Indoor Navigation for Personalised Shopping: A Real-Tech Feasibility Study

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Abstract: Consumers in brick-and-mortar stores are increasingly expecting a personalised shopping experience and digital assistance in finding the right products. The retail industry has already undergone a shift towards more ubiquitous in-store technology but smart shopping assistance for consumers is notably absent. Whether physical product search, localisation and navigation could work with contemporary technology is an open question. In an applied research setting conducted on behalf of a retail technology provider, we have analysed the feasibility of introducing a smart shopping workflow based on product search and indoor navigation. In this paper we provide our findings with key contributions in workflow design, mobile application design, and technology fitting concerning localisation and notification of customers.

1 INTRODUCTION

In the retail industry, physical stores are turning from merely places to sell products towards spaces for consumption experience. Technology is a key driver behind personal recommendations and other contributors to that experience. The targeted use of technology turns shopping places into networked cyber-physical deployments with the involvement of access points, mobile devices, smart shelves and dispensers, electronic shelf labels (ESL) and point of sales (POS) stations, cameras and other sensors, and industry-specific software such as Enterprise Resource Planning (ERP) for dynamic stock management, label designers, rule engines and campaign dashboards (Kellermayr-Scheucher et al., 2022). The more technology is installed, the more options there are for exploiting it in terms of providing a smart shopping experience; yet at the same time, store owners are cost-conscious and prefer low-cost, low-maintenance solutions. Moreover, the added value of the technologisation of stores is not always clear to owners, although it becomes more clear when it translates into higher customer engagement and satisfaction. Letting the customer find the right product with technology assistance, and not missing out an opportunity of purchase, is contributing to the added value as evidenced by recent empirical studies (Gong et al., 2022; Linzbach et al., 2019).

The focus in this paper is specifically to investigate the feasibility of cost-effective augmented product search within the stores. Consumers interested in fully defined products, brands or less defined categories need assistance in expressing their interests, getting an overview situation about the availability, and receiving guidance through signalling and navigation to ensure that the chosen products end up in the basket. From a technology perspective, this requires a complex workflow encompassing an interactive device (usually the consumer's mobile phone), beacons for indoor positioning, and shelf labels associated to products. Building an unconstrained lab-level technology could address this problem but would not have chances of being adopted on the market. Instead, we opt for a real-tech approach, intending to design and validate a solution that works in the constrained environments found in real stores and matches real cost requirements.

Our key contributions in this space are: (i) An abstract workflow for personalised and privacy-

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preserving physical product search in a shop, (ii) a concrete mobile application to realise this search with hybrid notifications based on plausible technologies, and (iii) a validation in a lab environment with real-tech equipment and processes.

The paper is structured as follows: First, we review existing approaches towards product finding and indoor navigation, and introduce additional preliminary knowledge. Then, as first contribution we present a custom abstract workflow for personalised shopping that takes the technological constraints into account. Next, we explain the customer interaction with the mobile device and its backend service, and in this context introduce the application as second contribution and explain the indoor navigation algorithm which reproduces state-of-the-art results. Finally, we discuss the technology fitting, validating the personalised shopping with real-tech infrastructure as third contribution, outlining potential improvements depending on technological evolution, before concluding with remarks on possible adoption of the results in industry.

2 RELATED WORK

Research on digital shopping assistance especially around navigation to products in the physical space has been a niche topic for a long time but has seen progress in the recent years. For visually impaired people, assistance is obligatory and can be addressed with autonomous navigation based on computer vision, text recognition and text synthesis (Miralles et al., 2022) as well as combinations of computer vision and barcode detection (Deshmukh et al., 2022) and the combined use of accelerometer, gyroscope and magnetometer (Perera et al., 2020). The effectiveness of search increases with the data and suitable data structure modelling and visualisation, and therefore research has also been conducted on taxonomies and ontologies such as OntoNavShop (Ruijgrok et al., 2018).

Researchers have also investigated the use of connected devices in shops for other purposes beyond impairment such as smart shopping carts that follows the consumer autonomously (Heyns et al., 2021), technology-enabled personalisation (TEP) (Riegger et al., 2021), and the effects of using mobile devices with augmented reality on consumer behaviour (Chen et al., 2022). A previous work studied product-awareness shopping through RFID (Chen et al., 2014) but required the consumer to be already close to the product to retrieve its information. Many of the studies are conducted with an economics background and do not dive deep into technical matters of feasibility and realisation. In contrast, our work combines physical product finding and hybrid notification about products of interest, an aspect lacking from many of the proposed approaches, and establishes a technological grounding. The hybrid notifications exploit the growing deployment of electronic shelf labels, a technology already investigated from a psychological perspective in terms of revenue effects (Boden et al., 2020) and customer acceptance (Garaus et al., 2016) but not yet in the context of navigation.

From an innovation perspective beyond the research, indoor navigation and physical product search is increasingly commercialised by startups such as MobiDev and Hyper, and attracting the interest of large mobile platform operators and advertisement brokers such as Apple and Google.

3 PRELIMINARIES

Localisation of moving entities, such as customers in a store, is possible with multiple techniques. Recent research reports about a precision of around 2 cm that can be achieved with a high number of Ultra-Wide Band (UWB) nodes, for instance (Vey et al., 2022). High deployment cost, low mobile device adoption and less stringent application requirement however lead to more balanced decisions on localisation technologies. Moreover, privacy concerns have been raised in the camera-based first smart shopping discussions (Bermejo et al., 2020), even leading to broad media coverage[1], leading to further trade-offs. QR codes alleviate these concerns but require active scanning, similar to NFC tags. Bluetooth Low Energy (BLE) beacons are another contender in this space but require dense deployments to achieve tolerable precision and expose a highly device-specific performance (Fürst et al., 2018). BLE technology is affected by the influence of obstacles (Ližbetin and Pečman, 2023). Limitations of precision or acceptance have little effect on the use case analysed in this paper. In our high-level workflow, we do not make any specific assumption and instead merely assume the presence of a suitable localisation subsystem. Table 1 gives a high-level indication of advantages and disadvantages of the main method families.

Similar to the localisation, there is an open design space concerning the notification channels for searching as well as guiding and navigating users. Technologies should be inclusive, not requiring any particular device (assuming the search could be initiated with a

[1] e.g. Swiss railways shops https://awiebe.org/en/sbb-uses-cameras-for-facial-recognition/

Table 1: Localisation methods and technologies.

Method	Indoor	Cost	Precision
GSM tracking	yes	high	low
Camera tracking	yes	high	med-good
GPS/GNSS	no	low	medium
BLE beacons	yes	medium	med-good
BLE AP	yes	high	medium
UWB	yes	high	good
QR codes, NFC	yes	low	–

kiosk at the entrance or via a service robot), and be of low cost from the store owner perspective. The corresponding overview is given in Table 2. It is evident that using the personal mobile phone has the advantage of supporting both visual and audible notifications. Electronic shelf labels (ESLs) are less intrusive and, despite having a certain installation and maintenance cost as well as potential security challenges (Mandyam et al., 2023), can be a suitable choice if already installed especially due to their proximity to the products. Again, our workflow abstracts from the possible notification options and only assumes the presence of at least one.

Table 2: Notification methods and technologies.

Method	Inclusive	Cost
Mobile phone	no	low
Mobile scanner	yes	high
Earplugs	no	low
ESL LED	yes	medium (battery)
ESL pageflip	yes	low
Kiosk screen	yes	high

4 PERSONALISED SHOPPING WORKFLOW

This section describes our first contribution, the workflow that allows customers to search for a product in the shop. The workflow shall be characterised by combining personalisation, i.e. considering the consumer's search preferences, and privacy preservation, i.e. allowing anonymous use. These characteristics furthermore relate to the coupling of search and notification through temporarily assigned numbers or colours, depending on the notification channel, in order to support multiple concurrent physical product search activities within a store.

In conjunction with the various options for localisation and notification, the scoping of the workflow is determined according to Fig. 1. It connects the three main activities with the necessary data structures, indicating an initial data curation effort by the

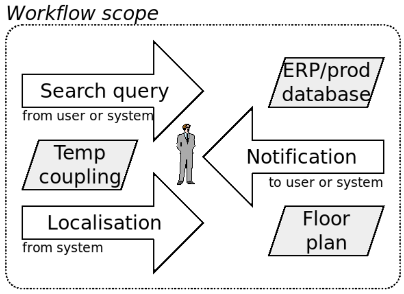

Figure 1: Scope for the personalised shopping workflow.

store owner which can however draw on what stores using shelf labels already have, thus not causing additional cost related to the input data.

Referring to the detailed workflow specification expressed as sequence diagram in Fig. 2, each phase will be described with greater attention to the most innovative technological components. The workflow either starts from the consumer who desires to search for a product in the shop, or by the system upon the consumer entering the shop with previous preferences saved. For simplicity, we focus on the first variant (Step 1 - User search product in the shop). The user types a text reference of the product (possibly using voice recognitition and speech-to-text conversion) and chooses the one that interests him/her from the list of available products, or a set of products matching a desired category. Again, for simplicity, we focus on the single product search case. At this point the application sends the data with the searched product to the Backend server (Step 2 - Receives user request through API). The server checks the availability of the product in the database (Step 3 - Looking for product availability). The database is updated by the shop owner or automatically from the shop management system. The Backend Server responds to the User App with a positive or negative ack of the research (Step 4a - Send Response). If successful, it returns the position of the product and some information. In parallel, the indoor navigation algorithm calculates the initial route to reach the product (Step 4b - Call indoor navigation system). Map and navigation information is then sent to the User App (Step 5 - Send map information).

The User App communicates via API with the positioning devices installed in the store; again for simplification, we refer to one option, BLE beacons (Step 6 - Exchange BLE info). The data exchange allows the indoor navigation algorithm to guide the user towards the shelves with the product (Step 7 - Navigate the shop). The User App is updated indicating the distance from the product which is recalculated during navigation (Step 8 - Calculate product distance). When the user arrives within "visibility" distance of

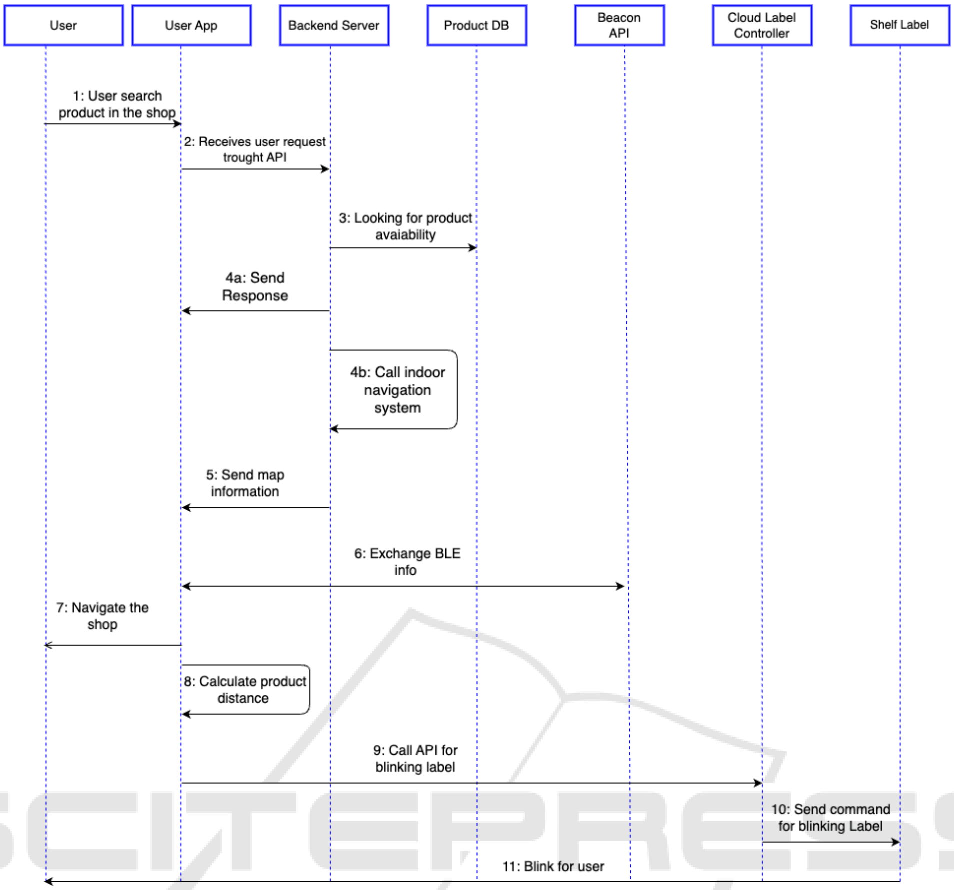

Figure 2: Sequence diagram of indoor consumer interaction.

the labels on the shelves, the User App via API passes the information to the Cloud Label Controller (Step 9 - Call API for blinking label). This component knows the position of the labels for each product. Moreover, depending on the chosen notification method, it is aware of the assigned color of the LED or number on the flipped label itself that the user expects to see. If the label exists and is working, the Cloud Label Controller sends a command to the label to make it flash or pageflip (Step 10 - Send command for blinking label). At this point, the label containing the information on the product sought flashes with a specific color or number which will be recognised by the User (Step 11 - Blink for user). The workflow described allows a user who is looking for a specific product in a shop to check its characteristics and availability and search for it on the shelves without wasting time physically searching for it. The flexibility of the workflow opens up the possibility of future developments that can, for example, suggest a product to the user on the basis of a profiling process and allow him/her to reach it, take it and paying the product directly in the app.

5 MOBILE INTERACTION AND NAVIGATION

This part of the paper discusses customers' interaction with the mobile application and underlying technologies. For the purpose of a better understanding of the technologies, the case of the search for a single product is reported. The functionality can be extended to a list of products. The mobile application is designed for the user's smartphone. Nowadays many people use smartphones on a daily basis. These devices are designed to work with different technologies including BLE-optimising battery consumption. There are three subsections through this section: Locate User, the part where the navigation process takes place; Search Product, where the customers search for a specific product they want to buy; and Navigate to Product, detailed information about the searched product. Each of those refers to a subprocess from the previously explained workflow, providing a concrete realisation for the mobile device side while remaining flexible for the infrastructure side in terms of beacons and ESLs. The interaction-centric discussion is based on a distributed software architecture connecting the necessary system components for search, localisation and notification as shown in Fig. 3.

5.1 Locate User

On the mobile application home screen, there are two main paths on with which customers interact: Locate User and Search Product. On the Locate User path, there is a straightforward process: indoor navigation using BLE and locating the customer on the floor map of the shopping store. Depending on the physical deployment, the Bluetooth signals may arrive from a ceiling-mounted access point; in this case, either a single AP provides angle-of-arrival support to determine the direction (and the user's mobile device supports the necessary BLE protocol version), or multiple APs are used for trilateration. Alternatively, if no AP is available or does not provide a suitable API, a mesh of BLE beacons can be deployed, calibrated and used for the same purpose, with configurable density to balance deployment cost and localisation precision. In our implementation, based on existing research we provide a Neural Network-based navigation algorithm which is competitive in accuracy. Combination of Bluetooth fingerprinting, a Neural Network, and a Kalman filter to predict the position of a user is used for the navigation, as expressed in Fig. 4. The algorithm is separated into two phases, which we refer to as the preparation and localization phases. For the preparation phase, training data is collected by moving a Bluetooth receiver device between as many different points on the shop floor as possible and collection signal strength (RSSI) measurements from the BLE beacons. This data forms our BLE fingerprint database and serves as the training data for a feed-forward neural network. It should be noted that by conventional terms this model is over-fitted, as all the training data is collected from the same location and so it would not work in a different location unless retrained. This is however the state-of-the-art in neural network-based fingerprint localisation, and the traditional alternative of multilateration based on the RSSI measurements (Cantón Paterna et al., 2017) also requires manual calibration on location. The model can then predict the location of the receiver (a user's smartphone) and the prediction passes through a Kalman filter for smoothing in between measurements to reduce the jittering of the position the user sees on their screen.

5.2 Search Product

The Search Product path in the application is designed for sending search queries to the database where all the products are stored, typically an ERP, but alternatively a Firestore database with generic schema that works out of the box in our implementation. Customers can easily search for any products they want on this page and then connect to the localisation to

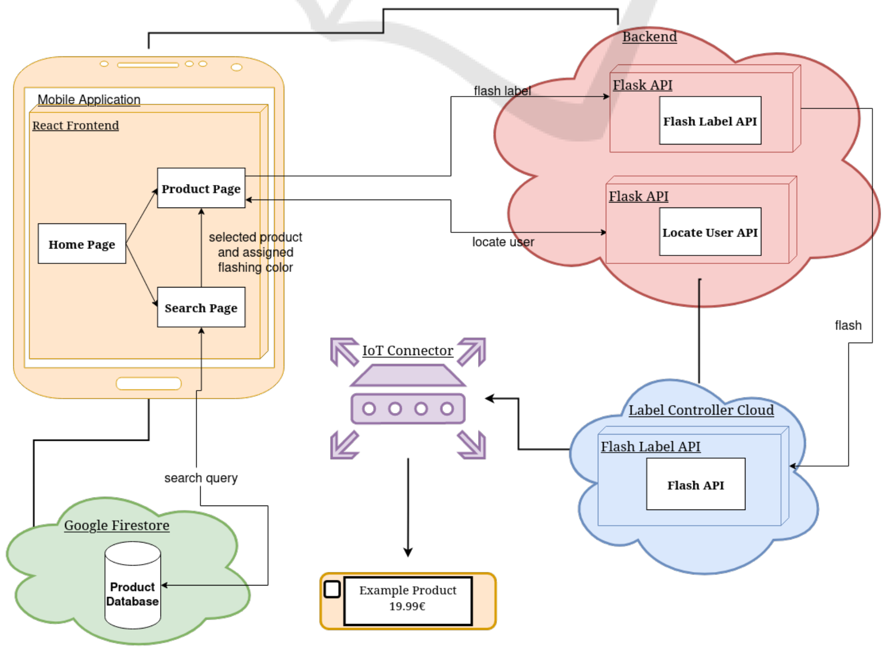

Figure 3: Mobile application architecture.

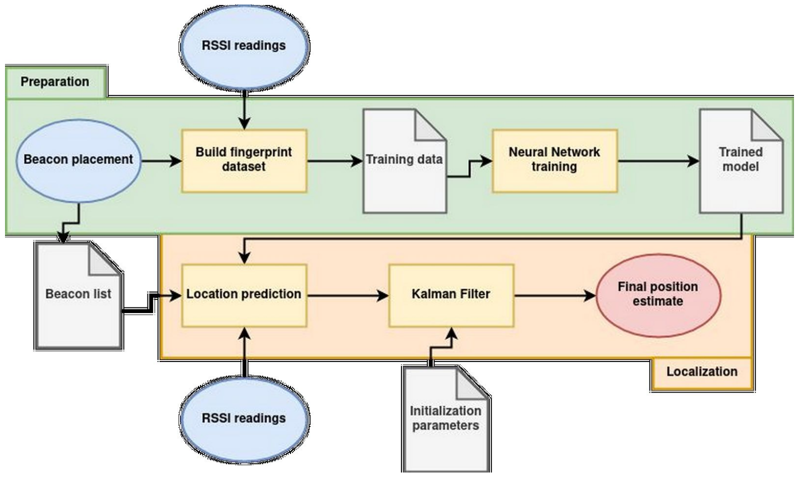

Figure 4: Beacon-based navigation algorithm.

correlate both the customer position and the product position. In addition to the search query feature of this page, the other important function is the personalised assignment of an anonymised results indicator, in the form of a colour or number related to the notification channel.

The ESLs available on the market and used in that research have limited flashing colours for flashing commands, and limited preloaded e-ink pages for pageflipping. To avoid customer confusion, each customer should have a unique flashing colour or display number to track the ELSs applying to the appropriate search results. Nevertheless, it is impossible to assign unique colours or numbers to each customer with the current hardware technology. Colours are usually limited to single-digit amounts, and e-ink pages to low double-digit amounts. Therefore, each customer will be assigned different colours or numbers temporarily during the product search, with the mobile application informing about the assignment. If all possible colours or numbers are occupied, customers will be informed and move to the standby list if they wish. Other possible approaches to increase the physical notification options beyond the phone itself are possible, but not currently implemented by us, such as combinations of colours and numbers, or different blinking LED frequencies or patterns.

A sample view of the Search Product entry page for a hypothetic store associated to our physical research lab premises, as outlined in the validation section below, is shown in Fig. 5.

5.3 Navigate to Product

Customers will arrive at the Navigate to Product Page if they search for a product and click that product on the Search Product page. The Navigate to Product step is the final yet potentially longer-run destination of the customer. Here, customers can find information about the product, such as product location on the floor map, distance from the product, price, and a descriptive image. In case no assignment was performed yet, the assigned colour or number will be first displayed on the Navigate to the Product page. The same assignment is then shown as a reminder on the Navigate to the Product page. In case of all colors are occupied, customers will see that in the pop-up screen, and if they wish, they will move to the standby list until a color becomes available. Even without assigned colour, the map-based navigation on the mobile device itself provides a suitable fallback, although it excludes customers without a phone or without the application installed.

Again, a sample view of this subprocess is provided in Fig. 6. It shows the floor map on the left side, with an overlay for navigation consisting of two to three main items of information: The current location of the customer, the location(s) of the product(s) resulting from the search, and possibly, although not presently implemented by us, a preferred path to collect all products, for instance based on the shortest path navigation. The addition of the path would be more useful in practice in larger stores or malls. On the right side, the page shows the next product in the results list along with navigation information and the assigned personalised indicator.

6 TECHNOLOGY FITTING

To determine the feasibility of our approach, we have validated it under realistic conditions, in a research laboratory for smart technologies, following a real-tech approach by using commercial technology

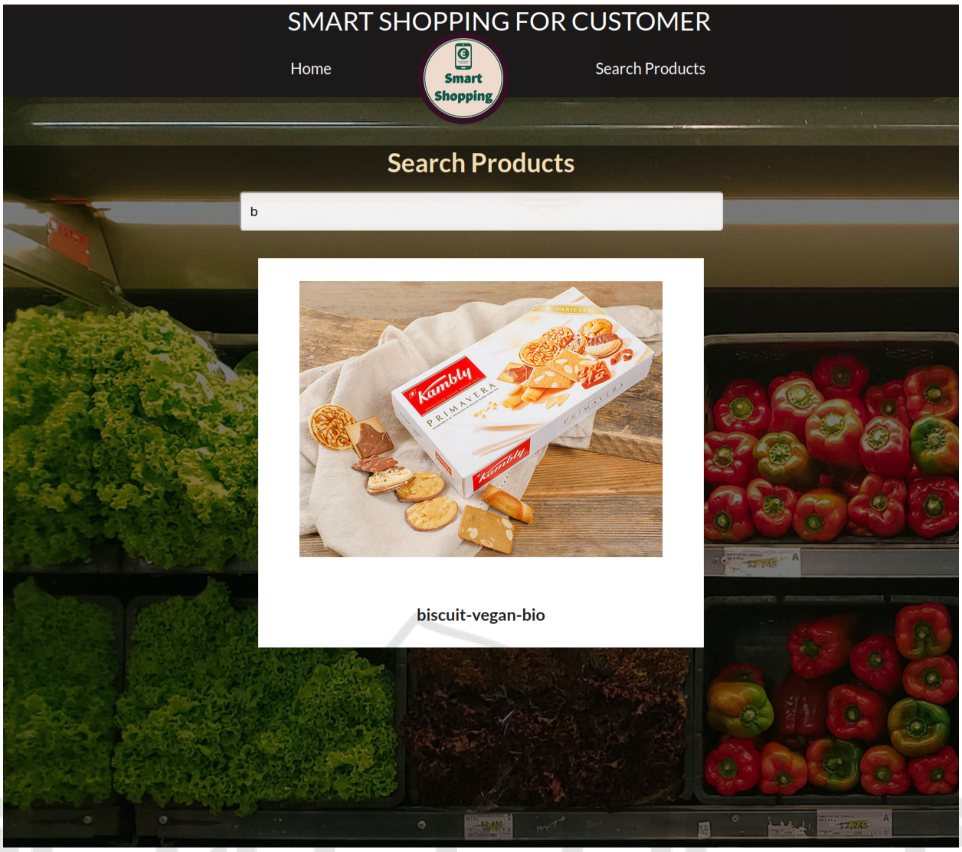

Figure 5: Search Product sample view.

widely deployed in stores today as integration points. This concerns especially the ERP to obtain product information, the ESLs, and the label controller to interact with the ESLs. Due to proprietary communication protocols, the tight coupling between ESLs and label controller is unavoidable, whereas the other technological choices permit a degree of flexibility. Table 3 contains the details on all chosen integration points. The table also informs about an approximate and rounded price point in € in order to facilitate the discussion on how economic the resulting solution can be especially for smaller stores. Of particular research interest in this context is the ability to replace existing functionality with an open source implementation that can be used to foster innovation. This analysis provides our third contribution.

6.1 Experiment Testbed

Our testbed setup resembles a small store with three longer shelves, a total of 30 ESLs in use to mark products, and 12 BLE beacons. The one-time hardware cost is around 200 € for the ESLs, 200 € for the IoT adapter, 700 € for the AP and 120 € for the beacons. In order to have greater flexibility for investigating mobile device behavior, we have used a Linux-based notebook instead of a mobile phone to interact with the system.

Table 3: Integration points (APIs, portals) for end-to-end validation and comparison.

Category	Solution	Cost
ERP	ExtendaGo	100 €/y
Label designer	Vusion Studio	400 €/y
Label controller	Vusion Optipick	350 €/y
Self-localisation	Mist API	300 €/y
Self-localisation	*our approach*	–
Mobile application	*our apporach*	–

By interacting with the ERP and generating label images dynamically on our backend system, both for the product and the numbered pageflip pages, we are in a position to discard the label designer. Moreover, by being able to tap into beacon-based positioning, we are also able to discard the existing localization API. Store owners who prefer to use those online platforms will still be able to do so with our implementation.

We set up the products on the shelves with a 1:1 mapping to ESLs. For labels that emit BLE signals, these could be used as a high-density grid for the navigation. However, most products on the market do not

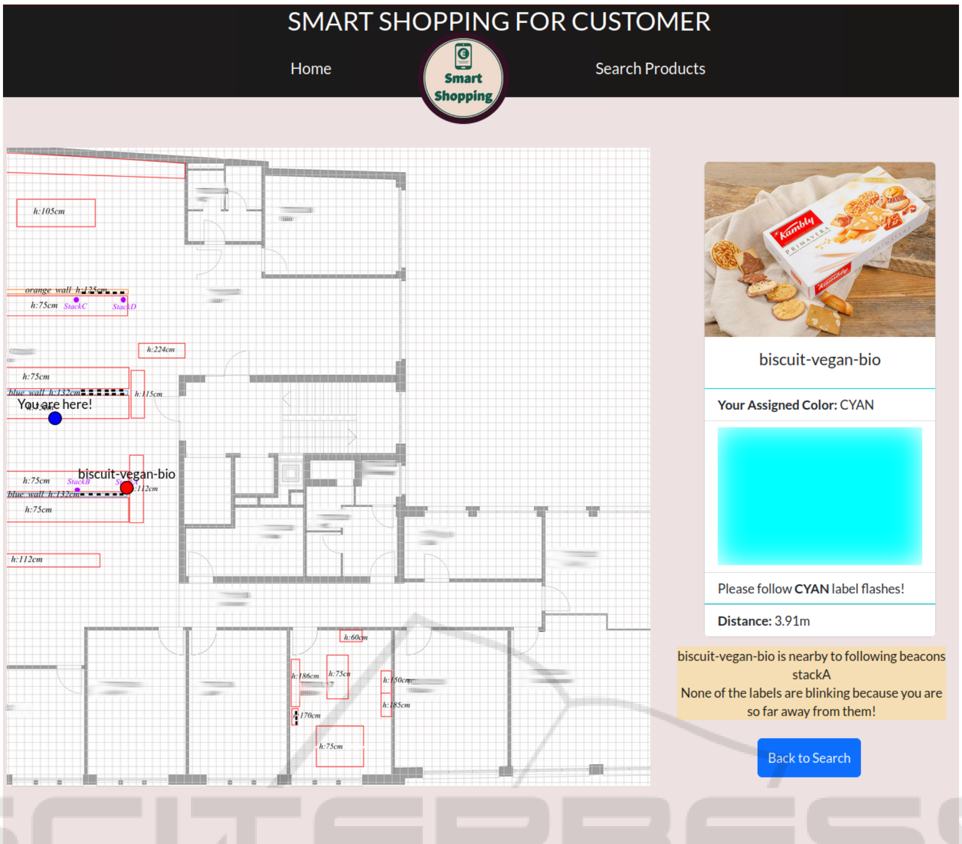

Figure 6: Navigate to Product sample view.

emit signals. Therefore, in our testbed, we assume one beacon per running shelf meter, with the aim to lure customers nearby the target shelf area. Once nearby, the local notifications such as label flashing and pageflipping can occur. An impression of the testbed is given in Fig. 7.

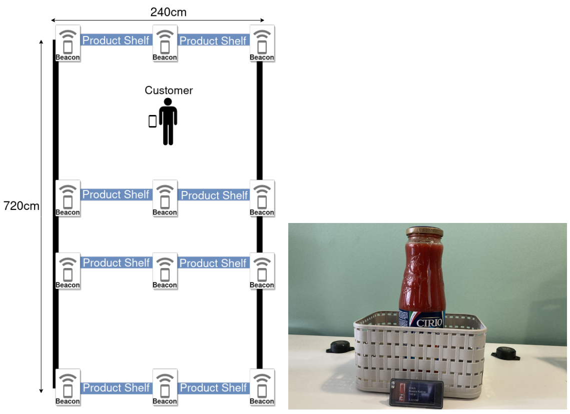

Figure 7: Schematic view of physical experiment layout, and impression of a product.

In the experiment environment, 12 BLE beacons were positioned in the research lab space at specific places to create a 4m x 7.2m grid spaced by 2m representing the shopping store along room dividers representing the shelves. The schematic grid is shown in Fig. 7, left side. RSSI measurements were then collected at different positions to collect a fingerprint dataset to train the Neural Network model. The dataset was used as training data to generate a Neural Network model that predicts customers' positions based on RSSI readings. The RSSI readings are collected in the background from the 12 beacons in the grid every 4 seconds. The frequency of 4 seconds was selected to ensure all beacons are given the chance to advertise and be received by the mobile device. The neural network inference itself is actually much faster. Since that technology will be used in shopping stores, the Neural Network model is purposefully overfitted to get more accurate predictions, meaning the model is only usable in the location it is trained in. Once the model is trained, it is used to predict a position which then passes through a Kalman filter to smoothen the value and rule out spikes. The output of the filter is the final output exposed by the localisation service. The final result represents the location of the customer on the floor map.

6.2 Software Implementation

The implementation of the web application used for validation purposes was built using several underlying technologies. For the front end, React JS was used to create the user interface. React JS is a widely used JavaScript library for building user interfaces and allows for the efficient and scalable development of complex web applications. The back-end service was built using Flask API, a microweb framework written in Python. Flask API allowed for the creation of RESTful APIs that could be used to interact with physical devices (label controller for ESLs, beacon/WiFi scanner). Requests sent through the React front-end were able to interact with these APIs to retrieve data from and send data to the IoT devices. Finally, the Google Firebase platform was used as the database for the web application. Firebase is a cloud-based database service that provides real-time updates, secure user authentication, and scalability, making it a reliable and effective choice for the web application's database needs.

The software implementation resulting from our research is available as open source (Sakman et al., 2023). We expect that it helps accelerating the setup of real-labs for personalised shopping and product search in the future.

6.3 Experiment Findings

Our findings cover both economic and technological considerations. Concerning the localisation, we can confirm that indoor navigation based on beacons is feasible for a shop environment concerning the navigation precision towards an area close to the target shelf, and that despite additional investment, the overall cost may be lower if such a deployment is planned from the start.

The mean positioning error of the model is typically 50–100cm (the resolution of the grid), although spikes occasionally occur (Step 6 - Exchange BLE info and Step 7 - Navigate the shop). The accuracy is generally higher than RSSI-based multilateration as used in the state-of-the-art and comparable with more advanced solutions such as angle-of-arrival-based detection (Paulino et al., 2022) or UWB (Vey et al., 2022) which is more expensive to install and also incompatible with the majority of customer smartphones. With further training rounds, which could be automated by piggy-backing on cleaning or restocking robots in stores, the precision can be expected to increase slightly.

Assuming a write-off period of five years for personalised shopping equipment, store owners today will have to invest 6850 € (including all hardware except for the beacons) to get production-grade support for introducing ESLs and for being able to access a raw positioning API. At this cost, they would still need an on-top solution for personalised navigation and physical product search. In contrast, our solution requires the beacons but is able to discard two existing platforms and the AP as mentioned above. If WiFi is required in the store, a more reasonably priced AP could replace it, with a presumed cost of 200 €. This results in a total cost of 2970 €, equivalent to 43% of the comparative investment, and with the added benefit of obtaining an integrated solution for search and navigation.

7 CONCLUSIONS

With our work, we have achieved to demonstrate technical and economic feasibility of physical product search and navigation to these products in stores. Through conscious technological choices, our result has proven to work in a real-tech environment, can be implemented with low-cost hardware and a minimum set of online platforms, and works with low power consumption. For the customers in the store, a privacy-preserving and inclusive experience is provided, increasing the likelihood to boost sales and revive physical shopping across target populations such as digital natives, elderly people or tourists. As a tangible result of our work, we have published an open source software implementation (Sakman et al., 2023).

Our research has focused on support for hybrid notifications including navigation on the mobile device. From a human-computer interaction perspective, additional modalities to receive nagitation advice and notifications could be built on top of our work. This includes augmented reality (AR) navigation to maintain the overview in larger shops with multiple separate shelves hosting the desired products. Our implementation is prepared for this modality and we are in the progress of building the first AR-based navigation as sketched in Fig. 8.

Our research moreover leads to a unique economic value proposition. According to our interation with store owners, especially for high-value stores there is a high need for such a solution. The economic potential is therefore in commercialising the research results. If a price tag of around 8000 € is aimed at, only slightly above the current mark but with better functionality, this would imply a possible range of more than 5000 €, divided into both the development cost and sales profits.

Figure 8: Ongoing augmented reality integration prototype.

In our follow-up work, we will therefore focus on the following directions. First, we will study the performance and price point for AR-based navigation. Second, we will investigate the scalability of the solution in larger stores, and the operational/maintenance perspective including the adoption of more sustainable technology such as solar-powered ESLs and beacons that are technically suitable for indoor shopping lighting conditions. As a third research direction, in order to support both customer and shop owner we will investigate additional features. For that matter, we expect an emerging mobile application to incorporate cutting-edge technology that enables users to search for a product and receive recommendations for related items. Once the customer has added all desired products to their basket, the application will generate the shortest walking path from their current location to the cash service, including all products in the route. The path precision will be increased by leveraging multi-sensor fusion and multi-perspective consensus voting (Gkikopoulos et al., 2022). Along this path, the application will suggest additional products nearby to the customer as they navigate through the market. If the customer accepts any of the recommended products, the application will automatically generate a new walking path with the same logic. This feature will provide a seamless shopping experience for users, helping them discover new products while efficiently navigating through the store.

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