dimensional map of the retail store. Similar approaches have been described earlier in [6]–[9].

An accurate self-localization of a mobile device based on very erroneous and noisy RSSI measurement data, resulting from hardware restrictions and the harsh indoor environment of a supermarket with shelves and other furniture mostly made of metal, is a rather challenging mathematical problem. The received signal strength can be related with the distance between the beacon and the smartphone via the path loss equation, but the direct approach of solving the system of equations algebraically or numerically for the position variables is prone to error propagation and hence cannot be recommended. Instead, to cope with the subsistent uncertainty, the localization problem is abstracted into a dynamic Bayesian network, where measurements and also positions are understood as observable and hidden random variables, respectively. Hence, by presuming Gaussian assumptions, RSSI measurement data from a beacon is interpreted as a realization sampled according to a normal distribution with appropriate standard deviation and its expected value functionally depending on the position variable via the path loss equation. Furthermore, a particularly suitable approximation of the localization problem is achieved by a discrete-time discrete-state Hidden Markov Model (HMM). Beside the described measurement model, an HMM also considers temporal dependencies among consecutive position states by modeling how the position can develop from one time step to another. The motion dynamics of a customer strolling through a supermarket are basically modeled by a Gaussian random walk, but under incorporation of geometric constraints represented by shelves, walls and other static obstacles. The latter geometry-awareness is crucial to the accuracy of the estimator and is achieved in two steps: first by quantifying the state space of possible positions down to a limited number of well distributed points or cells across the accessible part of the supermarket as illustrated in Fig. 4, second, by computing pairwise transition probabilities based on shortest inner paths between each two points and storing them in a matrix structure. The number of points is kept within reasonable limits, since the position error induced by the faulty measurement data predominates the error induced by the discretization to some degree. Having specified the parameters of the HMM, in particular by determining the state space of positions and modeling the measurement and transition distributions, the maximum aposteriori (MAP) trajectory estimate can be decoded with the Viterbi algorithm [10]. Additionally, some model parameters are adapted dynamically based on latest position estimates and RSSI measurements.

The computationally intensive incorporation of the geometry into the model parameters is performed only once for each supermarket according to their individual floorplan, as described in [11]. While the parametrization is defined and provided by the retail store in a preprocess step, the dynamic decoding of the MAP trajectory takes place solely on the smartphone. Compared to MAP position decoding, trajectory decoding results in a considerably better context of consecutive positions [12]. The apriori consideration of uncertainty, geometry and motion dynamics in the context of a probabilistic model results in robust position estimations. The accuracy has been determined in various field tests, with error statistics summarized in Table 1.

2.2 Smartphone Application

For the human-IoT interface, a smartphone application was developed and made accessible on Google Play Store. It allows the customer to specify preferences in four categories: environment, health, social and quality. Each category contains properties and/or statements that a customer can agree with or disagree with in various grades. These settings are individually determined and remain private (preferences are only available on the phone). For operation, a customer opens the app in the physical retail store, and the app identifies the local retail store using the unique BLE

IDs of the beacons. It calculates its position in a background service since the position accuracy increases with an increasing number of received RF packets from the beacons. The customer may then hit the button and the app presents the closest product groups to the customer's current position. Thus, the position of the product groups with respect to the floor plan of the retail store must be available for the app. Once the customer selects a product group, the app depicts the products available together with the derived individual rating in the form of a ranked list.

2.3 Product Information Data Base (PI-DB)

The foundation for complexity reduction is set via the product information data base. It comprises all available product data and the product-preferences ontology. The main source for product data is the retailer's merchandise management system. This data was preprocessed for further data aggregation. Publicly available databases such as openfoodfacts.org as well as wikirate.org were integrated as additional product data sources. Also, proprietary data was purchased from online retailers, as well as research cooperation agreements where applicable. Eventually, also product data was manually edited and added after inspection and research.

Even though product data from different retailers was obtained, data enrichment by cross fitting the different retailers' data was of little added value.

For linking the product-preference entities of the ontology, data from websites was used, such as Oxfam's behindthebrand.org. Further enrichment was obtained by conducting specific expert workshops, such as at the EthicalConsumer.org conference, as well as by collaborating with other EU-funded projects. The ASSET advisory board consisting of organizations in the area of sustainability, and customer support contributed in this regard. Finally, a hackathon challenge was conducted for further enrichment. The data collected forms the ontology, based on which the rating system operates.

Overall, the sources for the PI-DB were diverse, with different quality levels and objectivity. This compromise had to be made, as the given objective retailer's data was not sufficient for the different user perspectives. This status was pointed out to the field test users within their informed consent.

2.4 Rating System

The rating system provides a score in the range from 1 to 10 to all products identified close to the customers' location in the retail store. The rating system operates in a distributed fashion between the customers' smart phones and the PI-DB: The product information is treated as public information in the sense that they do not contain customers' private data. Therefore, computationally heavy processing of product information can take place out of the smartphones. In contrast, the personalization based on customer preferences and the received product data from PI-DB is performed locally on the phone. The rating is based on a content-based recommender system design, and its distributed design ensures maximum privacy protection, limiting nudging and increase of customers' trust on the system. The rating system comes along a reasoning engine that can explain and justify the rating values using the preferences and the ontology.

3 Deployment and Field Test

The IoT system was set up, deployed and operated in two retail stores in Estonia and Austria, respectively. From May to October 2018, the system was operational. By running the tests at two retailers, two totally different groups of test users were addressed. For example, participants in Estonia were rather young and considered themselves as technology-affine and more cost-conscious. Participants in Austria were already older, less technology-affine but rather aware about sustainability issues. Consequently, initial requests for test participation using leaflets, banners and signs brought significant downloads in Estonia, but obtained much less responses in Austria. To further foster downloads and to repeatedly initiate app usage, an information booth was set up near the entrance and manned several times a week on a regular schedule. Furthermore, a remuneration up to 100 Euros was hold out to recurring app users.

In total, the app was downloaded 378 times in Estonia, and 155 times in Austria. For analysis purposes, which is out of the scope of this article, we only used the data of customers that actively used the app at least twice within the testing period.

3.1 Preparation Effort

Besides inviting test participants, for each test location thorough preparation was required. In this section, the focus is on the field test preparation undertaken in the Austrian retail store.

The PI-DB used for the experiments in Austria was based upon the retailer's information system. Furthermore, data from external providers was used. However, for the vast majority of products, crucial data such as information on nutritional values, product packaging, the origin of the products and a product image had to be registered manually. In total, the PI-DB contained data of more than 5200 products. These products were assigned to appropriate product groups, for example "bread and bakery", "canned fruit", and so on. Based upon the retailer's existing system, 50 product groups were defined in total. The locations of these product groups on the floor were captured and integrated into the LocSys. Furthermore, 156 self–adhesive BLE beacons were mounted inside the retail stores in an unobtrusive way, for example underneath the shelves. Fig. 3 shows an unmounted BLE beacon with metric rule in cm for scale. Their locations and unique IDs were recorded and integrated into the LocSys.

3.2 Localization Results

During the field test, customers were asked to localize themselves in the shop to receive the closest product groups by pressing the "Find me" button. After the selection of a group, they receive their individual decision support in form of a ranked list. Each time a customer pressed this button, the location of the customer's smartphone was recorded as a find-me-activity. Note that this recording serves the system evaluation exclusively and the system can operate without it to preserve customers' privacy. A

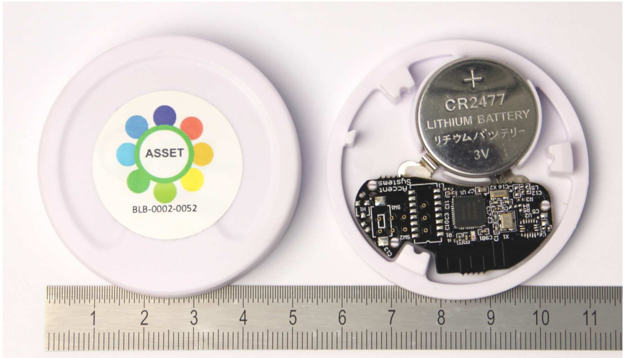

Fig. 3. A closed and an opened BLE beacon and a metric rule in cm for scale.

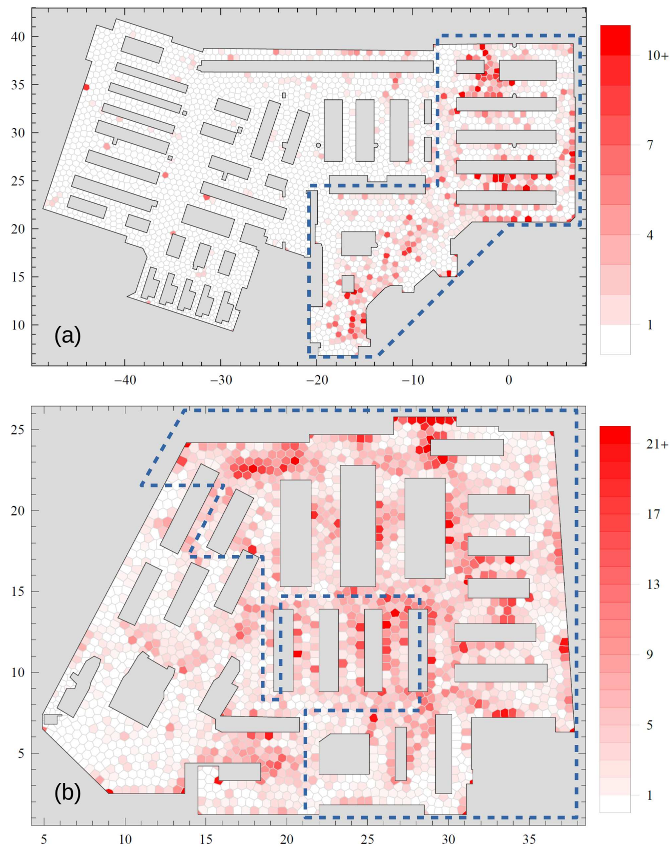

Fig. 4. Geometry-aware cell quantization and heatmap indicating the number of Find-me-activities in each cell of the Austrian retail store (a) and the Estonian retail store (b), respectively.

heatmap indicating the total number of find-me-activities at both retail stores during the whole field test period is shown in Fig. 4. The grey areas indicate places which cannot be entered (walls or shelves). Also the outer boundary contains shelves with product groups. The area surrounded by the blue dashed line roughly indicates the region with product groups which are included in the field test. During the field test, we recorded a total number of 1984 find-me-activities at the Austrian retail store and 7869 find-me-activities at the Estonian retail store.

Furthermore, the localization accuracy was evaluated using three different smartphones in a dedicated experiment at

TABLE 1
Localization accuracy in terms of RMSE using three different smartphones in a dedicated experiment at both retail stores.

	GS6	H6P	LG3	Average
Estonian Retail Store	1.395 m	1.544 m	1.509 m	1.483 m
Austrian Retail Store	2.001 m	3.277 m	2.150 m	2.476 m
Average	1.698 m	2.410 m	1.830 m	1.979 m

both retail stores. We have used an LG G3s (LG3), a Huawei Honor 6P (H6P) and a Samsung Galaxy S6 (GS6) as reference smartphones. Table 1 shows the root mean squared error (RMSE) of the different test settings. These tests were conducted by expert users, who followed a predetermined trajectory inside both retail stores. The differences between the actual positions on the trajectory and the calculated ones by the LocSys were used to determine the RMSE. The table indicates also that the performance can vary between smartphones and indoor environments. However, it is sufficient in any case for the envisioned application, where customers need to know their proximity to certain product groups in the supermarket: The achieved accuracy is at the same scale as the average width of individual product groups at the shelves.

4 Customer Feedback

The customer feedback is a result of the actuation functionality provided by the control model of the IoT decision support system, see Fig. 1. The rating system, playing the role of the system controller, determines the following actuation on customers: (i) It provides the required information to discover new products, potentially with a more personalized sustainable profile. (ii) It increases the overall awareness of sustainability aspects. This is implicitly a result of preference choices and the received rating values as well as the explicit reasoning engine that explains and justifies the rating values of each product using the designed ontology. (iii) Ultimately, a purchasing behavioral change is empowered by shifting shopping profiles to products with higher rating.

To track this actuation, the following methods are used during the field test: (i) An entry and exit survey, integrated in the app, that is answered by each participant before and after the field test respectively. (ii) Tracking smartphone activity (this means the number of clicks, changes of preferences, etc., to measure the exposure of customers to the product rating). (iii) Comparison of the shopping profiles before and after the field test using purchase information collected via the loyalty cards.

While presenting a systematic analysis of the results using behavioral theory and advanced statistical methods is out of the scope of this article, the results show that the actuation is effective: A statistically significant change is observed between customers that used the app and the ones who did not. More specifically, the likelihood to choose low-rated products decreases for customers with the app in exchange of products with the average rating value and above. Participants in both retail stores clearly declare the intention to choose highly rated products in their future purchases as well as they confirm a higher awareness on sustainability aspects after using the app.

5 Lessons Learned and Future Directions

By preparing and running the field tests, we discovered several challenges which had to be overcome. First, it is a challenging task to gather product information, since they are unstructured, and, if at all, stored in the retailers' databases with restrictive access rights. Maintaining the database manually is an interminable task, since the portfolio of offered products and their locations within the retail store undergo strong seasonal changes. We have experienced this at one of the two retail stores. Second, it is a tremendous workload to turn the unstructured product information into structured information which can be further processed. Third, it is very complex to design a flexible algorithm for the rating system, which is able to calculate a rating combining all the structured product information and the personal preferences. Different aspects and opinions from customers, producers, and experts have to be taken into account.

Regarding the LocSys, deploying it at both retail stores was not straightforward, since the provided map of the sales floor partially deviated from the real layout. This was only apparent during placement of the BLE beacons. Unfortunately, the LocSys integrates the product group positions within the retail stores, which was discovered as one of the major obstacles in the overall usability of the proposed IoT decision support system: Products of the same product group may be distributed across different shelves of the retail store, for example sweets are often placed at a designated section within the retail store and close to the counter, where customers have to queue. This may lead to a listing of rated products, which in reality are not located at a customers' current position. The only solution would be to rearrange products in the retail stores, which was not feasible during the field tests.

We have seen that the system is effective even in retail stores such as the Austrian one, which already actively targets customers with a sustainability profile.

The responsibilities regarding operating and maintaining the IoT decision support system are significant and challenging. Leaving the system manageability and governance to a single stakeholder may jeopardize the sustainable consumption paradigm with implication in privacy-preservation, tolerance to nudging and customers' trust. Alternatively, product data (PI-DB) could be treated as public good and made available by national or EU authorities. Producers could integrate their product data and keep them up to date. This participatory maintenance of the product data is vital for the overall system evolution. Furthermore, the functionality of the rating system will be disclosed to the public to increase customers' trust to the IoT decision support system. Again, the rating system should be maintained by an independent stakeholder, a consortium or ultimately by an open-source community. Moreover, the app could interoperate with the legacy systems of different retailers, this means their own loyalty apps, by exposing open interfaces. These interfaces should comply with recent guidelines for ethically aligned systems design in autonomous systems [13] to preserve a sustainability focus and prevent manipulative marketing practices. Finally, the LocSys itself should be deployed and maintained by the retailers themselves, since it is physically installed in their retail stores. However, the system could complementary operate with other technologies as well, for instance bar code scanning, for localizing products.

Retailers adopting such IoT solutions at large scale and in the long term can potentially achieve higher revenues by selling more products of higher value, by keeping customers longer in the stores and by easier exposing new products to customers with lower advertisement costs.

Future development may also target an increase of the augmented shopping experience by using 3D views, digital glasses or holograms as well as gamification. Furthermore, the decision support system could be also applied at virtual or online shops.

6 Conclusion

An innovative IoT decision support system was introduced and its components and overall functionality were outlined. Two field test deployments have shown the technological readiness of this approach to support the customers on the sales floor. The customers' smartphone located itself inside the retail stores, and the developed smartphone application provided a personal rating dependent on the specified individual preferences. One field test revealed significant purchasing behavior changes in favor of higher ranked products by using the app. Furthermore, surveys have shown that the customers' awareness on sustainability aspects increased upon app usage. We presented the lessons we have learned performing the field tests. For future project extensions, the manual information gathering and evaluation processes should be automated to provide a viable system in terms of operational costs. Retailers have to consider their support to (and naturally, their benefits from) an augmented shopping experience and adapt on future needs of their customers. The presented IoT decision support system aspires to settle a new IoT paradigm targeting to empower customers to act according to their attitute and to facilitate more sustainable consumption.

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