

How To Predict A Pop-Up Store – Developing A Data Based Framework For Digitizing The Location Choice Process And Prototyping At The Case Of St. Gallen (Ch)

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ABSTRACT

We target identifying the needs for the fulfillment of location factors of pop-up retailers being determined by their core motivations and retail sector affiliation. We undertake to do both, to qualify, and to quantify their needs to gain at end of the day a profound description of various pop-up retail patterns. Through the use of a mixed-methods approach containing qualitative research through conducting interviews and qualitative content analysis as well as quantitative fulfillment of location factors through data analysis of multiple location data sources like Open Street Map, we try to gain first indications towards a deeper understanding of pop-up location decisions as well as to validate our hypothesis of the existence of pop-up retail patterns. We were able to validate three retail patterns through our qualitative research. Furthermore, we saw differences reflecting the particular motivations of running the ephemeral retail project. Despite our small shown sample of quantitative data for St. Gallen, we figured out the first indications that store density is a suitable indicator to understand pop-up retailers' locations' decisions. Nevertheless, there is a need to continue research in both terms, more quantitative data like footfall and financial transactions (turnovers) as well as bigger, more representative samples. Within the undertaken literature review we saw a lack of research in gaining a deeper understanding of the nature of pop-up retail in terms of location needs and how location decisions are made. We present results that may deal as a foundation for upcoming research. Moreover, we contribute to the state of research in patterns of retail location choice through a data-driven approach, which presents reasonable insights into the field of location intelligence of temporary retail.

Keywords: Pop-Up; Location Intelligence; Location Choice; Retail Patterns

INTRODUCTION

*F*acing COVID-19, the future of brick-and-mortar retailing is more than ever in doubt. Even before Corona some mainstreaming developments and changing premises had to be noticed: Firstly, a shortage of lifetimes and dwell times of brick-and-mortar retailers. While in the '90s and early 20's long-term contracts containing Occupancy-cost rate (OCR) triggered rentals for ten years or even longer, we nowadays observe terms lasting significantly shorter (e.g. Segerer & Klein, 2015). Furthermore, there is a shift from fixed and retailer's turnover based rents towards more flexible models enabling seamless customer experiences (e.g. Childs, Banchflow, Hur & Matthews, 2019), contracts also including and enforcing non-financial measures such as footfall. So, if we point out flexibility being the key for on-site retail we also should reflect this being true for the facility and its possibilities for flexible interior store design, too (e.g. Petrova 2017; Taube & Warnaby, 2017;).

All these empirical developments are based upon a fundamental change in modern retail and omnichannel concepts. One outstanding trend is the uncoupling of retail functions to achieve higher performances due to specialization

(Wofle & Leimstoll, 2020): Except for (hard) discount formats, we see a movement and transformation in the landscape of brick-and-mortar retail from former times functionally “all-in-one-stop shops” containing transactions, communication, warehousing, and fulfillment towards specialized shops being focussed for more or less one function like brand experience or service. Within our literature review we saw several cases where pop-up shops dealt as a catalyst for a particular function along the (omnichannel) customer journey either it is generating leads for off- and online channels, making a brand feasible and catchy (Spena, Caridà, Colurcio & Melia, 2012), “testing the water” (Jones et al., 2017; Surchi, 2011;), or just boosting sales through selling-off the seasonal fashion collection. Zhang et al. 2019 figured out the huge potential of pop-up shops and events as conversion catalysts for online sales in an experiment at Chinese big one Alibaba. Indeed, nowadays retailers have to act like maestros for orchestrating different formats and instruments to create a holistic and well-tuned omnichannel shopping experience (e.g. Can & Wiid, 2020).

Pop-up retail is reflecting these developments. In contrast to traditional stores and formats, likewise, category killers born in the '80s (Sampson, 2008), pop-up stores do focus typically on one function, where their ephemerality, as well as perceived hedonic-shopping value, play a customer-attracting role (e.g.; Henkel & Toporowski, 2021; Surchi, 2011; Zogaj, Olk, Tscheulin, 2019). Moreover, pop-up retail seems to address modern lifestyles often wise tagged as SoLoMo (Heinemann & Gaiser, 2015). A way of life and consumption being navigated by mobile devices through a linked off- and online world (always on), where experiences and their Instagramability are critical. So pop-up retail may be part of the New Deal in Retail (e.g. Mende & Noble, 2019).

This paper reflects the first insights into an industry and Innosuisse (federal innovation agency of Switzerland) co-founded project. The overall goal is developing a recommender system based upon machine-learning optimizing and digitizing the process of location choice for pop-up retailers. At first, we try to create a system being able to predict the location’s suitability of the existence of shops through using two methods of data analysis in combination with a scoring framework based upon experts' knowledge. Afterward, we try to estimate the influence of the pop-up specific needs regarding the merchant group and core motivations of retailers (patterns). We will test and validate this procedure by using users' feedback on the platform popshops.com, our industry partner, and the place where the recommender systems will be finally launched. Within these first steps, we focus on the Swiss cities of St. Gallen and Zurich as our application partners. In this paper, we focus on the case of St. Gallen.

METHODOLOGY AND APPROACH

Literature and research about pop-up retail have been increasing for years (e.g. Schüller & Jud, 2018). Something barely observed and investigated is the process of location choice (e.g. Warnaby & Shi, 2018). Taking into account its ephemerality and the corresponding quantity of location choices and its processing we believe traditional methods and location assessments need to be digitized and shortened by using data and machine learning (Bethan, Nobbs & Varley, 2018). Therefore, the overall aim of our project is developing a recommender system optimizing the process of matchmaking of landlords and pop-up retailers. As such, a recommender system is based on pattern identification and recognition we stated two hypotheses as a starting point regarding assessing the habits of pop-up retailers:

H1: Existence of Pop-Up retail patterns (RePatS)

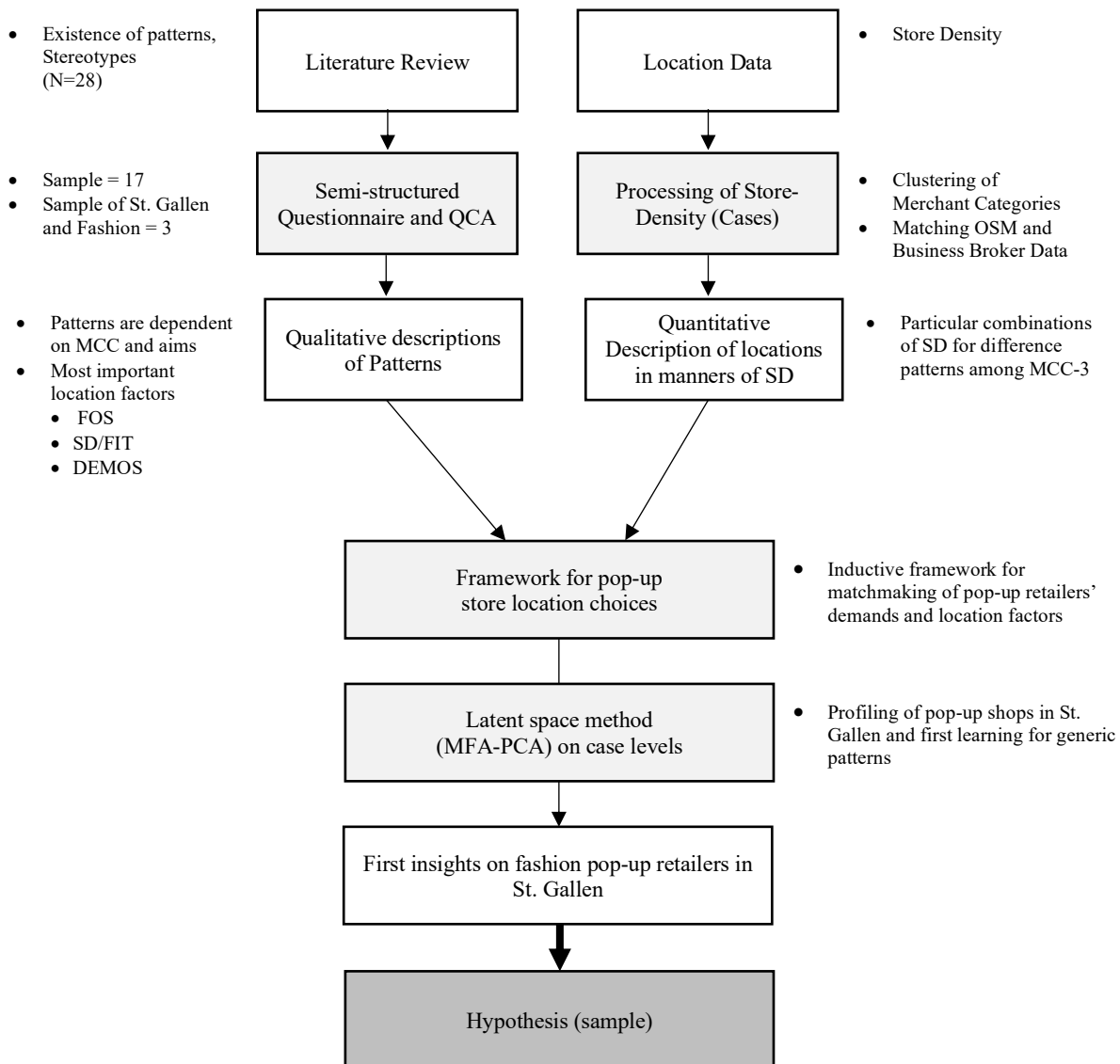
Our approach is based upon the idea that pop-up retailers’ demands regarding their location needs can be clustered into patterns depending on their retail industry and category (merchant category: MC) and their core motivation and aim to pop up, whether it is about selling the seasonal fashion collection (transactional), testing new markets, products, and customer segments (experimental) or generating buzz and providing unique brand experiences (communicational).

H2: Pop Up Patterns and process of location choice may be predicted through the structure of Store-Density (SD)

We believe in the existence of a clear interdependency of store-density structure within 100m x 100m of the particular location and the underlying pop-up retail pattern being dependent on the retail sector and the core motivation. We assume pop-up retail projects and their location choice can be explained and afterward predicted with a probability of more than 80% just through learning and analysis of the store-density structure within this perimeter.

We used a mixed-methods approach consisting of qualitative and quantitative instruments (see Figure 1). Through that combination of inductive based qualitative and deductive-driven based data analysis, we were able to gain both a framework explaining pop-up retailers' choice as well as a prototype or MVP for processing quantitative analysis deriving location intelligence about location factors and their impact for particular retailers' needs. So, this paper's aim is not explaining pop-up retail on a generic level based upon statistically robust findings being guilty all over the world, it is about setting up and trialing a processing pipeline and tool being initially validated through a small sample and using this for mainstreaming it in a sense of feeding it an even bigger amount of data to become a continuous growing holistic view.

Figure 1. Methodological approach



LITERATURE REVIEWS AND QUALITATIVE EMPIRICAL RESEARCH

Our literature review and bibliometric analysis tried to tackle two issues: Firstly, we analyzed the state of the science regarding H1. We found 28 sources reflecting pop-up retail, its habits, stereotypes, motivations, and characteristics – all attributes being able to be linked to patterns (e.g. Bethan et al., 2018; Pomodoro, 2013; Nertinger, 2017; Schüller & Jud, 2018; Warnaby & Shi., 2018). Based upon this, we conducted 17 qualitative interviews with pop-up retailers having run pop-up projects in St. Gallen (6) or Zürich (11). 14 out of 17 interview partners belonged to the retail sector of fashion and shoes, one was part of sports retail, two others sell furniture. We use St. Gallen und Zürich as pilot cities within our research.

We conducted Qualitative Content Analysis (QCA) for the assessment of these interviews and their data. In the first step, the types found whilst the literature review was clustered as patterns featuring characteristics, goals, and found location necessities. We created a semi-structured questionnaire dealing with their projects and whether and they may validate our H1. In a further step, the characterizing properties and features of these types are revised. If necessary, additional characteristics are added which are mentioned in the empirically collected material and which are decisive for the type formation (Kuckartz, 2018). For data analysis, and interpretation we used F4 software (<https://www.audiotranskription.de/english>) as all interviews were conducted in German. Subsequently, the coding of the collected material took place. This coding was done by using a category system. In a fourth step, the coded data were used to assign cases (17) to patterns. Subsequently, the relationships between types are analyzed to highlight any similarities and clear differences between the types. Finally, patterns formed from the research were double-checked with the patterns from the literature and validated. This explains whether the practice corresponds to the current literature and theory or whether there are differences.

At the end of the day, we were able to validate three patterns and some typical requirements for the corresponding location. Figure 2 is highlighting our results at a glance. One important learning is the process of location choice is barely strategically, for pop-up retail it is mostly forced by opportunism. This finding supports the findings of other studies (Bethan et al., 2018; Rudnowski, Heney, Yu, Sedlezky & Gunn, 2020). Only one interview partner undertook strategic planning using a checklist and GIS analysis to identify his pop-up location. In contrast to common literature, we were not able to validate more than three pop-up Retail Patterns (Bethan et al., 2018; Rudkowski et al., 2020 [in particular table 2]; Schüller & Jud, 2018; Surchi, 2011; Warnaby & Shi, 2018; give an overview). What we empirically found are three different generic Retail Patterns based on particular core motivations (likewise Picot-Coupey, 2014). Nonetheless, each pattern has a strong emphasis on a particular goal like pushing sales or testing products and markets among the crowd, there are also “secondary” goals like sales within a brand experience outlet, something we also found in preliminary studies (e.g., Surchi, 2011).

We asked all pop-up retailers about the importance of location factors like footfall (“FOS”), store density and competition (“FIT”), and the demographic structure of the neighborhood (“DEMOS”). Taking into account the lack of planning within their location choice, they were only able to qualify a hierarchy of location factors. These location factors are reflecting state-of-the-art literature concerning location factors (e.g., Ailawadi & Farris, 2017; Birkin et al., 2017; Dinesh, Trivedi & Grewal, 2008; Hikmet et al., 2012; Ögner & Larsson, 2014; Roig-Tierno, Baviera-Puig, Buitrago-Vera & Mas-Verdu, 2013). We learned and were able to prove that location necessities in manners of location factors are dependent on the pop-up retail format, in particular the retailers’ objectives (e.g., Lowe, Maggioni & Sands, 2018).

Overall, it is not surprising footfall and its structure being the most important factor. According to our interviews for Pop-up retailers being positioned within the luxury segment, footfall is less important compared to middle-class and budget-oriented players. This contributes to recent research that the playbook of luxury pop-up seems to be different compared to middle- and low-class retailers (e.g. Lunardo & Mouangue, 2019). Regarding store density and structure of competition as well as demographics we see slight differences between the testing pattern and the sales pattern. Moreover, testing oriented retailers pointed out a high density of competitors within the same merchant category as negative, whereas sales and communication-oriented retailers do welcome a high-density of competitors. This may support the findings of recent pop-up literature reflecting the effects of perceived hedonic and utilitarian shopping (e.g. Zogaj et al., 2019). Where shoppers ask for impressive experiences, instagrammability and emotional moments of the shopping experience “emotional worth of a shopping experience” (Jones et al., 2006, p. 979), a high density of

rather communicational driven retail formats might be delightful. If shoppers are seeking efficiency in getting things done like price comparison of products or multi-purpose shopping rather transactional (One-Stop-Shopping) formats enabling customers reaching their targets are asked.

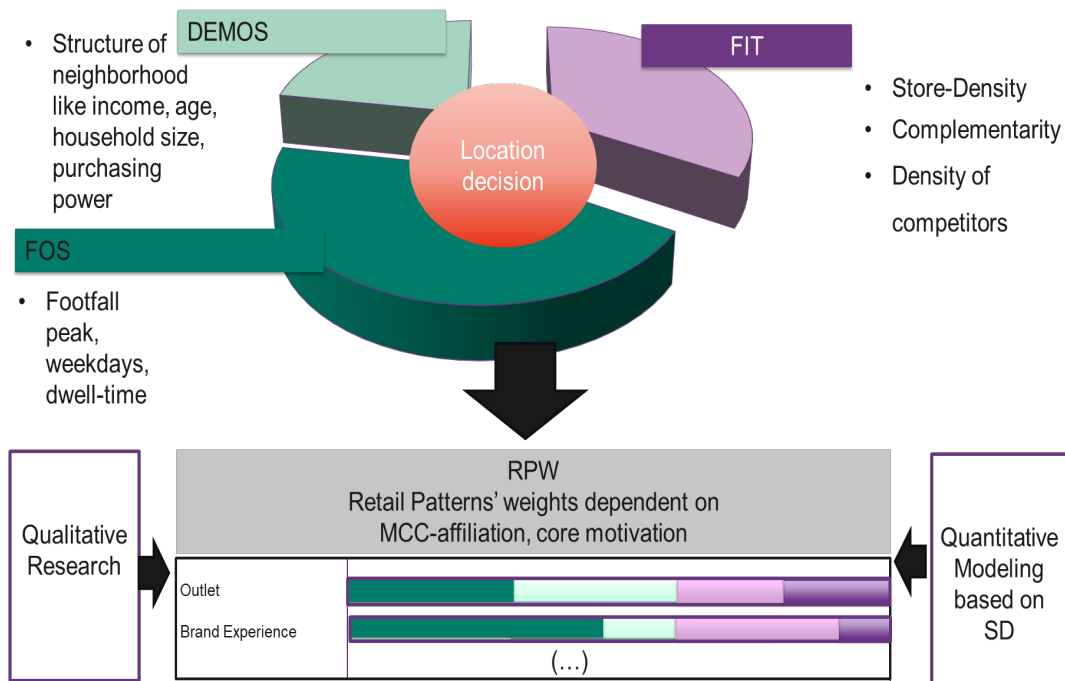
Figure 2. Found location factors, characteristics, and habits from qualitative research

Characteristics and KPI	Brand Experience	Market Tester	Sales and Outlet
Sample (17) 6: St. Gallen 11: Zurich	7/17	4/17	6/17
Core Motivation	Communication	Testing of product, market, category, and location	Sales
Further Motivation	Sales	Brand awareness (Communication)	Communication
In-store events	Regularly	Rare	No events
Seize of category/product range	Small	Small, focus on customers (data)	Medium
Necessity and quantity of Storing room	Small one	No need	Medium to a big one
Primary Location needs Location factors	1) Central place: Footfall (FOS) 2) Co-Location and store density (FIT) 3) Demographic neighborhood structure 4) and purchasing power (DEMOS)	1) Central place: Footfall (FOS) 2) Demographic neighborhood structure and purchasing power (DEMOS) 4) Co-Location and store density (FIT)	1) Central place: Footfall (FOS) 2) Co-Location and store density (FIT) 3) Demographic neighborhood structure 4) and purchasing power (DEMOS)
Branch structure	The density of competitors is positive	The density of competitors is negative	The density of competitors is positive
Typical endurance	1 week to 5 months	1 to 4 months	2 weeks to 3 months

A Framework Of Location Choice

Based on these findings we developed a framework illustrating the location choice decision made by pop-up retailers (Figure 3).

Figure 3. Framework illustrating Location Choice of Pop-Up Retailers



As we only received qualitative data and assessments regarding the undertaken location choice our next step is to use location-based data to validate these findings. Our approach contains investigating both, the correlation of density of competitors (we were curious about investigating whether it is negative in cases of market testers from a quantitative point of view) as well as if it is feasible to explain the location choice of pop-up retailers just through using store-densities in St.Gallen. So, the idea is to remodel the underlying store density of location where pop-up retail projects of our interview partners took place and to compare if this gathered combinations of store densities across different retail sectors as well as the overall density may be guilty on a generic level. For these investigations, we had to extract store densities from several sources to deal with sufficient quality. Quantitative modeling of pattern-specific location quality invokes the setup of a robust and comprehensive data pipeline. To be more precise, we define store densities' matrix at a specific location as a Retail Location Score (ReLocS) we call FIT (see framework) derived from various data sources, that quantify the feasibility of a given location for a specific retail pattern. The data sources are heterogeneous and currently consist of

- Location data of existing shops, restaurants, etc. from OpenStreetMap (OSM)
- Graph data of the city road network from OSM
- Generic transactional data ("Sales of merchants") from a business data broker

Forsakes of data protection we received the transactional data for particular merchant categories as clustered - clusters we had defined at the forefront according to retail sectors. We subsumed the different merchant categories according to ISO 18245 ("ISO 18245:2003 Retail financial services — Merchant category codes") into 7 clusters (MCC: Merchant category clusters). Moreover, we differentiated one cluster for leisure activities like bowling or SPA (MCC-1), periodical services like laundry services (MCC-10), hotels and restaurants (MCC-12,13), and sightseeing places like museums (MCC-11). To deal with OSM data and user-generated contents like particular tags for shops and amenities we defined a translation scheme to enable a matchmaking procedure of OSM and transactional data, likewise:

Key	Value	MC-Code	MCC-Cluster
Shop	Bags	5948	3-Fashion

Quality, granularity, and availability of the data sources vary heavily both within a given city (e.g. St. Gallen) and from city to city (St. Gallen and Zürich). To get a concise database for defining ReLocS like store density we use a data warehouse architecture (Kimball & Ross, 2002) and have developed ETL processes that transform the heterogeneous data sources to a location-dependent feature vector.

These high-dimensional feature vectors form our primary information source for the respective location. However, some of these features are highly correlated, which makes identifying relevant factors difficult. Latent space methods, such as principal component analysis, project the high-dimensional data to a low-dimensional subspace such that the projected data points have minimal correlation (Theodoridis, 2020).

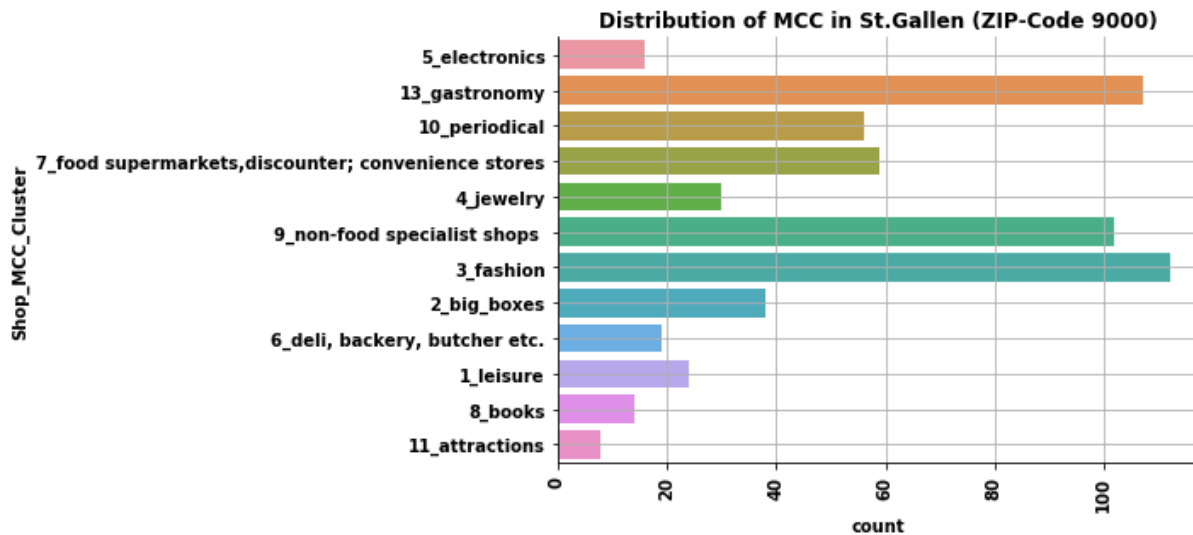
Generic Results – Principle Components Analysis (PCA) For Retail In St. Gallen In General

In this section, we briefly describe the used data sources and the preprocessing pipeline. As stated further above, the heterogeneous data sources have been transformed into a ReLocS feature vector that can be estimated at any given location. A portion of this vector is made up of the store density (FIT) which will be considered subsequently.

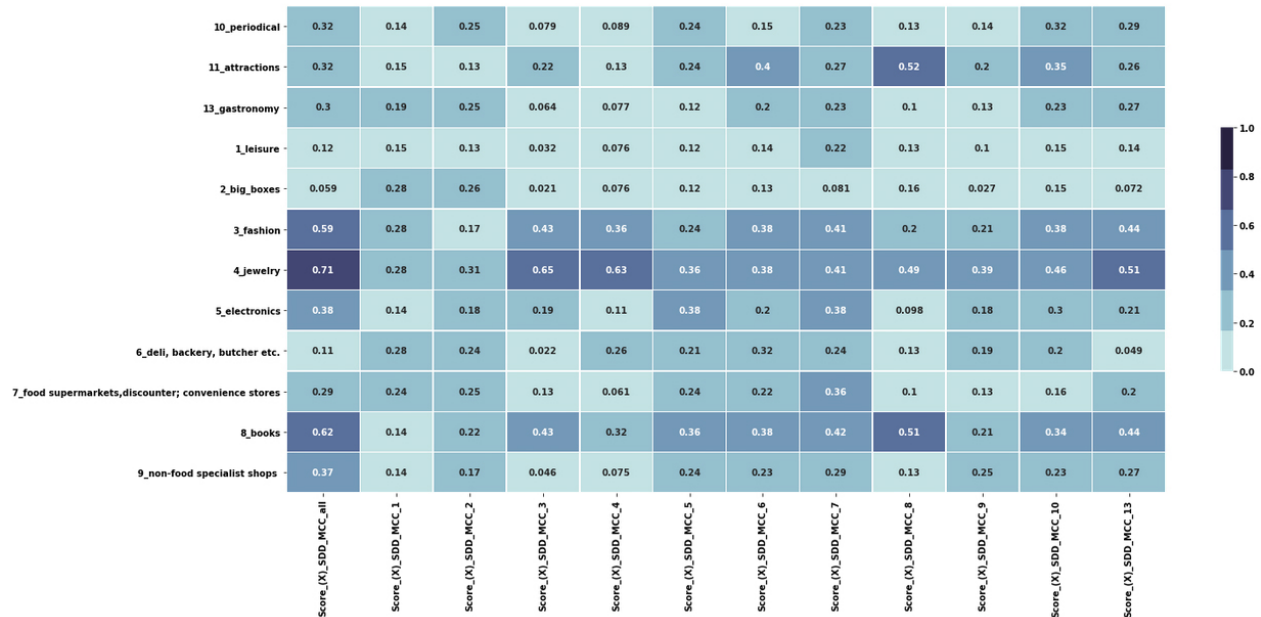
We distinguish the overall shop density and the MCC specific density, where only shops of one of the 13 MCCs are considered. The densities are computed by means of inverse distance weighting where the actual routing distance is used instead of the Euclidean distance. For each given location, the FIT value is computed from all shops within a 100m routing distance. Thus, we end up with 13 FIT score values (there is no data for MCC-12). Each FIT score is normalized by the best in town (BIT) score, i.e. the score values always range between 0 and 1.

Overall, there are 585 shops in St. Gallen, and the MCCs are distributed according to Figure 4. MCC-3 (fashion) and MCC-8 (non-food specialists) embody beside restaurants the highest footfall within St. Gallen.

Figure 4. Distribution of MCCs in the inner city of St. Gallen (ZIP Code 9000)



We split the data according to the MCC and perform a data imputation operation on the data to replace missing values. To this end, a k-nearest neighbor imputer with k=3 is employed. In Figure 5. FIT Matrix of Store Densities in St.Gallen

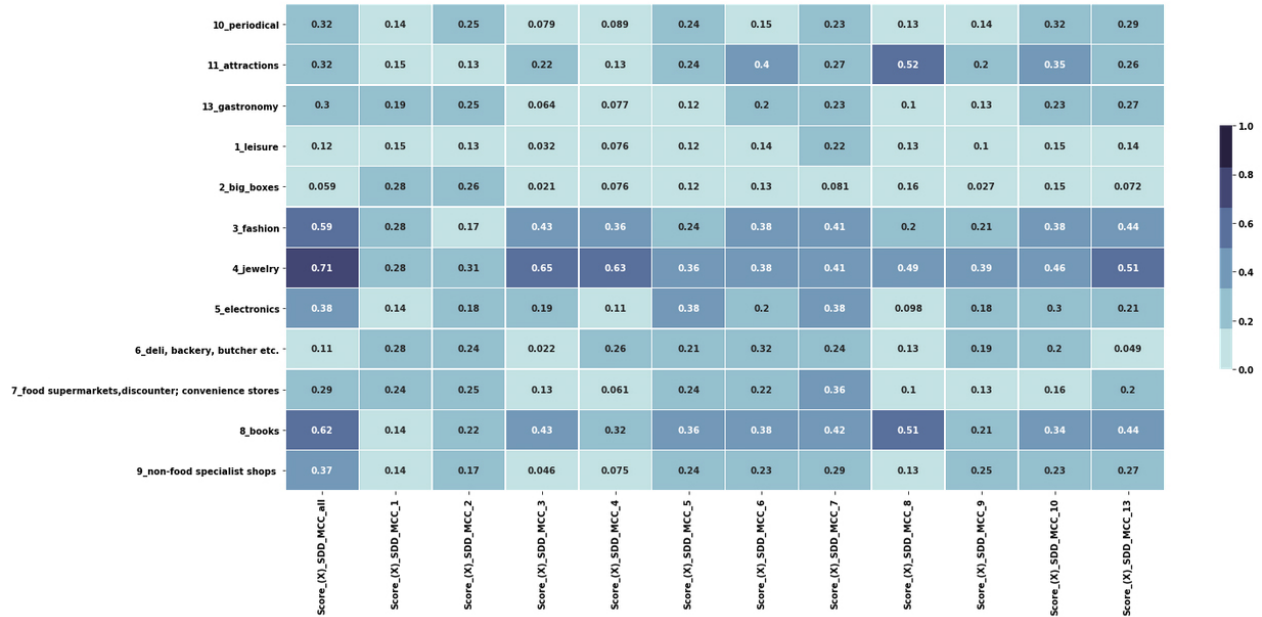


To figure out patterns, we performed a Principal Component Analysis on the individual subsets. It turned out that the variation within the data for all clusters can be sufficiently well modeled by three latent variables summing up approximately 90% of the variation. These three latent variables are linear combinations of the original FIT scores and the i-th weight in the linear combination can be considered the correlation between the latent variable and the i-th FIT score.

To make things clear, we will now focus on MCC 3 (fashion). In Figure 6 the weights for the first three principal components are shown.

we see the median score values for all the MC clusters. If an MCC combination in the table shows a high value (close to 1), this means that shops with these MCC typically are located nearby. Through this procedure, we can gain generic interdependencies of MCCs and their combinations of neighbors (Figure 5). So “fashion” and “jewelry” often are located in regions with many shops (first columns), but particularly close to other “fashion” and “jewelry” shops. “Leisure” and “big boxes”, however, are located in rather sparse regions (4th and 5th row from top).

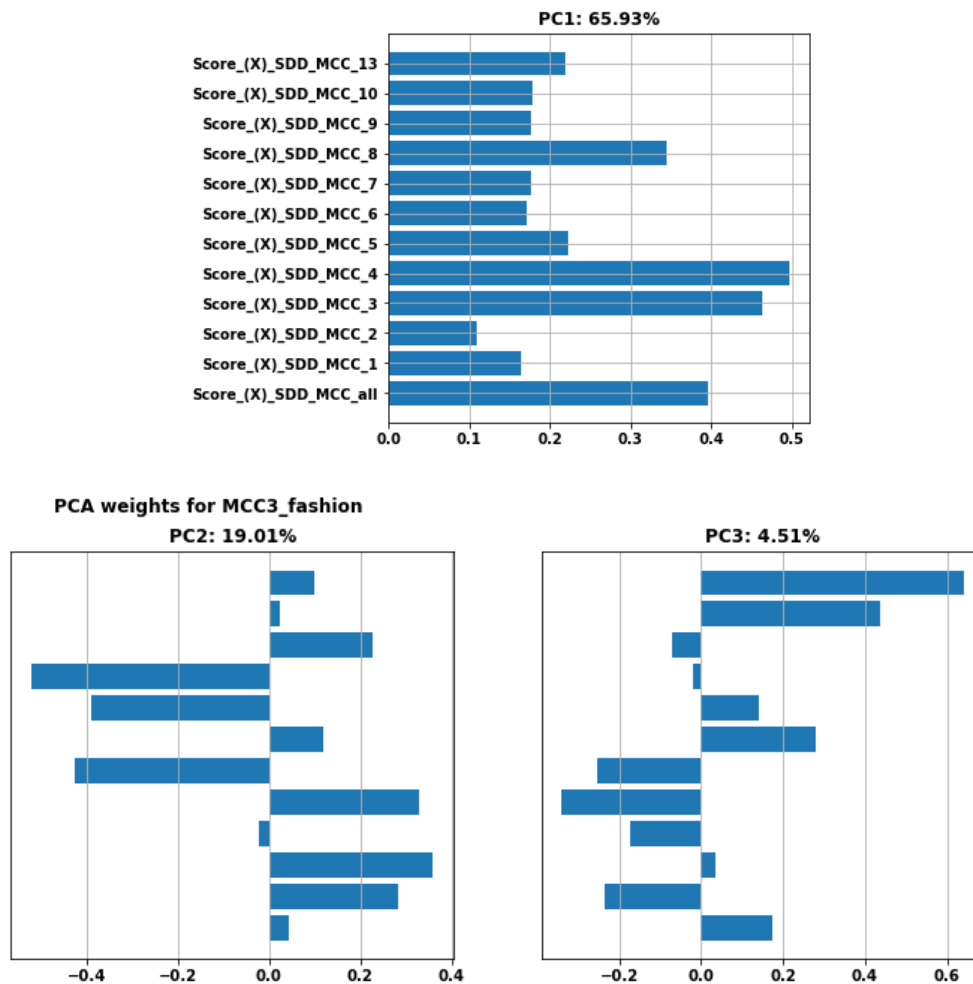
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Figure 6. Processed Principal Components (PC) at St. Gallen



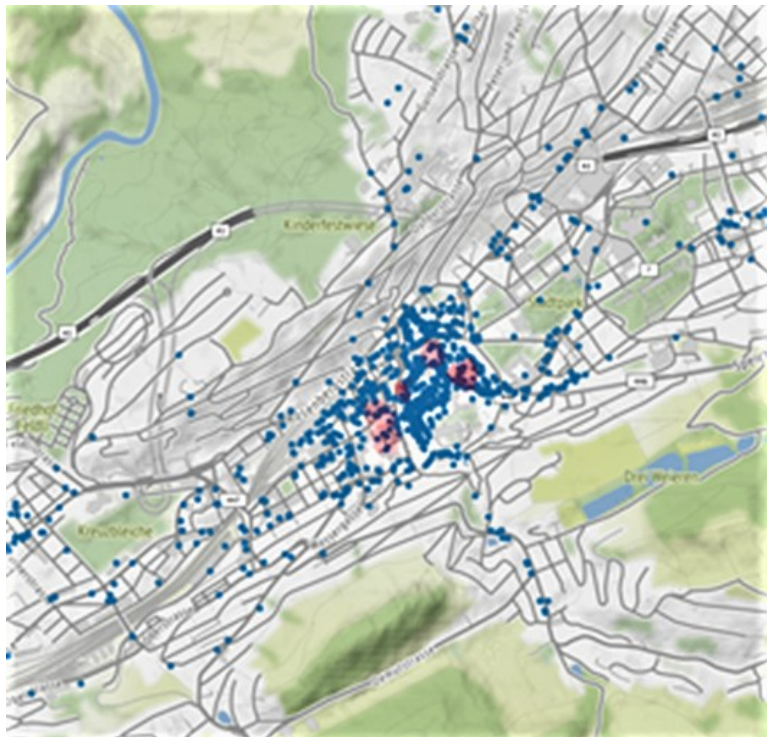
The PC-1 describing approx. 65% of all variations, is essentially the mean value of all FIT scores meaning that at fashion shop locations all other MCCs have either a large density (i.e., it is a busy place in general) or there are only some shops at all agglomerated (both indicating things we know from Christaller’s Central Place Theory). Large PC values happen to be at central locations. As stated above, fashion shops favor other fashion shops as well as jewelry and book shops in their vicinity. This can be seen from the large weights for MCC-3, 5, and 8. Put differently, a high value for PC-1 is a proxy for intense footfall, which we already identified as the most important ReLocS for retailers. In contrast to PC-2 and PC-3, the density of MCC-3 retailers is outstanding, something indicating Hotelling’s Theory of Minimal Differentiation.

PC-2 and PC-3 exhibit MCC specific patterns rather indicating Reilly’s Theory of Spatial Interaction: For fashion shops, we see PC-2 summing up approx. 19% of the total variation in the FIT scores. It is an indicator for having a difference in densities of MCC-1 and 2 on the one hand and of MCCs 5, 7, and 8 on the other hand. PC-3 only describes 4.51% percent of all variations and thus has to be considered as a nuance. The interpretation of PC-2 is that in the neighborhood of fashion shops either the densities of leisure (MCC-1) and specialist markets (MCC-2) are high and simultaneously only some shops for books (MCC-8), home electronics (MCC-5), and few supermarkets and convenience stores (MCC-7) are present or vice versa.

Pop-up sample related results of PCA in St. Gallen

Figure 7 is outlining St. Gallen’s stores and the locations of our sample may be found within the red districts. We deny pointing out the places in detail for the sake of the privacy of interviewees. Within our small sample, we saw that all pop-up projects had chosen locations with a higher store density compared to the means of the whole city overall.

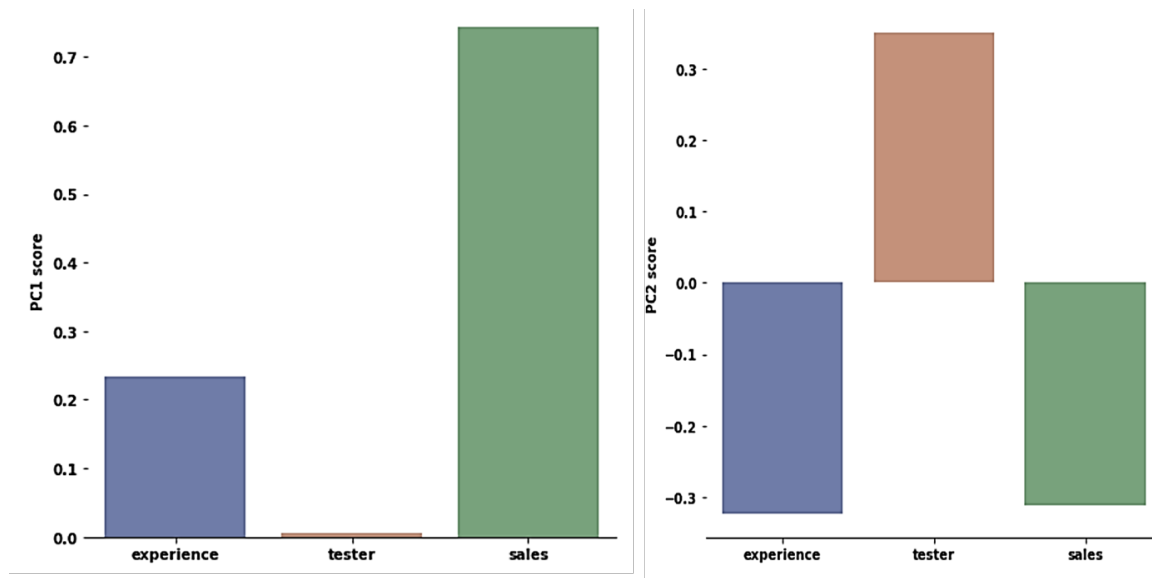
Figure 7. Stores in St. Gallen and footprint of our pop-up sample



For matching cases to the generic retails results above we examine the PC-scores for our pop-up sample in St. Gallen. In Figure 8 the scores are depicted. We see that the concepts “brand experience” and “sales” have similar patterns: they favor locations owning a high density of shops, where the "sales" pattern has the most pronounced need for footfall if we see high PC values as a proxy for footfall (see above). Regarding “brand experience” items, we may confirm the findings above, reflecting footfall being less important compared to “sales” outlets.

Regarding the case of the "market tester" pop-up, we see the underlying location choice fitting best to PC-2. This supports the findings of our qualitative research, in particular, that the density of competitors (MC3) seems to be qualified as negative. Future research has to deal with whether this finding is just due to an outlier or whether it is mainstream able. On the one hand, we have to take into account just having processed quantitative analysis for one location, on the other hand, we know from our QCA that needs of anyway four location choices being self-tagged as market tester affiliated interview partners pointed out the store density of competitors being negative.

Figure 8. PC scores for the sample of qualitative research in St. Gallen



CONCLUSIONS

Within this paper, we address recent calls for research, in particular approaches of balancing theory-driven and data driven perspectives (Ma & Sun, 2020). We combined qualitative and quantitative methods to gain out, whether pop-up shop patterns are existing and how they may be differentiated from the point of view of location factors. Therefore, we undertook qualitative research, and we were able to validate three patterns based upon a questionnaire being feed with the information we extracted from the literature. Based upon this we created a framework of different location factors being able to act as scores for location choice and matchmaking of free space and specific pop-up retailers' demands (Retail Location Scores). As a first step towards developing a more sophisticated data-driven location intelligence instrument using machine learning, we focused on store density as a main Retail Location Score. We subsumed the different store densities of various merchants (MCCs) as FIT consisting of a vector of store densities on 100x100m. To match our findings from qualitative research and our theoretical framework we undertook the first assessment on a very small sample in St. Gallen within fashion retailers. This pitch is likewise an MVP for upcoming research.

Analyzing store density of existing retailers leads to two relevant principal components describing the location choice of fashion retailers. PC-1 is pointing out the need for a high store density and in particular a high store density of fashion itself, jewelry, and books. In contrast, PC-2 is embodying the need for a high density of big boxes like DIY and furniture. For both, store density is important and positively correlated.

We matched these findings with five items of fashion pop-up store projects we had interviewed within our qualitative research. We were able to subsume all items to the two PCs. Despite all investigated projects took place within one square km, we see remarkable differences paying tribute to our very sensitive space latent method figuring out contrast within meters. While brand experience and outlet/sale patterns are sticking to PC-1 (the more centrality the better), the market tester seemed to work differently as it was best matched to PC-2. Communicational oriented pop-ups focusing on hedonic shopping value might own a higher (standalone) attraction for consumers, while transactional projects are rather committed on spending utilitarian shopping value is more dependent on a higher store density generally for one-stop-shopping and a higher store density of nearby competitors for comparison of prices and products (shopping goods). Of course, this sample is not representative, but it underlines the findings from our qualitative research on the existence of pop-up retail patterns going along with different weights on a set of location factors respectively retail location scores.

RESEARCH LIMITATIONS

We decided to present the results for St. Gallen as we were able to conduct five interviews (5/17) with pop-up retailers all belonging to the merchant category of fashion (MCC=3). Furthermore, this sample does represent all three patterns. Of course, this sample and its analysis do not enable representative or generic conclusions. But within the data, we see some proof of the qualitative data. Overall, we see some interdependencies we already have known from traditional retail location theory, such as the theory of minimal differentiation (high density of same merchant-groups) being very valid for fashion retailers. Within the city of St. Gallen, we were not able to identify pop-up retailers out of downtown – this could be an indication pop-up retail mainly focusing on central places embodying a high store density.

These provided results represent the first step towards a more sophisticated reflection on pop-up retail in manners of automatization and digitization of location choice. It is giving an outline of profiles, patterns, and foresight of a likewise prediction. Through using a mixed-methods approach consisting of qualitative research (interviews and content analysis) and a quantitative approach of geo-data analysis enables having a comprehensive view of pop-up retail location decisions. Our next step, besides broadening our quantity of items will be integrating more data sources and categories according to our framework, mainly transactional data and metrics of footfall and its structure at investigated locations.

AUTHOR BIOGRAPHIES

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