Are Local Retailers Conquering the Long Tail? A Web Usage and Association Rule Mining Approach on Local Shopping Platforms

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Abstract. Competitors and customers put Local Owner Operated Retail Outlets (LOOROs) under digitalization pressure. Local Shopping Platforms (LSP) seem to be a promising approach for LOOROs to tackle the digitalization challenge and to overcome their physical and locational disadvantages compared to e-commerce players. However, little is known about the actual performance of LSPs and the (shopping) behavior of the LSP visitors. In this study, we therefore assess the web usage data of five German LSPs. Our findings show that LSPs provide a digital sales and service channel to LOOROs that extends their local catchment area and facilitates their online visibility and accessibility. However, LSPs so far miss the opportunity to create an inter-organizational shopping environment. LSP visitors do not browse across product offers of various vendors, but they mostly follow a single product search strategy and ignore the intended local marketplace structure of the platforms.

Keywords: Local Shopping Platforms, LOOROs, Local Retail, Web Usage Mining, Association Rule Mining

1 Introduction

In an overall positively developing market environment Local Owner Operated Retail Outlets (LOOROs) face an intense business and market transformation [1]. Several independent studies predict a decline in revenue for German LOOROs of 30% within the next four years [2] and even 50% within the next ten years [3]. In particular, the digitalization of sales channels is challenging the traditional hit-driven business models of the small stationery retailers. For decades, a hit-driven approach was a natural consequence of their limited shelf space, preventing them from carrying everything for everybody [4]. According to Anderson (2008), traditional stationery

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retailers face two main disadvantages in comparison to online retailers: 1) Physically limited shelf and sales space forces them to focus on a strictly limited range of products and to exclude any (long tail) niche products from their shops. 2) Regional if not only local catchment areas and regulated opening hours limit the demand for their goods and services [5]. In today's age of the internet and e-commerce, digital distribution channels like esp. online shops and e-marketplaces challenge such traditional business models, as physical, regional and time limitations do not exist in online retail [5]. In his widely acknowledged book "Long Tail", Anderson (2008) summarizes the disruptive development in retail as follows: *"Our culture and economy are increasingly shifting away from a focus on a relatively small number of hits (mainstream products and markets) at the head of the demand curve, and moving toward a huge number of niches in the tail. In an era without the constraints of physical shelf space and other bottlenecks of distribution, narrowly targeted goods and services can be as economically attractive as mainstream fare*." [4]

However, LOOROs have options. Currently, Local Shopping Platforms (LSP), which act as intermediaries between LOOROs and their customers, are spreading in German cities [6]. The advent of LSPs has many ties to the long tradition of e-marketplaces, which, as inter-organizational information system, allow buyers and sellers to 1) exchange and negotiate prices and product characteristics and 2) to complete transactions [7]. The same is true for LSPs, but these added a very interesting twist to their business models. Striving for the critical mass of buyers, sellers and transactions, almost all well-known and successful e-marketplaces operate on a national if not international scale and address all types of customers, serving any sort of B2B, B2C or C2C transaction. In contrast, LSPs put forward locational self-restrictions and made them a fundamental part of their business models and marketing strategies. Either they allow only local retailers to operate on their platform, and/or they serve only local customers. LSPs harness the resulting local structure as a source of unique selling propositions, like e.g. delivery time advantages or service offers based on the direct neighborhood of the local shops (as decentralized storages) and the local customers [8].

LSPs are without question a promising option for LOOROs as they can help to overcome many of the e-commerce entry barriers (e.g. financial constraints, lack of knowledge, lack of infrastructure, etc.) [9]. Besides being a marketplace, they also act as digital service providers for LOOROs, releasing them from the burden of building up their own digital infrastructure and hiring expensive knowledgeable e-commerce experts. Furthermore, LSPs enable cooperation among competitors and thus facilitate synergy effects and cost savings for online activities [10].

On the other hand, joining an LSP can go along with problematic side effects, as LOOROs then become part of the self-reinforcing spiral of ubiquitous online price competition [11]. Further, LSPs charge LOOROs subscription and transaction fees, also drawing from their margins. Finally, it remains unclear, whether local people will accept the limited local e-marketplaces, when global competitors like ebay and Amazon with their unlimited customer base and their broad product and service range are just one click away [12].

Against this background, we aim to answer the following research questions:
RQ1: Do local shopping platforms in fact help LOOROs to overcome physical and locational disadvantages compared to e-commerce players?
RQ2: Do the origins and preferences of LSP visitors offer insights into potential "Long Tail" opportunities for LOOROs?
To answer the raised questions, we will use Web Usage Mining and Association Rule Analysis. We search for frequent usage patterns geared to Long Tail opportunities (e.g. expansion of the catchment area, the opening hours and/or demand for digital shelf extensions) within the web usage data of five local shopping platforms under the roof of one LSP provider in Germany. Each of the platforms is operating separately in one city and its surrounding region. Together, the platforms serve an installed basis of 238 LOOROs.
The remainder of this paper is structured as follows: In section 2, we discuss the methodological background. In section 3, we conduct the Web Usage and Association Rule Mining procedures and present the according results. In section 4, we discuss our findings to answer the research questions, highlight limitations and derive future research opportunities.

2 Methodology

2.1 Web Usage Mining

Web usage mining is the application of statistics and data mining techniques to discover usage patterns from web usage data like web logs and web tracking reports [13]. The goal of Web Usage Mining is to capture, model, and analyze the behavioral patterns and profiles of users interacting with a website [14]. The Web Usage Mining process consists of three phases, namely data preprocessing, pattern discovery and pattern analysis [15]. In the preprocessing stage, the web usage data needs to be cleansed from irrelevant and unreasonable items. In the pattern discovery stage, statistical, database, and machine learning operations are performed to obtain hidden patterns reflecting the behavior of users. In the final pattern analysis, the discovered patterns and statistics are further processed, filtered and used as input for a variety of data-mining algorithms [13].

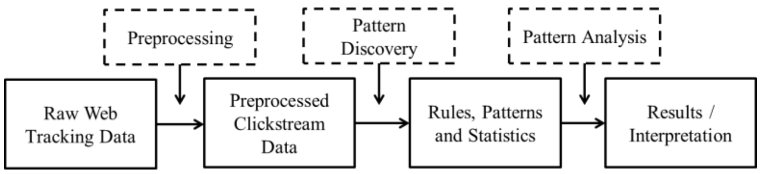

Figure 1. Research Procedure based on Nagi et al. (2011)

2.2 Association Rule Mining

Association Rule Mining on web usage data aims at finding "frequent item" sets, as groups of items (e.g. products or web pages) commonly accessed or purchased together [16]. Such item sets can be one-dimensional (e.g. only products) or multi-dimensional (e.g. products and time stamps) [17]. An association rule expresses an association between an antecedent and a consequent (sets of) item(s) in a shared interaction (e.g. page views in one session) [18]. The association rule r is an expression of $X \rightarrow Y$ (σr , αr), with X and Y as item sets, σ as support ($X \cup Y$), representing the share of interactions in which X and Y occur together, and α as confidence, representing the conditional probability that Y occurs in an interaction that already includes X [18]. An association rule is sound if the response within the target item group (confidence) is much better than the average response for the whole dataset. This is assessed using the metric lift, as the ratio of the response in the target item group and the average response of the whole data set. A lift of <1 or 1 implies that the probability of the occurrence of the antecedent and the consequent are independent of each other and that no rule exists. If lift is >1, the actual value indicates the degree to which a dependency exists, and thus how useful a derived rule would be for predicting the consequent in future data sets [17]. The Apriori algorithm is a well-known algorithm for finding association rules [18]. We used the version implemented by Borgelt (2002).

3 Analysis

3.1 Dataset

To answer the raised research questions, we analyzed the 1) web usage data and the 2) product databases of five LSPs managed by a German local shopping platform provider:

1) The available web usage data, retrieved from Google Analytics, consists of a custom session ID (int), the users' country and city (derived by Google from the IP addresses of the users (string)), the URL of the visited website (string) and the date, hour and minute of the visited webpage (string). The specification of the data is available as part of the Google Analytics Reporting API v4 reference [19].

2) The product data consists of the product name (string), the product URL (string), the product category (string), the vendor name (string), and the vendor category (string). Table 1 shows examples of the retrieved product and vendors categories.

We conducted the data preprocessing, the pattern discovery, and the analysis of the web usage data using the KNIME analytics platform (www.knime.com).

Table 1. Overview Top 8 Product and Vendor Categories

Top 8 Product Categories		Product Views	Top 8 Vendor Categories		Product Views
1.	Local Food & Beverage	9416	1.	Grocery Store	10238
2.	Home & Garden	7326	2.	Jewelry Store	6551
3.	Fashion	6996	3.	Book Store	6395
4.	Media & Books	5214	4.	Hobby Shop	5067
5.	Gifts	2927	5.	Furniture Store	3655
6.	Toys	2783	6.	Office Equipment Store	1708
7.	Sports Equipment	1954	7.	Liquor Store	1310
8.	Art	1860	8.	Pharmacy	1211

3.2 Data Preprocessing

For our analysis, we needed to transform and aggregate the web usage data on different levels of abstraction. In web usage mining, the most basic level of abstraction is a page view [15]. Regarding the website visitor, the most basic level of behavioral abstraction is a session, as a sequence of interactions (page views) by a single user in a given time (usually during a single visit) [15]. We examined frequent usage patterns and preferences on the following levels of abstraction: 1) page views 2) user sessions, and 3) location and time.

First, we cleansed the web usage data from entries not necessary/relevant for the mining process [13]. The initial data set included 487,906 unique page views. We removed all backend related page views (admin or login pages) to eliminate as many page views generated by vendors as possible. Further, we excluded all incomplete page view entries, for example in case of missing locational data, leading to 433,771 remaining datasets. These included 100,681 views of the global homepage, 56,555 views of global content pages (like the imprint, terms and conditions, jobs, etc.), 210,755 views of local product category pages, and 69,760 views of product pages.

In a second step, we preprocessed the sample of product page views for a location and time related analysis. As the time stamp for each interaction and the origin of the visitor were part of the data, only the platform location needed to be added as a reference for distance calculations. The online platform architecture uses one global homepage and local entry pages (as city names) for each local shopping platform on different domain levels. This way, we were able to derive the locational dependency of each page view directly from the URL structure.

In a third step, we joined the two tables (web usage data + product database) using the URL as a unique key available in both tables.

Table 2. Preprocessed Data Structure

Google Analytics						Products Database		
Session ID	Visitor Country	Visitor City	URL	Date / Time	Platform City	Product Category	Vendor Name	Vendor Category

3.3 Pattern Discovery

1) Location & Distance Categories: To identify locational usage patterns and preferences of LSP visitors, we developed a location & distance based categorization. Research on buying power and catchment areas of local shops usually sorts visitors into four different groups based on the distances between the location of the visitors and the location of the platform [20]: 1) Local Catchment Area: visits from within a fifteen kilometer radius around the location of the visited platform; 2) Distant Catchment Area: visits from outside the 15 km radius, but from within a 50 km radius around the visited platform; 3) Online Shopping Distance: visits from outside the 50 km radius of the platform, but from within Germany; 4) Foreign Country Distance: all visits from outside Germany. To implement these categories, we extracted the longitude and latitude of the cities using the Google Geocoding API [21]. With these coordinates at hand we then calculated the distances between each platform and its visitors, applying the Haversine formula. The Haversine formula, which is gaining growing attention in navigational contexts, calculates great-circle distances between two points (d) on a sphere (r), based on their longitude (λ) and latitude (Φ) coordinates [22].

$$d = 2r \arcsin\left(\sqrt{\sin^2\left(\frac{\phi_2 - \phi_1}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right)$$

Figure.2 Havesine Formular

Table 3 provides an overview of our findings. More than 60% of all LSP visitors accessed the platform from a location more than 50 km away, what we consider as online shopping distance. Only 15% of the users accessed the platform from within the city itself. The results indicate that the self-restriction of LSPs to serve only local customers is contradicting the actually visitor structure and needs revision [6, 8].

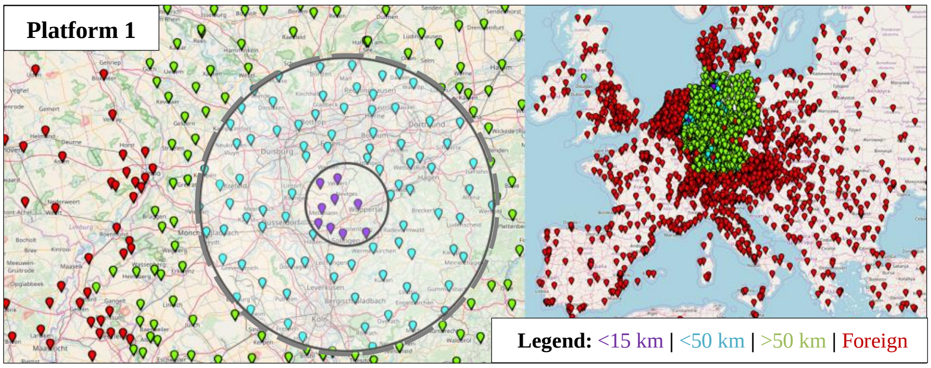

Figure 3. Distance Categories and Visitor Origins

Table 3. Overview Distance Categories / Product views

Location	Total	%	P1	%	P2	%	P3	%	P4	%	P5	%
Local	10263	14.7	7379	16.0	1391	12.6	364	7.0	606	12.3	523	21.6
Distant	8725	12.5	6963	15.1	805	7.3	720	13.9	194	3.9	43	1.8
Online	42170	60.5	26148	56.7	7444	67.2	3437	66.5	3533	71.5	1608	66.4
Foreign	8602	12.3	5653	12.3	1442	13.0	650	12.6	610	12.3	247	10.2

2) Time Categories: Also regarding time, we developed a categorization for platform visits, which we derived from the regular opening hours of local shops. As there are no standard opening hours in Germany, we defined the categories considering the development of the opening hour regulations. Traditionally, since 1956, German retailers had core opening hours between 10 am and 6 pm. A first extension allowed them to open their doors from 6am to 6pm. From on 1989, retailers were allowed to keep their stores open until 8 pm. Since 2006, opening hours are subject to state law and most federal states extended the timeframe to 10 pm or even midnight [23, 24]. Accordingly, we differentiate the following access time categories for platform visits: 1) Early opening hours, covering the time between 6am and 10am; 2) Traditional opening hours, covering the time between 10am and 6pm; 3) Late opening hours, covering the time between 6pm and 10pm; 4) Night / Closing time, covering the time between 22pm and 6am (when stationary retail stores are closed).

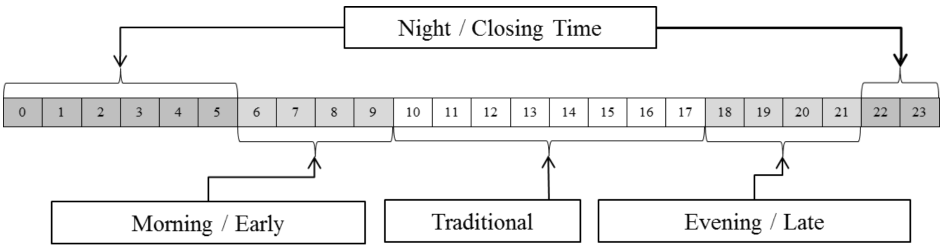

Figure 4. Time Categories

Applying these categories, the data reveals that the majority of users (49%) visited the platforms during traditional opening hours. At night (8%) and during early morning hours (11%), only few visits were recorded, while 32% of the visitors accessed the platform in the evening (see table 4).

Table 4. Overview Time Categories – Product views

Time	Total	%	P1	%	P2	%	P3	%	P4	%	P5	%
Early	8813	11.,3	5655	11.09	1572	12.5	694	11.7	576	10.5	316	11.9
Traditional	37842	48.7	24523	48.08	6337	50.4	3001	50.4	2592	47.1	1389	52.4
Late	24498	31.5	16407	32.17	3729	29.7	1791	30.1	1841	33.5	730	27.5
Night	6532	8.4	4420	8.67	936	7.4	466	7.8	492	8.9	218	8.2

To prepare the data for pattern discovery, we assigned each unique entry for page path (as a representation of a product page), distance, time, vendor and product category a numerical value. Table 5 shows the resulting data structure.

Table 5. Final Data Structure

Session ID	Visitor Country	Visitor City	URL	Date/ Time	Platform City	Product Category	Vendor Category	Distance Category	Time Category

3.4 Pattern Analysis

1) Session dependent Analysis: To identify Long Tail opportunities for LOOROs based on frequently viewed product sets within one session, we conducted a Market Basket Analysis using the Apriori algorithm [16]. Surprisingly, the algorithm was not able to detect any frequently viewed item sets, even when applying a very low threshold of 1% support and 5% confidence. We therefore looked at the session characteristics and found that the average visitor does not visit more than one product page, also indicated by a very low average session length of only 1.2 page views. Furthermore, we found a high number of direct bounces (84%) (see table 6).

Table 6. Session Length Overview

Single page session:	291.964	84.1%
Session 2 to 5 page views	53.145	15.3%
Session 6 to 10 page views	1.760	0.5%
Sessions > 10	296	0.1%

The average length of sessions including a product view was only 3 (page views), including only one product page view. This clearly shows that LSP visitors do not look around, but instead follow a very focused search strategy and usage pattern. Furthermore, the very short session length indicates a low transaction rate for the platforms, as the shortest path to complete a transaction requires six page views. Only 0.6% of the sessions reach this length and could thus carry a transaction (see table 6).

2) Distance and Time dependent Product Views: For further investigation of the Long Tail opportunities (extension of the catchment area, opening hours and/or demand for digital shelf extensions), we analyzed location and time preferences of LSP visitors, using a multi-dimensional association analysis [16]. To make sure that the rules that we discovered (using the Apriori algorithm) only represent frequent and important usage patterns, we defined high thresholds as filters: >25% for category support (support based on the distance categories), >15% for confidence, and >1 for lift [17]. Only rules above these thresholds will be part of the following discussion.

Regarding the impact of distance and time on product category views, we identified seven rules, revealing Long Tail potential mainly for Fashion and Home & Garden products. Rules 1, 2, 3 and 6 show that regardless their location, users especially visit Fashion product pages during traditional opening hours (e.g. "Local Customers + Traditional Shopping Time → Fashion Products"). The high lift (8.6) of rule 3 stresses the importance of this pattern. Further, rules 5 and 7 point at preferences of both, users visiting the platforms from online shopping distance in the evening hours and users visiting the platforms from outside the country during traditional opening hours, for Home & Garden product pages. Rule 4 indicates another interesting behavioral pattern, as it shows that local food and beverages are of special interest for LSP visitors from outside the local catchment area and during traditional shopping times.

Table 7. Association Rules – Distance / Time to Product Category

	Antecedent		Consequent				
No.	**Distance**	**Time**	**Product Category**	**Support %**	**Category Support %**	**Confidence %**	**Lift**
1.	Local	Traditional	Fashion	7.07	48.1	15.2	1.107
2.	Dist. Catchment	Traditional	Fashion	5.19	41.5	16.6	1.209
3.	Online Shopping	Traditional	Fashion	26.3	43.5	11.9	8.627
4.	Online Shopping	Traditional	Local Food	26.3	43.5	20.4	1.101
5.	Online Shopping	Late	Home & Garden	17.8	29.4	16.7	1.160
6.	Foreign Country	Traditional	Fashion	5.84	47.4	16.2	1.174
7.	Foreign Country	Traditional	Home & Garden	5.84	47.4	18	1.250

(Category Support >25%, Confidence >15%, Lift >1)

Regarding the impact of distance and time on the users' vendor preferences, we identified six rules. Rules 1 and 2 point at a book store and jewelry store focus of users, who are accessing the platform from within a local range and during traditional opening hours. As stated in rule 3, users from the Distant Catchment Area tend to look at Jewelry Stores. Further, rules 4, 5 and 6 (rule 6 with a high lift of 8.9) indicate that during traditional shopping times, visitors from online shopping distances or from outside the country mainly look at Electronic Stores.

Table 8. Association Rules – Distance / Time to Product Category

	Antecedent		Consequent				
No.	**Distance**	**Time**	**Vendor Category**	**Support %**	**Category Support %**	**Confidence %**	**Lift**
1.	Local	Traditional	Book Store	7.07	48.1	17.5	1.390
2.	Local	Traditional	Jewelry Store	7.07	48.1	15.6	1.210
3.	Distant Catchment	Traditional	Jewelry Store	5.19	41.5	17.2	1.335
4.	Online Shopping	Traditional	Electronics Store	26.3	43.5	22.2	1.103
5.	Online Shopping	Late	Electronics Store	17.8	29.4	22.6	1.120
6.	Foreign Country	Traditional	Electronics Store	5.84	47.4	18	8.929

(Category Support >25%, Confidence >15%, Lift > 1)

4 Discussion & Conclusion

Applying Web Usage and Association Rule Mining, we analyzed the web usage data of five local shopping platforms in Germany. Regarding our first research question, *"Do local shopping platforms in fact help LOOROs to overcome physical and locational disadvantages compared to e-commerce players?*, our findings show that LSPs do help LOOROs to tackle locational limitations, but do not help them so far to overcome physical limitations (regarding shelf and sales space).

Concerning the limited catchment area of LOOROs, the platforms attract visitors and potential customers from outside the local and the distant catchment area (60% from

online shopping distance, 12% from foreign countries) and thus help LOOROs to extend their market reach. Surprisingly, local visitors (15%) and visitors from within a radius of 50km (13%) account for only a small portion of LSP user traffic. Further, LSPs extend the opening hours of LOOROs into the late evening (32% visitors between 6 pm and 10 pm), but the platforms mainly attract visitors during traditional opening hours so far (49% visitors between 10 am and 6 pm).
Concerning the physical limitations of LOOROs, LSPs at this point do not attract their visitors to browse around on their platforms, to look at various offers of the local vendors, and to discover unknown niche products from the tail of the demand curve. Based on the examination of the session characteristics, our findings indicate a focused search and usage behavior of the visitors. If LSP visitors view a product page at all (average session length 1.2 page views), they mostly look at only one single product. Apparently, users so far access LSPs mainly for shopping preparation, contributing to the "Research Online – Purchase Offline (ROPO) Effect" (also known as webrooming / showrooming) [25]. Accordingly, so far LSPs miss the opportunity to establish an inter-organizational marketplace with digital shelf extensions for local online shopping (local commerce), and instead only act as information hubs with regards to product availability and opening hours.

As to our second research question, *"Do the origins and preferences of LSP visitors offer insights into potential "Long Tail" opportunities for LOOROs?*, the web usage data revealed several interesting demand patterns, indicating Long Tail opportunities for the expansion of the catchment area and opening hours, but also pointing at demand for digital shelf extensions (see table 7 and 8). For example, we found products of Electronic Stores to be mainly visited by users from online distance or even foreign countries (see table 8). Regarding time, the majority of the demand patterns relate to traditional opening hours. Only two of the discovered rules cover the late evening. In conclusion, at this point especially retailers dealing with "Fashion" and "Home & Garden" products seem to benefit from the Long Tail effects of LSPs (e.g. demand from outside the local and distant catchment area and outside traditional opening hours) and thus could learn from the discovered demand patterns. Additionally, they also could benefit from digital shelf extensions provided by LSPs, as Fashion products are characterized by a huge variety in terms of colors, sizes and cuts, and Home & Garden products (like garden furniture) are often bulky, so that locational limitations are of particular relevance for the according retailers and delivery is of special importance for the customers [4].

Practical Implications: Our findings provide valuable insights for both, the owners of LOOROs and the providers of LSPs :
LOOROs: 1) LOOROs can harness LSPs as information and service hubs, improving their online visibility and allowing potential customers to check e.g. on the availability of products. 2) LOOROs should familiarize themselves with the opportunities of the Long Tail and they should analyze the revealed demand patterns to develop targeted LSP sales strategies [4]. 3) Furthermore, as shopping frequencies in high streets are declining [26], the high numbers of online visitors during

traditional opening hours points at the opportunity for LOOROs to establish a live online touch point with their customers [5].
LSPs: 1) Considering the origins of the platform visitors, a self-restriction to serve only local customers seems questionable. Nearly 85% of the users visited the platform from outside the local area and virtual geo fences would thus simply cut down the demand side of the platforms. 2) So far, LSPs fail to keep visitors on their sites. Improved landing page design and the use of recommendation services could help to extend the average session length and duration of visits, leading to a more attractive local online marketplace environment.

Limitations and Future Research: 1) Web usage data captures behavioral patterns and profiles of users along with their clickstream data. However, it offers no insights into the users' perception of the quality of a website and the attractiveness of its products and services. Thus, for deeper insights, transaction data needs to be taken into account. 2) Further, as long as LSPs fail to attract visitors to browse around on the LSPs, association rule (Market Basket) analysis depending on clickstream behavior can only offer very limited insights.
Considering our findings and the limitations of the research approach, we suggest the following areas of future research: 1) Research is needed, that aims at a better understanding of the search behavior of LSPs visitors, as it is so far unknown, why they leave the platforms so quickly. 2) A possible answer could be that they are preparing online for later offline transactions, as suggested by the "ROPO effect". Of course, LSPs like to put forward this argument in their marketing messages, but so far there is no quantifiable proof of the ROPO effect, as it is very challenging to measure customer journeys across different channels (online / offline) and different devices [27]. Thus, approaches need to be found that can help measure and proof the ROPO effect.

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