Beacon-based Customer Tracking across the High Street: Perspectives for Location-based Smart Services in Retail

Completed Research

Jan H. Betzing
University of Münster – ERCIS, Münster, Germany
jan.betzing@ercis.uni-muenster.de

Abstract

Easy access to digital analysis of customer behavior and targeted advertising are principal advantages online retailers have over their stationary counterparts. Existing manual and digital means for monitoring customer behavior in high streets are expensive to employ and/or technically complex, making them unfeasible for many retailers. This paper shows an approach for individual stores and high streets as a whole to facilitate spatio-temporal customer data collection based on connected mobile devices, Bluetooth beacons, and an underlying multi-sided community platform. A framework of analytical perspectives on customer data regarding various levels of analysis and beneficiaries is conceived, which provides novel design knowledge on location-based smart services for customer behavior analysis and targeted advertising in high streets.

Keywords

Customer Behavior Analytics, Location-based Advertising, Bluetooth Beacon, Brick-and-Mortar Retail

Motivation

Online retailers and marketing companies track customers' every click to gain detailed insights into their online behavior and to personalize their service (Phillips 2016). Existing manual and digital means for tracking customer behavior within physical stores and across high streets, however, are expensive to employ and/or technical complex, making them unfeasible especially for small and medium-sized enterprise (SME) retailers and local owner-operated stores that do not branch at every other city (Bartelheimer et al. 2018). While these retailers often are vital for the attractiveness and individuality of high streets, they are already challenged by decreasing market share and increasing customer expectations because of positive experiences with e-commerce and omnichannel services (Betzing et al. 2018). So far, SME retailers rarely employ digital technologies to personalize their service and individually address customers, so e-commerce and large chain stores have a significant advantage (Bollweg et al. 2016).

In response, research investigates multi-sided community platforms for high street retail that enable groups of local retailers to provide their customers with a bidirectional digital channel (Bartelheimer et al. 2018). Customers access these platforms via mobile devices to interact with retailers and other customers while shopping, which makes them a viable channel for customer data collection and the provision of personalized location-based service (LBS). Furthermore, Bluetooth Low Energy (BLE) beacons, a pervasive technology for tracking customers' trajectories, by now reached market readiness (Varsamou and Antonakopoulos 2014). Beacons are small, low-range transmitters that are simple, and inexpensive to deploy and maintain, even in large deployments (Faragher and Harle 2015). These properties make the technology feasible also for SME retailers with limited financial resources and low digital readiness (Oosterlinck et al. 2017). So far, there is only a small body of knowledge on customer tracking across the realm of single stores (Bai et al. 2014; Lee et al. 2013; Oosterlinck et al. 2017) and literature has remained mostly silent regarding personalized LBS in retail that are enabled by spatio-temporal customer data (Bauer and Strauss 2016).

Against this backdrop, this work answers the following two research questions: (1) How can spatio-temporal customer data be collected on high streets? (2) How can this data be analyzed to yield value for high street stakeholders? To answer these questions, a design science research approach is followed (Peffers et al. 2007)

to make two contributions. First, this paper presents a novel conceptual framework that structures analytical perspectives and perceivable LBS on the levels of individual and aggregated spatio-temporal customer data concerning different beneficiaries of these services. In effect, it yields design knowledge on location-based smart services for customer behavior analysis and targeted advertising in high streets. Retailers, city managers, and third-party service-providers can adopt the presented concepts to improve their understanding of their customers' behavior on the store and high street levels to target their customers precisely and mitigate one of e-commerce and large retail chains' advantages. Second, this work presents a setting to collect spatio-temporal customer data using mobile devices and BLE beacons on high streets, whose implementation extends an existing community platform prototype (Bartelheimer et al. 2018).

The paper is structured as follows: Section 2 gives a background on community platforms in high street retail and on location-based customer analytics. Section 3 provides the research approach, whereas Section 4 shows, how spatio-temporal data can be collected. Section 5 illustrates the analytical framework and its perspectives. Section 6 provides information on the technical demonstration, while Section 7 discusses the framework, and Section 8 concludes with an outlook on the next steps in the research project.

Research Background

Multi-sided Community Platforms in High Street Retail

High street retail is a multi-sided market that includes among others local retailers and businesses, customers, cooperatives, local marketing organizations, and municipal representatives (Neirotti et al. 2014). In this market, both the high street and individual retailers are units of analysis because the "health" of the high street as a whole has a strong influence on the well-being of its constituents and vice versa.

Bartelheimer et al. (2018) conceptualize multi-sided community platforms in high street retail as a class of information systems (IS) that networks and provides digital service to different stakeholder groups and fosters the co-creation of value on high streets. As such, it constitutes a central IS to link actors, infrastructure, and data in high streets (Neirotti et al. 2014). This class of IS provides a set of stable core components (McIntyre and Srinivasan 2017), such as the technical infrastructure, general data structures, and client interfaces (e.g., web, mobile app) for various stakeholders. A generic community platform must be instantiated for a high street, and additional functionality in the form of digital services can be designed and implemented to cater to their individual needs. Exemplary customer-facing services provided through community platforms are retrieving information on businesses, products, promotions, and events nearby, rating and reviewing content, and getting in contact with local businesses. In Germany, we see a market uptake of community platforms with more than 150 local platforms active in 2018 (cima 2018). However, so far most community platforms focus on static information provision and do not collect information on customers' trajectories in high streets to provide personalized LBS (cima 2018).

Location-based Customer Analytics and Advertising

Location-based service (LBS) is an umbrella term for all services that use the absolute or relative geographical position of the service user as a resource in service delivery (Kelley et al. 2011). Location-based analytics, a subset of LBS, applies data-analysis techniques to low-level spatial user data to report high-level insights. Traditionally, this data has been gathered by manual traffic counting, photoelectric sensors, surveys, and videotaping (Underhill 2008), but WiFi- and Bluetooth-enabled smart devices now allow for location-based *smart* services, where the customers' devices become a part of the service system (Beverungen et al. 2017). BLE beacons are battery-powered, matchbox-sized devices that regularly broadcast predefined information to their surroundings. The beacon itself is independent and unaware of the presence of other devices (Faragher and Harle 2015). The signal spreads in an area around the beacon, inside the so-called geofence. BLE-enabled smart devices in the vicinity can identify the beacon's signal and instantiate interaction between the retailer and the customer (Schulz et al. 2016).

Most related approaches for location-based customer analytics do not include active interaction, but passively track signals emitted by the customers' devices throughout stores and shopping malls without the customers' knowledge (e.g., Lee et al. 2013; Oosterlinck et al. 2017; Schauer et al. 2014). These fingerprinting

techniques have three major drawbacks: First, the collection of personal information is subject to international data-protection regulations like the EU General Data Protection Regulation (GDPR), which require customers to actively opt-in to personal data collection (European Union 2016). Second, recent versions of mobile operations use obfuscation techniques as a privacy-enhancing feature (Martin et al. 2017), which interferes with reliable tracking. Third, location-based customer analytics often provides the foundation for location-based advertising (LBA), but fingerprinting can identify only a few of the customer's contextual parameters. For example, Lee et al. (2013) infer the customer's current activity from trajectories, and Kim et al. (2011) use visit patterns to predict the customer's next movements. Both approaches provide LBA but do not take into account customer segments, interests, and demographics—information that is usually gathered in traditional customer behavior analyses and targeted advertising (Underhill 2008).

Against this backdrop, this research refrains from passive fingerprinting but actively incorporates customer data collection in a community platform, where customers can consciously opt-in and freely provide their contextual parameters. Data is not collected for the benefit of a single store or mall operator but to enable LBS that benefit multiple actors, including customers, in the high street.

Research Approach

This research follows the mission of design science research (DSR) to construct socio-technical artifacts that solve organizational problems (Gregor and Hevner 2013). It is part of the consortium research project *smartmarket*^{2} on community platforms in high street retail (Österle and Otto 2010). This paper addresses a particular class of problems—those related to actively monitoring customers' trajectories in high streets.

In keeping with Peffers et al.'s (2007) DSR process, first, the *problem* is identified, and the research is motivated. Whole high streets in general and SME retailers, in particular, are challenged by decreasing market shares and increasing customer expectations. SME retailers rarely have access to customer behavior analytics and targeted LBA with which to personalize their services and improve their customers' experience. The *underlying problem* is a lack of easy and inexpensive means for SME retailers to monitor their customers' behavior while they are in their stores as well as in other stores and community spaces. Subsequently, the *objectives of a solution* are derived (Peffers et al. 2007), informed by kernel theories on community platforms in high street retail and LBS. As for *design*, the DSR process yields two artifacts. First, design knowledge in the form of a conceptual framework has been created, which structures analytical perspectives and perceivable LBS based on spatio-temporal high street customer data. Second, customer data collection through BLE beacons has been *implemented* as an extension to the *smartmarket*^{2} prototype. An artificial formative evaluation strategy was chosen to *demonstrate* the technical viability in a laboratory setting (Venable et al. 2016). The framework has been iteratively designed and tested using feedback from interviews with exemplary customers, SME retailers, a community platform provider, and city managers of two German cities, as well as feedback from workshops with retail experts. Currently, the framework guides the prototypical implementation of the proposed LBS, which will be subject to a holistic *evaluation* in the near future.

Customer Data Collection

BLE Beacons on the High Street

The technical prerequisites for collecting spatio-temporal customer data in high streets include rolling out BLE beacons, setting up corresponding data structures in the back-stage IS, and providing customers with a front-stage mobile app that collects the data.

At first, participating retail stores are equipped with BLE beacons that broadcast a predefined payload. The Apple iBeacon standard is selected, which works with all major mobile operating systems. Its payload consists of a universally unique identifier (UUID), major and minor values, and a received signal strength indicator (RSSI) (see, e.g., Schulz et al. 2016; Varsamou and Antonakopoulos 2014). In the design, the UUID is identical for all beacons in a particular deployment, which allows the user's smartphone to perform a local look-up on a hard-coded UUID table to identify relevant beacons without relying on an online database (Schulz et al. 2016). Major and minor values are used to distinguish among retailers and beacon intents (purposes). Figure 1 shows that the *entrance*, *point of sale (PoS)*, and *promotion* beacons are distinct.

Entrance beacons are installed at the store entrance(-s) and broadcast at high signal strengths to cover the public space in front of the store. Beacons at the PoS identify customers who visit the store and may have bought something. Promotion beacons, used as triggers for LBA, are attached to specific promotional displays and use low signal strength to cover only a small area.

Based on the RSSI, clients can calculate their distance from the beacons. Nevertheless, studies have identified robust errors in these calculations that result from signal strength attenuation, interference, and multipath propagation (Bai et al. 2014; Faragher and Harle 2015). While these errors complicate indoor navigation scenarios, LBA and behavior analyses have lower accuracy requirements, so instead of precise distance estimates, the ranges defined in the iBeacon standard (near, immediate, far) are recorded.

Embedding into the Community Platform

LBS extend and build upon the prototypical core community platform *smartmarket*[2] that already has central functions like master data management for the stakeholder groups (Bartelheimer et al. 2018). Figure 2 depicts an excerpt of the platform's data structures, which are extended to store spatio-temporal customer data and relate it to the existing objects. Beacons are registered with the community platform before deployment. Each beacon belongs to a specific store of a specific retailer (since some retailers might operate more than one branch within the deployment). Retailers define the intent (purpose) of the beacon and can specify a precise beacon location. During registration, customers are asked to provide (voluntarily) their age group, ZIP code, and gender as demographic context. Customers also select their interests from a predefined list (e.g., beauty and care, books, and electronics). High street customers take part in the community via a mobile app that they use to browse stores and products in their vicinity, rate and review retailers and products, get promotions, and interact with retailers and other customers in the service ecosystem (Bartelheimer et al. 2018). The app is now extended to collect customer data in the background. When a customer first starts the app, he or she traverses an onboarding process that explains the app's main benefits and details data collection and processing practices in accordance with the EU GDPR (European Union 2016). Then the user is asked for consent to the data practices, to enable Bluetooth, and to authorize access to beacon data.

When a customer enters or leaves the geofence of a beacon that belongs to the community platform, the smartphone sends the beacon payload, timestamp, fence transition, measured distance range, and the beacon's battery status to the platform's back end. On the server side, the transaction is associated with the corresponding beacon and customer. Most beacon events are cached in the client app and are sent periodically in bulk to limit potential battery drain. Promotion beacon sightings are directly transmitted since they can be used to trigger targeted LBA while the customer is near the promotion. Customers' locations are tracked in close distance to the beacons only to promote a modicum of privacy.

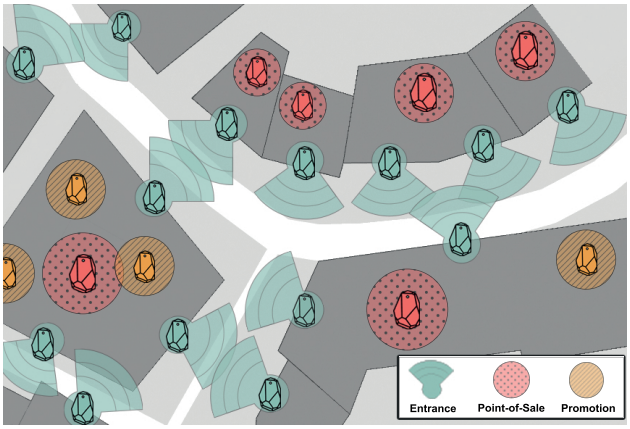

Figure 1. High Street with Beacons

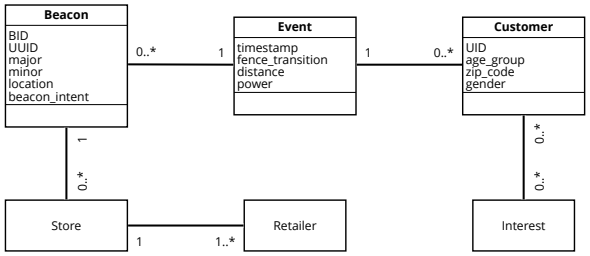

Figure 2. Main Data Structures for Customer Data Collection

Analytical Perspectives on Spatio-temporal Customer Data

The spatio-temporal information collected from beacon sightings enable new LBS on different levels of analysis that yield value to the various stakeholder groups in the high street service ecosystem. Figure 3 provides the main contribution of this work, a conceptual framework that structures analytical perspectives and conceivable LBS on the micro, meso, and macro levels. In the following, these perspectives are further detailed out with regard to the previously presented scenario.

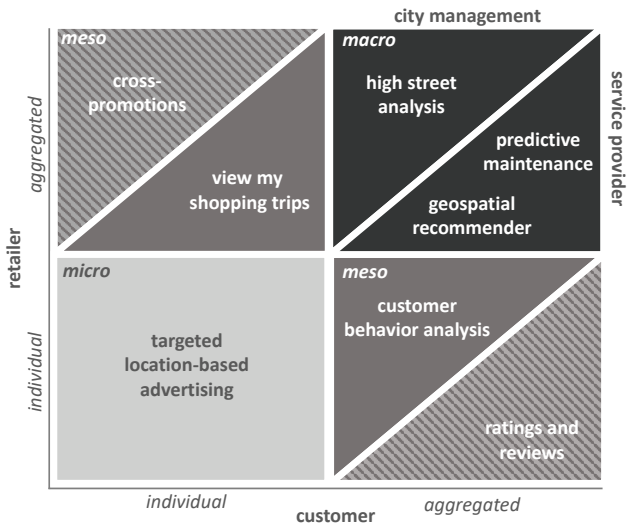

Figure 3. Perspectives on Customer Data with Regard to Different Levels of Analysis and Beneficiaries *(The quadrants are divided to highlight the respective beneficiary of a service, which is named on the closest axis.)*

Micro-level Perspective

Micro-level analyses concern the relationship between an individual retailer and an individual customer (third quadrant in Figure 3). Collected data is analyzed primarily to provide context for customer segmentation; that is, the resulting service enables retailers to create promotions for a single customer or a target group defined by contextual factors, who then receive tailored promotions that fit their interests.

Several studies suggest a general advertisement overload and identify relevance as a primary criterion to raise customers' awareness (Bauer and Strauss 2016). Bauer and Strauss urge retailers to bear in mind the benefit the advertisement gives the target audience before launching a promotion. Customers should be able to limit their exposure to location-based promotions to increase their relevance. In effect, customers could be enabled to select their interests, to white- or blacklist individual stores, and to temporarily turn off all promotions. Furthermore, Xu et al. (2011) suggest pull-based over a push-based delivery of promotions to reduce advertisement overload and increase the customer's perceived benefit.

Based on the predefined beacon intents (cf. Figure 1) and the low-level beacon events collected, various high-level events can be derived for LBA. As soon as a customer enters the geofence of an *entrance* beacon, the retail store is defined as having been "seen". If the customer subsequently enters the geofence of a *promotion* or *PoS* beacon, the retail store is defined as having been "visited". As Figure 4 shows, the dwell time can be inferred from the time when an entrance beacon is first seen to the time when an entrance beacon is last seen, given that, in the meantime, the customer has seen an in-store beacon. Incomplete data, such as a missed second sighting of an entrance beacon, complicates the dwell time calculation; in this case, the dwell time is calculated from the time at which the entrance beacon is first seen to the last sighting of any of the retailer's beacon in a sequence. Additional plausibility checks, such as limiting the number of visits in a given period and suitable data-smoothing mechanisms must be put into place to increase the data quality. However, data-quality requirements for targeted advertisements are comparatively low. (For example, a coarse classification in short $t < 10m$, medium $10 \leq t < 60m$, and long $t \geq 60m$ visits suffices).

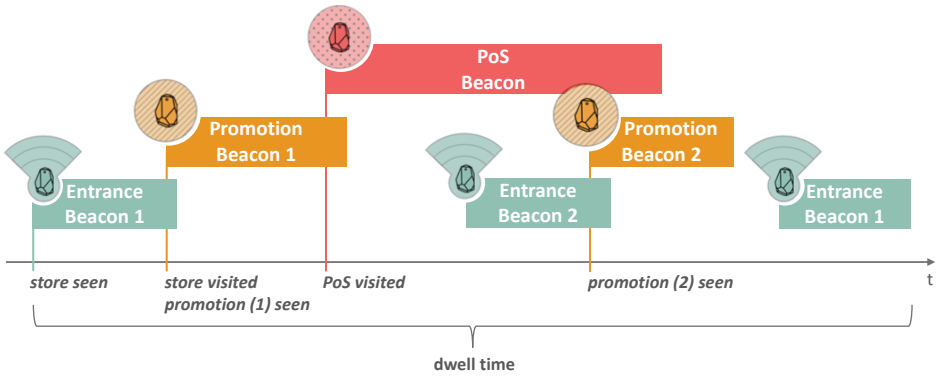

Figure 4. Events Inferred from Collected Customer Data

Following Bauer and Strauss's (2016) analysis on context attributes that are considered for targeted mobile LBA in the literature, several measures that retailers can use as conditionals are feasible:

- On the *store* level, passersby and visitors can be differentiated. The number of visits and the dwell time are additional attributes that allow the store to target repeated visitors and customers that have spent a set amount of time in the store.
- On the *beacon* level, the number of sightings and the distance to the beacon can be used to trigger, for example, a promotion when the customer is in *immediate* proximity to a particular beacon.
- On the *customer* level, age group, gender, and ZIP code can be used for demographic segmentation.
- On the *app* level, the mobile operating system used, the time since installing the app, and the frequency of app use can be used as conditionals.

All of these attributes can be combined with a relative or absolute period to narrow the targeted scope. For example, the visit rate could be limited to consider only customers who have repeatedly visited the store in the last month. Combining contextual attributes allows for the kind of fine targeting that has until now been exclusive to online advertising (e.g., Facebook ads) and largely unavailable to SME retailers. Conceivable use cases include targeting loyal customers who frequently visit, providing additional information to a nearby promotional display, and increasing the penetration rate by targeting customers who never visited the store.

Meso-level Perspective

On the meso level, one of the two perspectives (retailer, customer) is viewed on the individual level, while the other is viewed on an aggregated level, which results in customer-facing (second quadrant in Figure 3) and retailer-facing services (fourth quadrant in Figure 3). Some services are only indirectly enabled by spatio-temporal data (highlighted by the striped areas in the quadrants).

From the individual customer's perspective, data collection is a means to an end to receive personalized service and promotions. Also, the spatio-temporal history allows the customer to reflect on the shopping trips made. Like reviewing tracked runs in a fitness app, reviewing the history gives customers insight into their behavior. Based on going through their shopping trips on the community platform, customers can receive further information on single retailers and get in contact. By rating and reviewing a retailer on the platform, customers collaborative to provide a service for each other. Viewing past shopping trips also extends the customer journey beyond the high street visit, as they are more likely to recall their (positive) experiences, which can encourage them to use high street retail in their buying decisions. Looking up the promotions received during the high street visit at a later time can also stimulate subsequent visits, thereby marking the start of new customer journeys.

From a retailer's point of view, aggregated customer behavior as it relates to a particular store yields valuable insights into the store's customer base and its behavior over time. Individual reports can be created interactively from aggregated customer data by combining dimensions like demographics, store visits, dwell time, beacon sightings, promotions issued, and time. Retailers can analyze aggregated sightings for each beacon at a defined point in time and over a defined period. Time series analyses graphically show rush times and

slow times. While retailers often rely on their experience and "gut feeling", they can receive actual numbers to use for staff planning or to adjust their opening hours. For each beacon, retailers can drill down based on the customers' demographics so customer segments can be pinned down to single beacons in particular parts of the store. The resulting service could also make traditional retail key performance indicators (KPIs) visible (Underhill 2008):

- *Penetration rate*: The ratio of customers who visit the store to all customers who pass by.
- *Loyalty rate*: The ratio of customers who revisit the store to first-time visitors.
- *Engagement rate*: The percentage of customers who view a promotion in the app.
- *Capture rate*: The ratio of customers who received a promotion in the app and subsequently visited the store. The capture rate is a subset of the engagement rate.

Retailers can precisely scope the target group for their location-based promotions. On meso-level, partnering retailers could offer cross-promotions for complementary products, where a customer's visit to the first retailer results in receiving a promotion for the second retailer, and vice versa. Aggregated customer behavior can show which customer segments respond to a promotion, an insight that is difficult to retrieve from traditional print and broadcast ads. Customer behavior analysis supports retailers in their continuous improvement process to maximize their advertising efficiency and the return on investment in advertising.

Macro-level Perspective

On the macro-level, both customer data and retailer data are aggregated (first quadrant in Figure 3). This bird's-eye view concerns the state of the high street as a whole, so municipal city managers and local marketing cooperatives are the main target groups. Depending on individual high street configurations, these bodies act as the central point of contact and as mediators among the high street retailers, united by the common goal of increasing the high street's overall well-being. Typical tasks are event management, tourism management, space management, and coordinating and executing marketing activities. Information about spatio-temporal customer behavior can contribute to customer behavior analyses, which are a central input for planning any activity (Oosterlinck et al. 2017). Expert interviews with city managers in two German cities revealed their central questions regarding customer movements:

- *Pedestrian flows*: How do customers traverse the high streets? Where do they enter and exit the city center? What are the major pedestrian flows? Live information can inform local authorities and first responders in emergencies so they can steer pedestrian and road traffic.
- *Hot and cold spots*: Which areas are frequented the most and which areas are frequented the least? Historical pedestrian flows and crowd-density information can help to optimize infrastructure developments like paths and public facilities and support decisions about space management.
- *Customer loyalty*: How many customers repeatedly visit the high street? How often do customers return? This information helps to distinguish tourists from locals and aids in tourism management.
- *Customer migration*: How do customers move between stores? At which stores do customers begin and end their high street visits? Which are the most frequented stores? Information on anchor stores can support marketing activities that attract additional customers.
- *Scope of visit*: How many stores do customers patronize during a high street visit? How much time do they spend on the high street? These numbers can provide a baseline to so the impacts of marketing campaigns can be quantified.

A near-real-time dashboard that depicts the current "health" of the city is feasible. Besides aiding first responders, real-time analyses can be undertaken while interventions like marketing campaigns and events take place. These reports can be confined to a time dimension and drilled down by demographics, and external data sources, such as weather reports and event guides, can be linked to enrich them.

Further, given the sequence of stores a customer visits, a geospatial recommender service becomes feasible. Similar customers can be clustered, and collaborative filtering techniques can be employed to provide spatial recommendations (Li et al. 2008). Customers can then receive recommendations for stores they have not visited, but similar customers have visited. This LBS can foster positive customer experiences as they make serendipitous discoveries (Lemon and Verhoef 2016).

Finally, the community platform service provider can use aggregated data for administrative purposes. Each recorded transaction contains the beacon's self-reported battery status, so customers automatically provide maintenance information to the service provider. Although off-the-shelf beacons can run on a single battery for up to four years (Varsamou and Antonakopoulos 2014), they eventually require a battery change. As a form of proactive maintenance, retailers can task the local platform provider with automatically servicing the beacons before the batteries fail.

Demonstration

Following Peffers et al. (2007), a demonstration took place to evaluate the technical feasibility of the proposed design and to identify caveats for the presented LBS. Beacon-based customer tracking has been implemented as an extension to the prototypical community platform *smartmarket*^{2}. The testbed comprised the platform, an office building equipped with BLE beacons by different manufacturers (Kontakt.io, BlueUp, LANCOM Systems), and test users who strolled an artificial high street while carrying smartphones with the *smartmarket*^{2} app. These walkthroughs were performed to test the influence of the Beacons' transmission power, broadcasting protocols, and the users' walking speed on the data collection.

As a result, the Apple iBeacon protocol was favored over the competing Google Eddystone broadcasting protocol (Statler 2016) because the latter was only recognized in 88 % of cases in the setting. The accuracy of distance measurements and the detection rate depended heavily on the type of smartphone and beacon model used, an observation confirmed by Faragher and Harle (2015) and Schulz et al. (2016). Additionally, fast walking pace leads to lost records when entering a geofence. Smartphones only periodically scan for beacon signals when not already in a geofence to prevent battery drain (Statler 2016), and these intervals were larger than the user's period of stay in the geofence.

Both issues have significant impact on the LBS presented in the framework: Inaccurate distance measurements could result in showing a location-based ad for a product that is several aisles away. Missing beacon sightings impact dwell time, store migration, and shopping trip calculations, so customers are not appropriately targeted. Missing data also skews the calculation of retailer KPIs. However, both beacon manufacturers and academia (e.g., Varsamou and Antonakopoulos 2014) advice on signal configuration, beacon placement, and beacon shielding, which improve detection rates. During the test, it further became prevalent that sequential analyses of store visits and shopping trips require synchronized clocks across customers' devices so that the timestamps of beacon sightings are recorded with regard to the same master clock (Oosterlinck et al. 2017). Otherwise, temporal analyses such as the identification of hotspots or pedestrian flows lack explanatory power because of time differences between recorded and actual times of the beacon sightings.

Discussion

We have seen that spatio-temporal data collection using BLE beacons is technically feasible, but inaccurate and missed beacon sightings can hamper its utility for downstream LBS. Furthermore, LBS that are based on collected beacon sightings suffer from inherent limitations. Since any nearby user can receive beacon signals, employees and people who live in direct proximity to a store might skew reports and incorrectly identify themselves as frequent customers. Schulz et al. (2016) even mention beacon-forging as malicious behavior in which users counterfeit beacon signals, so they receive targeted LBA. However, even when such counterfeiting occurs, promotions are redeemed at the PoS and are subject to store policy.

Overall, customer behavior data's explanatory power for LBS depends on the sample—that is, the number and demographic distribution of customers who use the underlying community platform. Anecdotal evidence indicates that tech-savvy millennials are more likely to participate than are, for example, those in the baby boomer generation. A participatory, beacon-based approach requires customers to carry a smartphone, which must be switched on, have an active Internet connection, have Bluetooth switched on, and have the community platform app installed and authorized to collect beacon information (Statler 2016). Nevertheless, tech-savvy millennials are a preferable target group in light of the overarching socio-economical goal of strengthening the role of high streets in customers' buying decisions, since these customers are inclined to use e-commerce.

The presented framework not only holds prospects for high street stakeholders (see Figure 3) but the underlying data can also serve as a primary source for behavioral research in service marketing. In the marketing literature on brick-and-mortar retail, archetypal patterns and what influences customers' shopping behavior (e.g., the type of shopping trip, the motives for visiting the high street) are only rarely described and tend to be assessed by means of surveys (e.g., Hunneman et al. 2017), which inherently can suffer from incomplete results and confirmation bias. Given the customers' spatio-temporal data, future studies might elicit archetypal patterns of customer behavior. For example, utilitarian customers who buy only a particular product to satisfy their high street shopping needs could be differentiated from hedonically motivated customers who wander around the high street as a form of leisure. Marketing researchers can also build on the solution presented here to conduct customer behavior analysis in the field.

Conclusion and Outlook

This research shows an approach how customers' mobile devices, BLE beacon technology, and a community platform as underlying IS can be used to collect spatio-temporal customer data in high streets. The main contribution is a conceptual framework that structures and details the merits of this novel data source on different levels of analysis and for different beneficiaries in the high street ecosystem.

Based on the framework, the various location-based smart services are currently being implemented in the *smartmarket*^{2} community platform. Subsequently and in line with Venable et al.'s (2016) *Human Risk & Effectiveness* evaluation strategy, a formative naturalistic evaluation will take place in near future, which explores the solution's utility in a real-world environment. Selected retailers in a German city center will be equipped with BLE beacons and be set up for targeted LBA. Participants then stroll the high street and use the prototype. In parallel, their digital interactions and spatio-temporal movements are monitored using screen recording and user shadowing to establish a ground truth. Retailers, city managers, and participants will be surveyed ex-post. From a technical viewpoint, the evaluation will help to understand better where differences in structural and geographical properties impact broadcasting of beacon signals and how beacon configuration and placements can be optimized. From an academic viewpoint, evaluation results and the situated implementation of the artifact will be used to further abstract design knowledge in order to advance theory (Gregor and Hevner 2013). Finally, for customers to adopt the solution, perceived benefits must outweigh the perceived risks of tracking (Kelley et al. 2011; Schauer et al. 2014). Future research will use the prototype to survey and field test customers' acceptance of high street location tracking with regard to customer types, privacy decision-making, and the perceived value of LBS on local community platforms.

Acknowledgements

This paper was developed in the research project *smartmarket*^{2} (`www.smartmarketsquare.de`), which is funded by the German Federal Ministry of Education and Research (BMBF), promotion sign 02K15A074. The author thanks the Project Management Agency Karlsruhe (PTKA).

References

Bai, Y. B., Wu, S., Ren, Y., Ong, K., Retscher, G., Kealy, A., Tomko, M., Sanderson, M., Wu, H., and Zhang, K. 2014. "A new approach for indoor customer tracking based on a single Wi-Fi connection," in *International Conference on Indoor Positioning and Indoor Navigation*, IPIN '14, Busan, South Korea.

Bartelheimer, C., Betzing, J. H., Berendes, I., and Beverungen, D. 2018. "Designing Multi-sided Community Platforms for Local High Street Retail," in *Proceedings of the 26th European Conference on Information Systems*, ECIS '18, Portsmouth, UK.

Bauer, C., and Strauss, C. 2016. "Location-based advertising on mobile devices: A literature review and analysis," *Management Review Quarterly* (66:3), pp. 159–194.

Betzing, J. H., Beverungen, D., and Becker, J. 2018. "Design Principles for Co-Creating Digital Customer Experience in High Street Retail," in *MKWI 2018 Proceedings*, Lüneburg, Germany.

Beverungen, D., Müller, O., Matzner, M., Mendling, J., and vom Brocke, J. 2017. "Conceptualizing smart service systems," *Electronic Markets* (in press).

Bollweg, L., Lackes, R., Siepermann, M., Sutaj, A., and Weber, P. 2016. "Digitalization of Local Owner Op-

erated Retail Outlets: The Role of the Perception of Competition and Customer Expectations," in *PACIS 2016 Proceedings*, Chiayi, Taiwan.

cima 2018. "Gemeinsam Online - Untersuchung von Online-Plattformen mit lokalem Fokus," Last accessed: 2018-04-15. URL `https://gemeinsam.online/`

European Union 2016. "Regulation 2016/679 of the European parliament and the Council of the European Union," Last accessed: 2017-06-23. URL `http://eur-lex.europa.eu/eli/reg/2016/679/oj`

Faragher, R., and Harle, R. 2015. "Location Fingerprinting With Bluetooth Low Energy Beacons," *IEEE Journal on Selected Areas in Communications* (33:11), pp. 2418–2428.

Gregor, S., and Hevner, A. R. 2013. "Positioning and Presenting Design Science Research for Maximum Impact," *MIS Quarterly* (37:2), pp. 337–355.

Hunneman, A., Verhoef, P. C., and Sloot, L. M. 2017. "The moderating role of shopping trip type in store satisfaction formation," *Journal of Business Research* (78), pp. 133–142.

Kelley, P. G., Benisch, M., Cranor, L. F., and Sadeh, N. 2011. "When Are Users Comfortable Sharing Locations with Advertisers?" in *Human Factors in Computing Systems*, CHI '11, Vancouver, Canada.

Kim, B., Ha, J.-Y., Lee, S., Kang, S., Lee, Y., Rhee, Y., Nachman, L., and Song, J. 2011. "AdNext: A Visit-Pattern-Aware Mobile Advertising System for Urban Commercial Complexes," in *12th Workshop on Mobile Computing Systems and Applications*, HotMobile '11, Phoenix, AZ, USA.

Lee, S., Min, C., Yoo, C., and Song, J. 2013. "Understanding customer malling behavior in an urban shopping mall using smartphones," in *Pervasive and Ubiquitous Computing*, UbiComp '13, Zürich, Switzerland.

Lemon, K. N., and Verhoef, P. C. 2016. "Understanding Customer Experience and the Customer Journey," *Journal of Marketing* (80:6), pp. 69–96.

Li, Q., Zheng, Y., Xie, X., Chen, Y., Liu, W., and Ma, W.-Y. 2008. "Mining User Similarity Based on Location History," in *16th Conference on Advances in Geographic Information Systems*, GIS '08, Irvine, CA, USA.

Martin, J., Mayberry, T., Donahue, C., Foppe, L., Brown, L., Riggins, C., Rye, E. C., and Brown, D. 2017. "A Study of MAC Address Randomization in Mobile Devices and When it Fails," *Proceedings on Privacy Enhancing Technologies* (2017:4), pp. 268–286.

McIntyre, D. P., and Srinivasan, A. 2017. "Networks, platforms, and strategy: Emerging views and next steps," *Strategic Management Journal* (38:1), pp. 141–160.

Neirotti, P., De Marco, A., Cagliano, A. C., Mangano, G., and Scorrano, F. 2014. "Current trends in Smart City initiatives: Some stylised facts," *Cities* (38), pp. 25–36.

Oosterlinck, D., Benoit, D. F., Baecke, P., and Van de Weghe, N. 2017. "Bluetooth tracking of humans in an indoor environment: An application to shopping mall visits," *Applied Geography* (78), pp. 55–65.

Österle, H., and Otto, B. 2010. "Consortium Research," *Business & Information Systems Engineering* (2:5), pp. 283–293.

Peffers, K., Tuunanen, T., Rothenberger, M. A., and Chatterjee, S. 2007. "A Design Science Research Methodology for Information Systems Research," *Journal Management Information Systems* (24:3), pp. 45–77.

Phillips, J. 2016. *Ecommerce Analytics: Analyze and Improve the Impact of Your Digital Strategy*, Pearson Education, 1st ed.

Schauer, L., Werner, M., and Marcus, P. 2014. "Estimating Crowd Densities and Pedestrian Flows Using Wi-Fi and Bluetooth," in *11th International Conference on Mobile and Ubiquitous Systems*, London, UK.

Schulz, T., Golatowski, F., and Timmermann, D. 2016. "Secure privacy preserving information beacons for public transportation systems," in *International Workshop on Context-Aware Smart Cities and Intelligent Transport Systems*, PerCom Workshops, Sidney, NSW, Australia.

Statler, S. 2016. *Beacon Technologies: The Hitchhiker's Guide to the Beacosystem*, Berkeley, CA: Apress.

Underhill, P. 2008. *Why We Buy: The Science of Shopping–Updated and Revised for the Internet, the Global Consumer, and Beyond*, Simon & Schuster.

Varsamou, M., and Antonakopoulos, T. 2014. "A Bluetooth Smart Analyzer in iBeacon Networks," in *Fourth International Conference on Consumer Electronics*, Berlin, Germany.

Venable, J., Pries-Heje, J., and Baskerville, R. 2016. "FEDS: a Framework for Evaluation in Design Science Research," *European Journal of Information Systems* (25:1), pp. 77–89.

Xu, H., Luo, X., Carroll, J. M., and Rosson, M. B. 2011. "The personalization privacy paradox: An exploratory study of decision making process for location-aware marketing," *Decision Support Systems* (51:1), pp. 42–52.