Designing City Center Area Recommendation Systems

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Abstract. To decide in which part of town to open stores, high street retailers consult statistical data on customers and cities, but they cannot analyze their customers' shopping behavior and geospatial features of a city due to missing data. While previous research has proposed recommendation systems and decision aids that address this type of decision problem – including factory location and assortment planning – there currently is no design knowledge available to prescribe the design of city center area recommendation systems (CCARS). We set out to design a software prototype considering local customers' shopping interests and geospatial data on their shopping trips for retail site selection. With real data on 500 customers and 1,100 shopping trips, we demonstrate and evaluate our IT artifact. Our results illustrate how retailers and public town center managers can use CCARS for spatial location selection, growing retailers' profits and a city center's attractiveness for its citizens.

Keywords: Town Center Management, High Street Retail, Recommender Systems, Geospatial Recommendations, Design Science Research

1 Introduction

For centuries, the principal attraction of our cities was its town center. According to Guy (1994), a city center is "central to the town as a whole", since it forms the central retail area of the city and also serves as a central location for business, culture, and entertainment [1]. The sustained rise and success of online shopping has, however, dealt a blow to many city centers and contributed to their decline in terms of economic and cultural significance [2]. This triggers a downwards spiral, as the decrease in the attractiveness of a city center – defined by the number and diversity of retail stores, social and cultural events, accessibility, and ambiance[3] – further reduces both the number of visitors [4] and the number and range of retailers, in turn reducing the center's attractiveness in the eyes of retailers considering to open new stores [5].

Apart from executing governmental policies on a municipal level [6], public administrations have a strong motivation in keeping their cities attractive and do all they can to maximize footfall in city centers by customers and visitors alike. A reason for this is the financial benefit generated by taxes from retailers. Town center management (TCM) is a public office funded by city authorities – rather than by the corporate sector – to this effect [7]. Amongst other duties, TCM supports local

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retailers in setting up stores in the right locations in town. Proper site selection is important for retailers, since routes traveled by high street customers highly depend on the location and distribution of shops [8]. As competitive intensity increases customer satisfaction and, therefore, positively influences repurchase behavior [9], the clustering of retailers serving similar customers' interests in the same area will likely lead to higher sales.

Knowledge about customer behavior in a city center can help both TCM and retailers improve the customer experience in and attractiveness of local high streets. Hitherto, retailers have based their site selection decisions on their experience, on checklist methods, or on simple regression models [10]. As these methods are rather inadequate, we design a recommender system called CCARS (City Center Area Recommender System) as the foundation for a public service able to provide a more robust approach toward retail site selection. Based on customer interests and trajectories, the system supports TCM in advising retailers to find an optimal location for their store. CCARS features two core functionalities. First, it recommends a best fit for certain types of retailers for a city center area. Second, CCARS identifies optimal locations for stores based on customers' interests. The system, therefore, enables local administrations and retailers to perform improved site selection by analyzing customers' interests and trajectories.

The paper unfolds as follows. In Section 2, we review related research on retail site selection, city center attractiveness, and recommender systems. In Section 3, we present and justify our research method. In Section 4, we present the implemented IT artifact, which we demonstrate with real data on customers' interests and trajectories in Section 5. Section 6 concludes the paper.

2 Related Work

2.1 Retail Site Selection

The act of decision making in site selection is defined as the decision and selection of a potential site of a business or retailer with a view to impacting profit not only in the selected location, but also on other sites [11]. Additionally, the allocation aims to minimize transportation costs from customers to sites and to satisfy the maximum number of customers in the catchment area [12]. Catchment areas are geographic spaces, in which customers that demand a specific service or good in a particular location are dwelling [13]. While customers do not have to live in the same area, they have to spend at least a minimum amount of time there to be considered as customers.

Retail site selection depends on the type of retail site [14], namely, a solitary site, a planned, or an unplanned shopping area. In solitary sites, shops of different retailers stand isolated from each other, e.g., on roads. Unplanned shopping areas contain several shops in close proximity to each other, while the area regularly expands and shrinks without a plan. Unplanned shopping areas are characteristic of bigger cities in Central Europe [15]. Planned shopping areas feature shops in close proximity, provide a unified theme, and are often integrated physically, e.g., in shopping malls. As of today, the number of planned shopping areas is increasing [16]. Since city centers

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compete with online shopping channels and with planned shopping areas, many have been facing declining business success for some years.

The allocation process – also called spatial location selection – is a cross-disciplinary challenge common to, e.g., urban planning, transportation, and retail [17]. For retail stores, spatial location selection is the most important decision, as it impacts on high and long-term investments [10], drastically influences a store's profit and performance [18], builds the basis for customer attraction, and can even compensate for mediocre retail strategies [13]. Thus, finding and selecting the best location in retail is classed as a key strategic decision [19, 20], a business goal [21], and able to lend a significant competitive advantage to a retailer [13].

Retail site selection according to Brown [22] is a decision process that involves three phases. First, the organization has to select the region in which a new branch is to be established. Second, the most suitable areas in the selected region are identified and considered further. Third, the consideration set is examined to identify the most suitable site. In this step, all features relevant to the potential performance of a new branch have to be considered [13]. Features and, therefore, criteria usually applied for retail site selection include: market potential, parking facilities and their capacity, presence of competitors, pedestrian traffic patterns, available store area, population and demographic data, number of existing stores, types of store, urban growth rate, etc. [12, 16, 16, 17, 23, 24]. In contrast, traffic pattern variables might predict sales better than a site's demographic data [16].

Conventionally, retailers base their site selection decisions on their experience, on checklist methods, or simple regression models [10]. Other examples of techniques for location planning and site selection are multivariate statistical techniques, spatial interaction models (see [25] for further details) or network analysis tools [26, 27]. Kuo, Chi & Kao [10] even developed an expert system, based on a large database, which can rate a possible location for a convenience store. With the availability of big data and more sophisticated computing resources, retail site selection has increasingly shifted away from managers' experience and towards data analysis and computer models to support decision making [11]. As decision models, by definition, foreground some decision variables, while abstracting from others, they need to be used judiciously to augment – rather than substitute – human decision making [28].

2.2 City Center Attractiveness

Research has consistently emphasized the central role played by retail in determining a city center's attractiveness [3, 29–33], based on both the number and the diversity of stores. Besides retail, the amusement industry, comprising restaurants, cafés, and other locations for entertainment, is another key factor [3, 29–33]. The two are of course closely related, and for all local establishments – whether corporate chains or smaller retailers – city center customers are their main source of income. Other factors contributing to a city center's attractiveness include good access, public transportation to and within a city center, car parking [3, 29, 33], permanent and temporary attractions and events [3, 32], the architecture and natural ambiance of a city [3, 30–33].

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Town center management (TCM) in central Europe differs from TCM in North America and the United Kingdom [7]. In this research, we focus on the central European view of TCM. Coca-Stefaniak et al. (2009) define TCM in central Europe as a strategic way of connecting stakeholders and revitalizing city centers for customers [7]. Stakeholders include retailers, city government, restaurants, and customers, amongst others [34]. TCM and stakeholders may take a different stance towards a city center's attractiveness and, at times, their objectives might conflict. Retailers and restaurants vie for the best location in cities, and parts of cities, with high attractiveness and their opening of stores or venues often increase the latter. TCM, however, with its focus on cities as units of analysis, aims to increase a city center's overall attractiveness. Their objectives mostly align, as both TCM and stakeholders want to attract as many potential customers as possible. However, their views might differ as when, for example, TCM wants to raise the attractiveness of certain areas which, because of their lower attractiveness, might not appeal to retailers looking for new sites to open.

2.3 Recommender Systems

Recommender systems support decision-making processes without necessarily requiring decision-makers to possess detailed knowledge of the different alternatives [35]. They enable decision-making in complex information environments [36] and address the problem of information overload [37]. The purpose of recommender systems is to recommend items, e.g., products, services, or locations, to a decision-maker as user. Based on additional information about users, the system recommends items that best match a user's preferences [37].

Previous research conceptualized two basic types of recommender systems. Content-based systems recommend items based on data about user characteristics and the attributes that describe the items favored [38], e.g., product properties or price. Collaborative filtering systems recommend items based on identifying users that have similar preferences [37] and on their opinions and tastes, e.g., user ratings of items [39]. Hybrid recommender systems include both content-based and collaborative filtering techniques [37].

Recommender systems are used in both B2B [40] and B2C. Apart from e-commerce, recommender systems are primarily used to recommend items in music and movie streaming services such as Spotify or Netflix [41, 42], for news services [43], or for touristic services [44, 45]. For local high street retailers in city centers, however, few approaches have been made to recommend their items for sale. Offline retailers might use a mobile application to recommend items to visitors present in a high street, to improve their customer experience in a city [46]. In our research endeavor, we design a B2B recommendation system based on content-based filtering techniques that recommend retailer types to TCM that match the interests of customers frequently strolling through a particular area of town.

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3 Research Method

We design a City Center Area Recommender System (CCARS) that assists TCM and retailers with retail site selection. CCARS can either be implemented as a public service or as a self service. The recommendations are based on evaluating the interests and the attendance of customers in different city areas. We classify our research as an 'improvement' in terms of the knowledge contribution framework for design science research [47], developing superior solutions for the problem of retail site selection.

While we start our research process by developing an innovative IT artifact [48], our design will also enable us to conceptualize an IS design theory that prescribes how CCARS ought to be designed in order to support retail site section in a way that benefits retailers and city centers at the same time.

For designing and implementing our recommender system, we instantiate the design science research approach as proposed by Peffers et al. (2007) [49], visualized in Figure 1. The approach is based on the following steps: problem identification and motivation, definition of the objectives for a solution, design and development, demonstration and evaluation, and communication [49]. As a decision problem, retail site selection is rooted in the uncertainty about the attractiveness of particular city center areas perceived by customers. Knowledge about customers' interests in city center areas, however, could support TCM's decision-making on how to attract retailers best suited for an area. Establishing new stores might then lead to increasing the attractiveness of the city itself. As regards evaluation, we show that our algorithm identifies retailers that fit into different areas of a city, based on real consumer data and geospatial data. We make use of data of over 500 customers and 1,100 trajectories inside the city center. We demonstrate and evaluate our artifact by using one retailer, who is looking for a location in the city of the field study for its store opening, as an example.

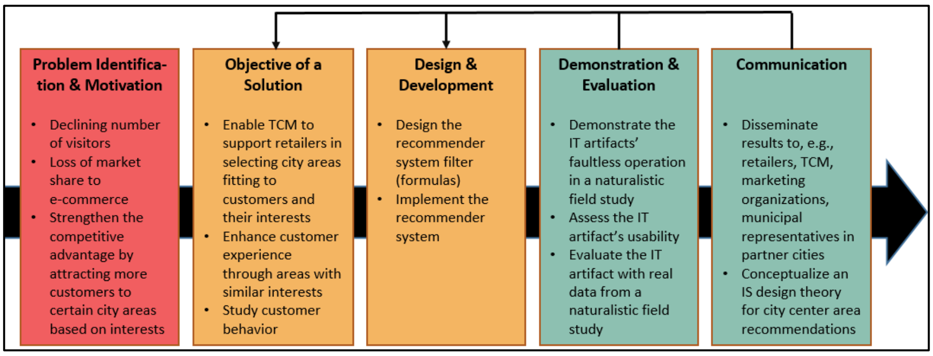

Figure 1: Instantiated design science research process (adapted from [49])

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4 Recommender Systems for Retail Site Selection

4.1 Designing a City Center Area Recommender System (CCARS)

The design of our recommender system is based on content-based filtering techniques that supports TCM and retailers to identify attractive locations in city centers. The system also supports TCM in attracting new retailers for a vacant location that matches best the interests of customers strolling in the area of the vacant location. We identified three use cases, in which the recommender system can support TCM (Table 1).

Table 1: Use cases for the proposed CCARS

No.	*Goal*	*Unit of analysis*	*Input*	*Output*
1	Support TCM in finding fitting retailers to enhance a city center's attractiveness	City center	Location	Target customers' interests
2	Support TCM in advising retailers on finding an attractive location	Store	Targeted customer interests, weighting (rent, interests, customers)	Best matching areas for the store
3	Support TCM in advising retailers on finding an attractive location	Store	Targeted customer interests, weighting (rent, interests, customers), price range	Best matching areas for the store within price range

The first use case focuses on supporting TCM in finding fitting retailers to strengthen the overall attractiveness of a city center. In this scenario, our algorithm recommends business categories with the best fit for a location, based on the interests of customers that regularly linger in this area. In the second use case, our algorithm supports TCM in advising retailers on finding an attractive location for his/her store. The system, therefore, recommends places based on categories of goods sold by a retailer. Thus, the unit of analysis in the first use case is the city center and its particular areas, and in the second use case it is the store. In the third scenario, CCARS considers price range data in addition to taking into account a retailers' ability to pay the rent for a store.

For our three use cases, we define the decision problems as follows:

$$f1 = \frac{V_{a,c,t}}{\max\limits_{c \in C}(V_{a,c,t})} \tag{1}$$

$$f2 = \alpha \frac{\min\limits_{a \in A}(R_a)}{R_a} + \beta \frac{V_{a,t}}{\max\limits_{a \in A}(V_{a,t})} + \gamma \sum_{c \in C} \delta_c \frac{V_{a,c,t}}{\max\limits_{c \in C}(V_{a,c,t})} \tag{2}$$

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$$f3 = \begin{cases} s2, minR \leq R_a \leq maxR \\ 0, else \end{cases} \quad (3)$$

with
$C = set\ of\ interest\ categories\ c$
$A = set\ of\ areas\ a$
$t = time\ span$
$V_{a,t} = visitors\ of\ area\ a\ during\ time\ span\ t$
$V_{a,c,t} = visitors\ of\ area\ a\ during\ time\ span\ t$
$R_a = monthly\ rent\ at\ a$
$\alpha, \beta, \gamma = weighting\ parameters$
$\delta c = weighting\ parameters\ for\ interest\ category\ c$
$f1, f2, f3 = output\ of\ the\ formulas\ for\ use\ case\ 1{,}2{,}3$
Depending on the use case for the desired result (Table 1), different input data are required. Given the customer data in a city, the algorithm requires a city area (a) to generate the best fitting interest categories (use case 1, f1-score). In use case 2, the algorithm requires the interests of the targeted customers (δ values for each interest category), the weighting of the different factors for rent (α), the total number of visitors (β) and the number of visitors with certain interests (γ). The third formula extends the second one by taking price range into account, to find locations that best fit the given interest categories. Applying one of the formulas results in computing a score between 0 and 1, with 1 indicating a complete fit and 0 a non-existing fit. On execution, our proposed recommender system calculates the scores for each interest category (use case 1) or city area (use cases 2 and 3). Then, the system displays the values of the chosen use case in descending order, considering the input parameters.

4.2 Demonstration

The aim of CCARS is to identify optimal areas for new stores in a defined region, implementing the second stage of Brown's process for retail site selection [22] (cf. Section 2.1). First, a region has to be selected (Step 1). In the case of high street retail, this region is the city, in which a retailer considers opening a new store. A certain part of the city or a high street area is then selected as the optimal area (Step 2). Step 3 of Brown's process focuses on identifying the final location [22]. In our case, this location is the specific address of the retail site, including level and access. Therefore, we first split the city into spatial clusters based on customer trajectory data. In a second step, we combine the spatial clusters with the representative list of land values to get a more detailed spatial allocation of the city center. Thereafter, the customer trajectory data and the land value data are used to execute CCARS and to identify the areas in the city center in which new stores can attract customers best, considering retailers' rent budgets. Finally, we report on demonstrating our software prototype, based on our field data in the city of Paderborn, Germany.

Data Collection. Our research uses an implemented community platform to identify data on customers' preferences and shopping routes. The platform features different frontends for users and retailers, building a multi-sided community platform for a city center. The platform is built on Bluetooth Low Energy (BLE) signals from beacons that were installed in the stores, to notify users via a mobile application about personalized offers or events published by retailers. To improve beacon coverage in the city center, we placed additional beacons in public areas around the city center. Furthermore, as contacts made by the mobile application with beacon signals are stored in a database, retailers can access information about customers visiting their stores on a detailed level. Therefore, the data generated using the community platform is used by the platform to communicate retailer information and offers to potential customers. With CCARS implementing a secondary use of these data, no incentives are needed to elicit the participation of the different stakeholders in the community platform. The beacons are installed in Paderborn, Germany. With a population of 144,000, the city represents one of about forty cities in Germany with a similar city center structure. Some of the beacons are installed located in close proximity to each other, and others are farther away from each other. The spatial allocation of all 218 installed beacons is visualized in Figure 2 with green dots.

On completion of our research, the multi-sided community platform will be handed over to and hosted by the local TCM, which is interested in making use of the customer trajectory data to improve city center attractiveness. The data generated through the CCARS recommender system could be used by the TCM to provide a self-service to retailers interested in obtaining valuable information about optimal areas to locate their businesses.

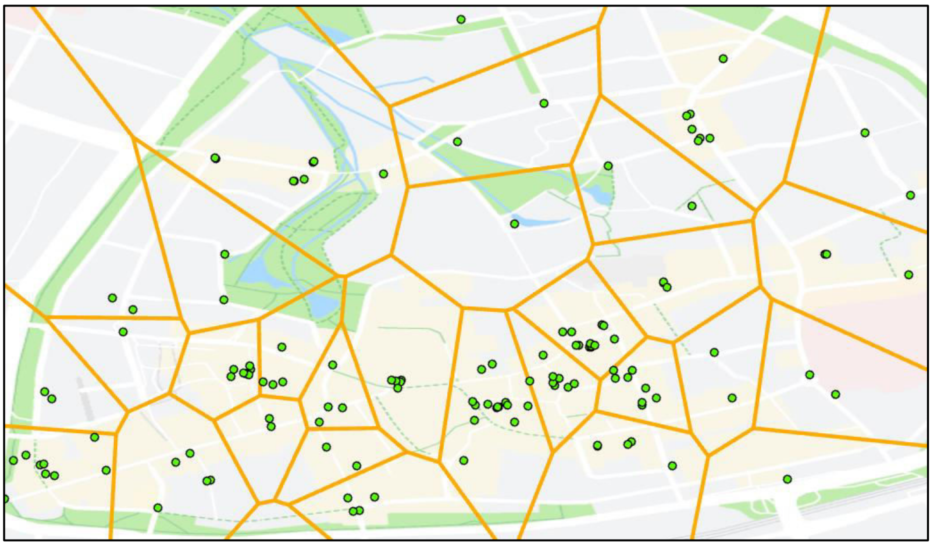

Figure 2: Spatial allocation of all 31 clusters in the city center, as identified with k-means

Deriving Spatial Clusters. To identify an optimal location for a new store, the city center is divided into smaller areas. We could either automate this process by assigning every beacon to an area with the same size, or by combining beacons to form bigger areas. As the distance between beacons (representing stores participating

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in our field study) varies a lot in our dataset, with some beacons located within a range of less than 20 meters and others in a range of more than 200 meters, we defined the areas irrespective of the number of beacons they include. Brown recommends a similar approach [22] for distinguishing optimal areas from final sites.

For the automated approach, we used the k-means algorithm, which is one of the most popular algorithms for clustering, since it is simple and efficient. Since its development in 1955, it has been successfully applied to a large variety of clustering problems [50]. As k-means clustering needs numerical input and we need spatial clustering to identify the areas, we define the beacons' longitude and latitude as the input parameters for clustering. The k-means algorithm also requires a number of clusters as an input. This number can be calculated using the silhouette score – an indicator displaying how well different input values fit into the clusters [51]. In our case, the silhouette score for 31 clusters proved to be the best result, leading us to identify 31 clusters for our city center (Figure 2). The border between any two clusters is calculated based on the clusters' centroids.

The representative list of land values is the second dataset that we used to identify areas in our city center. The list shows the benchmarked valuation of properties that is calculated biennially by all states in Germany and used as a baseline for taxation as well as for comparing different areas in a city[1]. However, we could not use the land value areas without processing the data further, because the beacons we used to measure the customer trajectory data were not distributed according to the land value list, but based on the stores that joined or study, and, therefore, overlap partially. Furthermore, the representative list of land values mainly focusses on streets rather than on city areas, and sometimes span huge parts of a city center. Selecting such an area in Step 2 of retail site selection would, however, not be sufficient to solve the decision problem, since the area would be too large to identify a particular location for a store.

In order to combine both spatial datasets, we used an intersection method that is provided by a geographical information system (GIS) [52]. This takes two spatial features as input and writes one output feature class containing every area that is intersected by both input features. The resulting 136 identified areas in our city center are visualized in Figure 3.

[1] A further explanation and the public representative list of land values can be accessed online: https://www.bodenrichtwerte-boris.de/borisde/

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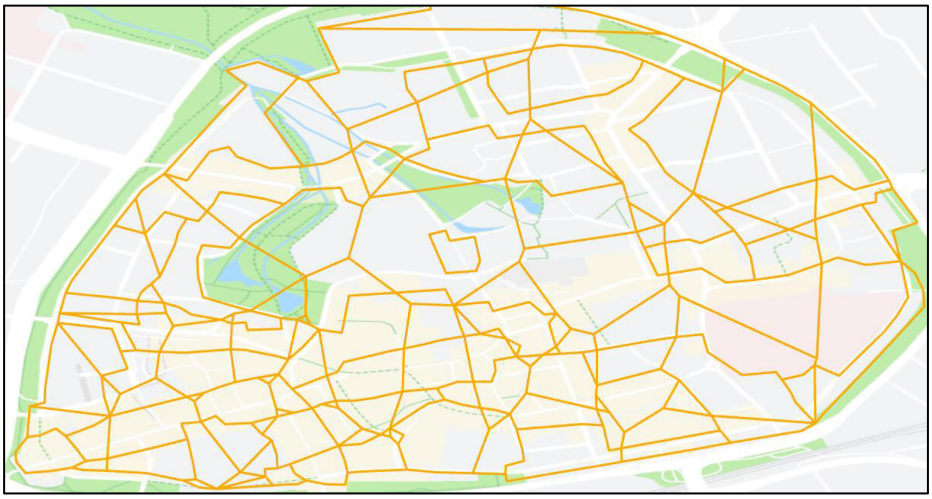

Figure 3: The 136 spatial clusters, identified based on our beacons and the list of land values

The resulting clusters vary significantly in terms of their size. We argue, however, that their size is negligible, because our algorithm maximizes an area's utility and is not dependent on the size of the recommended areas. Furthermore, some of the spatial clusters contain parks, local recreation areas, or non-commercial buildings such as churches or government buildings. Because the features of our input areas are recorded in the output areas of the intersection, these areas can clearly be identified as being unavailable for private or commercial use.

Demonstrating the recommender system. In a field study, we collected customer trajectory data with a group of 500 students using a mobile application, which resulted in data on 1,100 trips inside the city center. As this is the first field study to demonstrate our prototype, we aim to make our mobile applications publicly available and eliminate the inherent limitations of using students as subjects in further evaluations. In our mobile application, every user could customize his/her interests from a predefined list of interests that we derived from literature and large e-commerce stores. As final data preparation, we aggregated the data based on the areas we identified in the city center.

To demonstrate the recommender system, we implemented CCARS in a spreadsheet. In the first use case, users – either TCM or retailers – could input the ID of the target area (a). Our CCARS, therefore, calculates the scores and sorts categories of interests in descending order. A user can use the tool to identify the interest categories best fitting the customer trajectories in each area. Figure 4 shows a screenshot of the different use cases implemented by the system.

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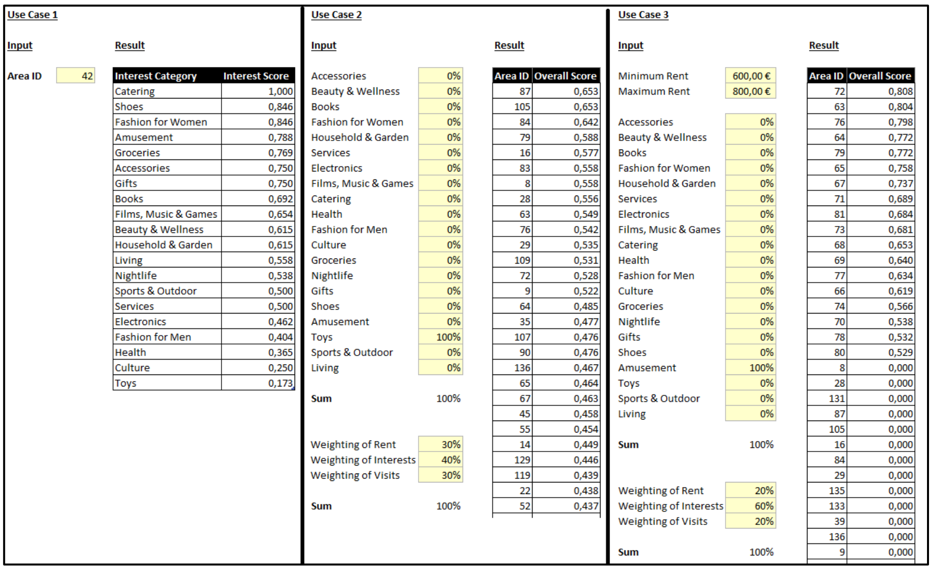

Use Case 1

Input

Area ID	42

Result

Interest Category	Interest Score
Catering	1,000
Shoes	0,846
Fashion for Women	0,846
Amusement	0,788
Groceries	0,769
Accessories	0,750
Gifts	0,750
Books	0,692
Films, Music & Games	0,654
Beauty & Wellness	0,615
Household & Garden	0,615
Living	0,558
Nightlife	0,538
Sports & Outdoor	0,500
Services	0,500
Electronics	0,462
Fashion for Men	0,404
Health	0,365
Culture	0,250
Toys	0,173

Use Case 2

Input

Accessories	0%
Beauty & Wellness	0%
Books	0%
Fashion for Women	0%
Household & Garden	0%
Services	0%
Electronics	0%
Films, Music & Games	0%
Catering	0%
Health	0%
Fashion for Men	0%
Culture	0%
Groceries	0%
Nightlife	0%
Gifts	0%
Shoes	0%
Amusement	0%
Toys	100%
Sports & Outdoor	0%
Living	0%
Sum	100%
Weighting of Rent	30%
Weighting of Interests	40%
Weighting of Visits	30%
Sum	100%

Result

Area ID	Overall Score
87	0,653
105	0,653
84	0,642
79	0,588
16	0,577
83	0,558
8	0,558
28	0,556
63	0,549
76	0,542
29	0,535
109	0,531
72	0,528
9	0,522
64	0,485
35	0,477
107	0,476
90	0,476
136	0,467
65	0,464
67	0,463
45	0,458
55	0,454
14	0,449
129	0,446
119	0,439
22	0,438
52	0,437

Use Case 3

Input

Minimum Rent	600,00 €
Maximum Rent	800,00 €
Accessories	0%
Beauty & Wellness	0%
Books	0%
Fashion for Women	0%
Household & Garden	0%
Services	0%
Electronics	0%
Films, Music & Games	0%
Catering	0%
Health	0%
Fashion for Men	0%
Culture	0%
Groceries	0%
Nightlife	0%
Gifts	0%
Shoes	0%
Amusement	100%
Toys	0%
Sports & Outdoor	0%
Living	0%
Sum	100%
Weighting of Rent	20%
Weighting of Interests	60%
Weighting of Visits	20%
Sum	100%

Result

Area ID	Overall Score
72	0,808
63	0,804
76	0,798
64	0,772
79	0,772
65	0,758
67	0,737
71	0,689
81	0,684
73	0,681
68	0,653
69	0,640
77	0,634
66	0,619
74	0,566
70	0,538
78	0,532
80	0,529
8	0,000
28	0,000
131	0,000
87	0,000
105	0,000
16	0,000
84	0,000
29	0,000
135	0,000
133	0,000
39	0,000
136	0,000
9	0,000

Figure 4: Screenshots of the software prototype, displaying all three use cases

The second and third use case require specifying input data on the weights of different interest categories (δ_c). A user can input values into the different categories up to a sum of 100%. Additionally, the user can change the weights of rent, interests, and total visits (α, β, γ). As with the category values, these values have to be provided as percentiles. Furthermore, in the third use case, the user has to provide values for the minimal and maximal value of rent he/she wants to spend. This value is a benchmark taken from the representative list of land values[2]. Output values of the second and third use case consist of the area IDs, in descending order of their suitability. Zero values indicate that an area is either too expensive, too cheap, or is in governmental administration. It is important for a retailer to consider multiple areas for their final site selection, as not all areas might be open for new stores, contain vacancies or fulfill the criteria that a retailer has to consider for a new store. In other words, the recommender system identifies a weighted consideration set of suitable clusters, while the final decision must still be made by a human decision-maker.

5 Evaluation

To evaluate our implementation of CCARS, we use real data from a field study that we conducted in November and December 2018. Let us assume that a retailer wants to open a new location for nightlife and culture. The retailer already selected the city and is looking for the optimal area of town for the new store. TCM enables the retailer

[2] The representative list of land values is measured in Euro per square meter. This unit does not directly relate to the rent per month, as rent depends highly on the size of a store. In a further instantiation, a slider can be used to give the user an idea of the value range.

to use the recommender system. This is an example for the second use case defined in section 4.1. As input parameters, we set the interest categories $\delta_{Nightlife}$ and $\delta_{Culture}$ to 50% each. As the retailer wants to focus on customers interested in nightlife and culture, we set α (*Weighting of Rent*) to 20%, β (*Weighting of Visits*) to 20% and γ (*Weighting of Interests*) to 60%. The resulting recommendation is visualized in Figure 5. Green colors indicate a higher overall score, whereas red colors indicate a low score. Grey areas cannot host stores, because they are governed by, e.g., the local administration.

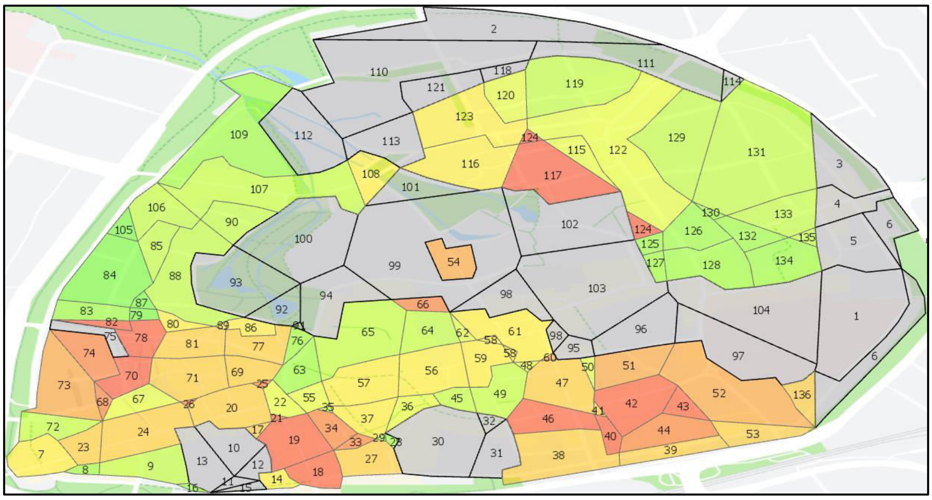

Figure 5: Recommended areas (dark green) for the decision problem exemplified

The best overall scores are identified for areas 87 (0,769), 105 (0,769) and 84 (0,762). The green areas on the right also show good areas for the proposed use case. TCM should guide the retailer in our example in finding a location in one of these areas. Although the overall score of areas 87, 105, and 84 are higher than the overall score of the green areas on the right, the retailer should consider both options and search for vacancies to open the new store. As a side note, a few months after having conducted our field study, a new nightclub opened in area 87 [53]. This fact might indicate that the proposed system might indeed identify suitable areas in which to open a new store.

6 Conclusion

We designed CCARS, a recommender system to help TCM supporting retailers in city centers to find suitable areas for opening a new store. The potential impact of our recommender system's recommendations can be very high because, previously, such information was not available. TCM, as a public administration office interested in keeping the city center attractive, would be the ideal host of CCARS. Future research

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should aim at implementing the system and evaluating its contribution to solving real retail site selection problems. Also, the formulas used to identify the decisions could be extended with additional decision variables that are relevant for retail site selection. To help users start using the system, further research could also empirically investigate the weighting factors α, β, and γ, to find the best values for different decision problems.

Our research is subject to limitations. For instance, the proposed recommender system is currently not linked to current vacancies in a city center. However, for TCM it might be important to fill vacancies early to preserve a city center's attractiveness. Combined with a list of vacancies that TCM is aware of, the proposed recommender system could, therefore, be improved considerably. As emphasized, the representative list of land values does not directly relate to the rent values in different areas, but it can indicate differences. If TCM wants to implement CCARS, they might have better datasets to use for rent values in the city center or only include areas with vacant sites.

TCM could also aim to implement a completely different approach towards recommending areas to retailers. If TCM uses CCARS, new retailers might be advised to open a new site in areas that are already popular with similar retailers. This preferential attachment could strengthen city areas that are already well established, while underdeveloped areas of town might fall behind even further. Future research should identify to what extent the goals of retailers and TCM align or contradict each other, and develop the recommender system accordingly.

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