Deal or No Deal? Assessing the Daily Deal Shopper

Bettina Beurer-Zuellig
Zurich University of
Applied Sciences
bettina.beurer-zuellig@zhaw.ch

Roger Seiler
Zurich University of
Applied Sciences
roger.seiler@zhaw.ch

Abstract

We build upon previous work done in online shopping segmentation but follow a customer-revealed approach by using an explorative cluster analysis on a sample of 11,848 daily deal shoppers located in Switzerland. We identify six segments into which the daily deal shoppers can be categorized: recreational shoppers, mobile shoppers, traditionalists, bargain hunters, socializers, and convenience seekers. These clusters are distinctively different in terms of shopping motives, online behavior, and demographics. By following these clusters, our research maps for the first time the field of daily deal shopping in Switzerland. Our findings have implications for business, as they suggest how to best serve different segments to enhance the customer experience, and for research, as they complement daily deal literature by identifying daily deal shopper segments.

1. Introduction

"e-Retailers that continue to assume that all online visitors are alike will continue to miss opportunities to maximize the loyalty of their existing customer base, to attract customers from other sites, and to educate and convert non-customers." [1, p. 331]

In the recent past, e-commerce and m-commerce have become fast-growing industries, with consumers spending considerably more as technology and acceptance mature. E-retailers such as Amazon, marketplaces such as Alibaba, and auction platforms such as eBay are well established, as evidenced by the turnovers generated from online sales. According to the U.S. Department of Commerce, Web sales rose from 91 billion USD to 342 billion USD in 2015 [2]. The concept of couponing itself is not new to the retail world, whereas daily deal platforms and coupon websites are the latest addition to e-commerce, beginning with the establishment of Living Social in 2007. Daily deal platforms constitute a specific type of e-commerce, resting upon the principles of social buying [3]. While coupons are valid for several days or weeks, daily deal offers usually last no longer than 24 hours and include coupons as well as products and services [4]. According to Statista [5], in spring 2015, 50.03 million Internet users had accessed daily deal sites within the last month in the United States. Spending by U.S. citizens on online deals, including daily deals, instant deals, and flash sales, are expected to reach 5.2 billion USD in 2016 [6]. In Switzerland, too, e-commerce has become popular. One Swiss daily deal platform appears on the top-ten list of Swiss B2C online shops, and it has a turnover of 77.1 million USD [7].

Although researchers have thoroughly analyzed online shopping behavior, research on daily deal platforms and coupon websites is rather scarce. The objectives of this research were therefore to assess the shopping motives of daily deal customers and to identify the customer segments of this specific e-commerce type. This complements the still-small body of research on daily deal platforms by introducing daily deal customer segments. From a business perspective, the growing numbers of daily deal users justify a closer examination of the existing segments to better serve customers and maximize benefits on both the customer and business sides.

2. Relevance

In researching the different shopping motives and segments of daily deal customers, it is important to understand shopping motivations, online customer segmentation, and the specifics of daily deal sites.

2.1. Daily deal format

Daily deal sites differ distinctly from traditional e-commerce. Product and service availability is limited, vouchers often have local reference, and coupons have

URI: http://hdl.handle.net/10125/41657
ISBN: 978-0-9981331-0-2

very limited validity [4]. Large price discounts and restrictions on time, and often quantity, affect this buying setting. This contention is in line with current research on online daily deal settings, which has highlighted the strong effects of this special context on consumer purchasing behavior [8, 9]. Boon et al. [10] examined 847 deal-of-the-day offers across 44 U.S. cities, where 90% of the offers had a time restriction (between 1 and 3 days) and 93% a limitation on the number of products a customer could buy. Byers et al. [11] examined Groupon customer behavior over several weeks, showing that demand for vouchers is relatively inelastic. In their study, they emphasized the importance of soft factors, such as the validity of deals and combination offers.

Kruzka [3] stated that daily deal shoppers are motivated by utilitarian concerns, such as savings and discounts, rather than by hedonistic or impulsive causes. Furthermore, customers display different coupon redemption behaviors online than offline, with many more coupons being redeemed online [12]. Research on daily deal platforms follows various approaches: the economics of daily deals [11, 13], price comparisons [14], the effect of word of mouth on daily deal sites [13], the profitability of daily deal promotions for businesses [15, 16], impulse buying in the context of daily deals [3], and the maximization of the consumer welfare function [17]. To our knowledge, no research exists on customer segments within daily deal platforms. In addition, numerous authors have noted that more research is needed [10, 18-24], as the topic constitutes a specific form of purchasing with special characteristics.

2.2. Online segmentation

Online shopping scenarios and settings differ from offline ones, leading to distinct online and offline customer segments [25] with contextual factors influencing customers [8]. Classification systems can be used for segmentation, and the number of customer segments found online ranges from three [27] to six [1]. Doty and Glick [26] identified three main systems: classification (attribute-based), taxonomy (hierarchical, nested decision rules), and typology (a conceptually derived set of types), while Swinyard and Smith [25] conducted an integrated study comparing online and offline segments and identified four offline and four online segments of U.S. customers.

Online shopping customer segmentation research covers countries such as Singapore [28] and the United Kingdom [29], and in a cross-country study additional countries, such as Australia, Canada, China, South Korea, and Japan [21] have been analyzed. Furthermore, past research may be classified and distinguished according to product types and goods analyzed. In Switzerland, online customers shopped most often for flights (44.7%), followed by holidays or hotel accommodation (19.1%), books (16.3%), and computers and accessories (15.9%) [30].

Based on these findings and the aspects mentioned above, to the knowledge of the authors, there is no common agreement or understanding regarding online segments, nor is there agreement on the number of segments, or common ground regarding regional influences. Nevertheless, both current and past research concluded that regional differences in segmentation exist [21, 31]. Segmenting customers online in the buying setting of daily deal platforms in Switzerland should therefore be no exception to this pattern. Daily deal platforms in particular are under-researched. Authors of preliminary research on deal-of-the-day scenarios call for further research [13, 18], as “a greater understanding of the DOD effect is necessary” [10] and to obtain further insights regarding hedonistic and utilitarian shopping motives [32].

Furthermore, past methodological approaches include qualitative (e.g., Hill et al. [27]), quantitative (e.g., Swinyard and Smith [25], Kau et al. [28], Lim et al. [33]), and combined (mixed method) approaches (e.g., Chen and Chang [19], Christodoulides et al. [21]), most with sample sizes ranging from 306 [19] to 1,738 [25]. Two notable exceptions are Kau et al. [28], with a sample size of 3,700 [28], and Zuccaro and Savard [34], with a sample size of 39,191. Thus, we intended to contribute to current literature by conducting further research, which we present in this paper, with a focus on the daily deal online shopping scenario and its customer segments, and by conducting an analysis with a relatively large sample size of 11,094 data sets.

3. Theoretical context

We do not develop our hypothesis explicitly in this section, as we followed an explorative, consumer-driven approach to customer-revealed segmentation. According to Allred et al. [1], this approach identifies naturally occurring target customer groups, giving companies a strategic advantage over their competition.

3.1. Segmenting customers

Both marketing and online-commerce researchers have studied offline and online customers; in addition, past research on customer segmentation employed demographic, psychographic, geographic, family lifecycle, lifestyle, product-specific criteria, and benefit- and behavior-based segmentation approaches, depending on product type, target group, and buying situation. Essentially, there are two established approaches to segmenting customers: an *a priori* (*ex-ante*) and an analysis-based (*ex-post*) one [1, 31, 35], with the latter based on actual customer buying behavior rather than customer characteristics. A further approach divides customers into two distinct groups by classifying them as people who shop online and those who do not (e.g., Swinyard and Smith [25] and Kau et al. [28]). This approach found higher rates of coupon redemption for online shopping than for offline [12].

Past and current research on segmentation do not agree on a general number of segments, which ranges from three [27] to six [1, 21, 28] distinct customer segments. Surveying Internet users regarding online shopping [21, 36], focusing on a specific product type [31, 37, 38], or focusing on a specific region or country [27, 39, 40] may explain the different numbers of segments found. Online and offline context may further explain why researchers found different numbers of segments, as these two purchasing environments are substantially different (see Passyn et al. [41] for an overview of customer-perceived problems and benefits of the two scenarios).

Furthermore, the daily deal shopping setting is a specific one in terms of contextual factors influencing buying decisions [8], and time and quantity restrictions further add to the specificity of the setting [10]. These aspects render this buying setting an interesting one worthy of further investigation.

4. Methods

Researchers have discussed customer segmentation for offline and online commerce. Nevertheless, to our knowledge, no customer segmentation is available for the specific format of daily deal platforms, which constitute a form of social buying. Our study followed an explorative approach, although it closely aligned our items with previous research in online customer segmentation and shed light on segmentation in Switzerland. Items were concentrated in higher order constructs by factor analysis. Clusters are revealed by customers, as suggested by Allred [1], when employing cluster analysis.

4.1. Sample

The data in this study represent a survey of a sample of 11,848 daily deal shoppers located in Switzerland. Participants were recruited via e-mail using the database of a daily deal–shopping club offering both products and vouchers. The dropout rate was relatively low, with 526 participants not completing the entire questionnaire and being deleted from the data set. The sample represents male (37.4%) and female (62.6%) respondents with an average age of 41. The ratio of women to men corresponds to the findings of a U.S. study that indicated women (57%) shop online more than men (52%) do, whereas in mobile commerce men (22%) outpace women (18%) [42]. The average household income, which we prompted via income bands, was 88,000 USD, although 42% of respondents opted not to disclose information about household income. The majority of respondents (43.7%) lived in households of more than two people, 37.3% lived in two-person households, and only 17.3% were single. Of the total, 32.9% had children below the age of 12 living in the same household, and 26.8% of the respondents held university degrees. In addition, 53.9% were employed full time, 26.7% were employed part time, and 4.6% were homemakers.

The structured questionnaire covered Internet usage patterns, online purchasing behavior, online shopping motivations, online payment preferences, and psychographic traits. Effects were measured using statements rated via 7-point Likert scales, with the endpoints “do not agree at all (= 1) and “fully agree (= 7). The questionnaire was pretested with experts and adapted according to their feedback. The quantitative questionnaire was distributed via the e-mail newsletter of a Swiss daily deal platform.

4.2. Measures

Tauber [43] identified two aspects of shopping motivations: the need for a product (utility) and other motives such as passing the time. Hirschman and Holbrook [44] further extended the latter motives, and identifying these motives lay the groundwork for research on more emotional (hedonic) shopping motives. Moreover, according to Wilson [45], utility segmentation is the most frequently used and most adequate method to determine market segments. Similarly, Babin et al. [22] defined two basic values, hedonistic and utilitarian, that underlie a purchase. They provided empirical evidence of the concepts put forward by Tauber [43] and Hirschman and Holbrook [44]. While utilitarian values such as convenience [1, 19, 38, 46-48] and price [28, 49] have a rational dimension, hedonistic values such as enjoyment and entertainment [28, 38, 44, 47, 50] are of a more affective nature. Nevertheless, these values can be applied to online shopping experiences that provide the hedonic values of enjoyment and fun via users’ interactions with the online store.

Christodoulides et al. [21] highlighted the importance of this affective state and identified it as a research gap. Morganosky and Cude [51] identified convenience or time as an important factor, and we therefore added mobility as a construct, as people commuting and accessing online stores on the go may do this to save time. Chen and Chang [19] mentioned privacy concerns and considered them important, thus we added them as a construct, too. Given the importance of hedonic aspects of online shopping, we added the constructs of social exchange [38, 47, 49] and amusement [22]. Drawing on the literature review, we operationalized the variables for measuring utilitarian and hedonistic values.

5. Data analysis

This section contains a description of the statistical tests conducted on the data sample. To elicit the different daily deal shopper typologies, we performed a cluster analysis. Prior to cluster analysis, the data was reduced and aggregated via an explorative factor analysis with the objective of bringing to light the interrelation between the single variables.

5.1. Descriptive statistics

Our data show that the majority of participants were Internet-savvy: 70.5% had been using the Internet for 10 years or more, and 14.5% reported having used the Internet for practically their entire lives. Nearly 60% spent one to four hours on the Internet per day, and 99% reported having previously made online purchases. Non-shoppers were deleted from the data set to avoid hypothetical answers, which reduced the data set to 11,680 participants. The products purchased most frequently were travel tickets and accommodation (75.1%), clothing (69.5%), books (60.3%), and vouchers (60%). Compared with the BFS [30] data, daily deal shoppers are more likely to buy clothing and vouchers. In addition, 41.7% have spent more than 1,000 USD and 49.8% between 100 USD and 1,000 USD online in the past year. Window-shopping also is common, with 61.1% stating that they often visited shops without intending to buy something. The 77% agreement with the statement "I enjoy online window-shopping without the need to buy something" supports this statement. Moreover, 55.4% agreed that they enjoy bargaining, and 82.2% stated that they shopped online to save money.

Convenience is another important factor, with unrestricted opening hours showing the highest agreement with a mean value of 5.7, followed by home delivery with 5.3. This aligns with the utilitarian aspect of online shopping. Social exchange with friends or experts and communities shows low agreement, with mean values of 2.24 and 2.51, respectively. This is surprising, as the literature suggests that online conversations and social influence affect online buying decisions [52]. Privacy concerns creating barriers to online shopping show high mean values regarding the perceived uncertainty of m-commerce (M = 4.72) and credit card payments (M = 4.63).

5.2. Factor analysis

Based on the literature review, we employed 28 items to describe the shopping motivation of daily deal shoppers. We computed a Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy to explore whether factor analysis was suitable. This yielded a KMO value of 0.84 for the 28 items, which is considered adequate [53]. Subsequently, we conducted explorative factor analysis using the principal component analysis method with Varimax rotation and Kaiser normalization. According to Hair et al. [54], variables with factor loadings above 0.5 are very significant. After the deletion of seven variables due to low factor loadings, the final factor analysis included 21 variables that load on six factors. The factors explain 62.9% of the variance.

We identified six constructs that define the shopping motives of daily deal customers: convenience, bargaining, mobility, social exchange, privacy concerns, and amusement. "Convenience" comprises the possibility of shopping from home, unrestricted hours for home delivery, and the elimination of waiting time. "Bargaining" involves saving money, taking part in online auctions, product-specific information, and greater choice. The immediate availability of mobile coupons and location-based offerings are included under the term "mobility." "Social exchanges" concerns exchanges with friends and experts or communities, and "privacy concerns," specifically regarding credit card information and personal data, create a barrier to online shopping. Finally, "amusement" concerns the fun of experiencing new products and trends, and spending leisure time.

5.3. Construct validity

For measuring the reliability of the instrument, we used Cronbach's alpha coefficient. Table 1 provides the computed values for the constructs. Eckstein [55] proposes that an alpha of 0.6 or higher is acceptable; therefore, we concluded that the constructs are reliable.

Table 1. Reliability coefficients

Measure	Alpha
Total items (21)	0.815
Convenience	0.815
Bargaining	0.665
Mobility	0.729
Social exchange	0.819
Privacy concerns	0.714
Amusement	0.722

5.4. Cluster analysis

To classify participants according to their shopping motives, we employed cluster analysis. First, we excluded participants who indicated extreme values from the sample to ensure the correct determination of the number of clusters. We identified 60 outliers, leaving us with 11,094 participants remaining relevant for cluster formation. In the next step, we used the Ward method [56] to elicit the number of possible daily deal shopper profiles and the participants belonging to each cluster. We standardized factor scores using the Anderson-Rubin method and arrived at a six-cluster partitioning that ensured the highest increase of the heterogeneity coefficient [55, p. 334]. Table 2 shows the cluster centers of the initial solution. To optimize the cluster solution and assign participants to a shopping profile, we employed the *k*-means method [57]. Punj and Stewart [58] stated that the *k*-means method leads to a more exact cluster assignment when the Ward start partition is used.

Table 3 presents the final cluster centers and hence the mean values of each factor within the cluster. High values mark agreement with the factor, while negative values represent rejection. After identification of the final cluster solution, we denominated groups according to the major characteristic value of the segment and the interplay of the components. To determine the variance of variables within and across different clusters, we conducted a one-way ANOVA [59]. Variables differ significantly between clusters, as F-value ratios are high between and within clusters and all p-values are < 0.001. All variables differ across the clusters, with “bargaining” showing the smallest variation and “social exchange” the highest.

6. Findings

The final cluster solution consists of six clusters describing the shopping motivation of daily deal shoppers. The first cluster, recreational shoppers, contains those who showed high values for the fun side of shopping (n = 1,964). The second cluster (mobile shoppers, n = 1,782) includes those who were especially interested in mobile commerce options such as mobile coupons and location-based services. Members of the third cluster, traditionalists, showed overall low values for all six factors and spent the lowest amount shopping online (n = 1,624); these participants were more often offline than online shoppers. Although we expected the cluster to be larger, as the core of daily deal platforms offer the best prices on a daily basis, bargain hunters, who focus on finding the best prices and special deals, comprised the second-smallest segment of the daily deal shoppers (n = 1,572). Socializers, who are interested in a communicative exchange with friends, experts, and communities while shopping, constituted the biggest cluster (n = 2,572) Finally, the smallest cluster (n = 1,570) emphasize the convenience of online shopping, and enjoy unrestricted opening hours and the possibility of escaping crowded shopping malls. Table 4 depicts the demographic characteristics of the segments.

6.1. Recreational shoppers

Recreational shoppers showed the highest values for the factor of amusement, representing hedonistic shopping motives. They enjoy online window-shopping (M = 5.69) and spending leisure time in online stores. This segment is interested in new product information and trends (M = 5.43), appreciating the larger product variety found in online stores (M = 5.05). Privacy concerns are an issue for this group, with the second-highest value for the factor across all clusters. Recreational shoppers have the highest female ratio (74.5%) and are the second-youngest cluster, with an average age of 39.

6.2. Mobile shoppers

Mobile shoppers are especially interested in mobile coupons (M = 5.12) and location-based offers (M = 4.5). In contrast to the other clusters, mobile shoppers are unconcerned with mobile payments (M = 4.75). Bargaining plays an important role for this cluster, and 57.6% of it spent more than 1,000 USD online in the previous year. This segment is characterized by the highest ratio of male participants (44.7%), the lowest average age (38), and the highest rate of full-time employment (63.1%).

Table 2. Initial cluster solution

	Cluster					
	1	**2**	**3**	**4**	**5**	**6**
Convenience	.45359	.13626	-1.50453	.11699	.19394	.39645
Bargaining	-.30526	.14860	-.42582	.36488	.07077	.17434
Mobility	.35259	.57225	.01553	-1.53829	.22934	.05564
Amusement	.55008	.26414	-.14509	.32365	.21610	-1.51943
Social exchange	-.66343	-.54982	-.10807	-.23824	1.28437	-.29555
Privacy concerns	.83226	-1.20383	.17803	-.12145	.05797	.16245

Table 3. Final cluster solution

	Cluster					
	1	**2**	**3**	**4**	**5**	**6**
Convenience	0.10999	-0.50468	-1.03436	0.06804	0.17455	0.81120
Bargaining	-0.01015	0.18279	-0.69588	0.34236	0.12035	-0.25330
Mobility	0.58398	0.40480	-0.21830	-1.52733	0.22056	0.00072
Amusement	0.50635	0.19096	-0.67038	0.30644	0.17911	-0.82935
Social exchange	-0.59837	-0.43605	-0.23948	-0.20539	1.06307	-0.51810
Privacy concerns	0.67909	-0.81638	0.50311	-0.00537	0.09012	-0.13699

Table 4. Cluster profiles based on demographics

		Recrea-tional Shopper	**Mobile Shopper**	**Tradition-alist**	**Bargain Hunter**	**Socializ-er**	**Conve-nience Seeker**	**Total**
		n = 1,974 (17.8%)	n = 1,782 (16.1%)	n = 1,624 (14.6%)	n = 1,572 (14.2%)	n = 2,572 (21.8%)	n = 1,570 (13.3%)	11,094
Gender	Female	74.5%	55.3%	67.2%	64.1%	57.1%	58.3%	62.6%
	Male	25.5%	44.7%	32.8%	35.9%	42.9%	41.7%	37.4%
Ø Age		39	38	41	46	41	41	41
Age Group	Up to 19	2.2%	1.8%	2.7%	.8%	1.7%	1.0%	1.7%
	20–30	25.9%	28.3%	25.1%	12.9%	22.0%	21.6%	22.8%
	31–40	27.6%	32.8%	21.8%	19.2%	24.7%	28.3%	25.8%
	41–50	27.1%	23.1%	24.7%	30.9%	26.6%	27.4%	26.6%
	51–60	13.2%	9.8%	16.8%	22.8%	17.1%	14.7%	15.6%
	61+	3.9%	4.2%	8.9%	13.3%	7.9%	7.1%	7.4%
Family Status	Single	24.8%	21.7%	23.8%	23.1%	25.4%	25.2%	24.1%
	Married/ Partnership	75.2%	78.3%	76.2%	76.9%	74.6%	74.8%	75.9%
Children in HH	0–2 y	30.3%	33.5%	21.6%	16.9%	24.4%	23.9%	29.9%
	3–6 y	35.7%	34.4%	34.8%	34.2%	37.7%	35.0%	35.6%
	7–12 y	34.6%	30.4%	37.1%	37.8%	38.5%	35.9%	35.8%
Online Spending	<100 USD	1.6%	.3%	3.7%	1.3%	1.7%	1.4%	1.7%
	100–1,000 USD	53.3%	39.3%	58.4%	50.5%	51.9%	44.1%	49.8%
	>1,000 USD	37.4%	57.6%	28.8%	41.3%	40.4%	46.0%	41.8%
	not stated	7.7%	2.8%	9.1%	6.8%	6.0%	8.5%	6.7%

6.3. Traditionalists

Traditionalists showed low overall values for online shopping motives, spending the least amount of time online of all clusters (M = 1.93). In addition, this segment spends the lowest amounts shopping online, with 58.4% of participants having spent between 100 and 1,000 USD and 3.7% less than 100 USD in the past year. Traditionalists, like recreational shoppers, are concerned with privacy issues.

6.4. Bargain hunters

This segment is defined by high values for bargain hunting, and members are motivated by finding the best deals (M = 4.49) and saving money (M = 5.59). Nevertheless, bargain hunters are not driven only by utilitarian motives but also enjoy online shopping, as reflected in the second-highest values for the factor of amusement. Bargain hunters was the oldest segment, with an average age of 46, and members had the lowest ratio of children aged 0–2 years.

6.5. Socializers

With 2,572 participants (21.8%), socializers constituted the largest segment in our data set and the only segment showing positive values for social exchange. Socializers enjoy virtual communication with friends while shopping (M = 4.04), and contacting experts and engaging in communities (M = 4.23). Participants in this segment agreed that recommendations simplify their shopping decisions (M = 4.78). Socializers showed positive values for all factors, displaying a mix of utilitarian and hedonistic shopping motives. Socializers spent the most time online per day of all clusters (M = 2.21).

6.6. Convenience seekers

At 13.3%, convenience seekers formed the smallest cluster. This segment enjoys aspects of online shopping such as home delivery (M = 5.54), unrestricted opening hours (M = 5.9), and reduced waiting times (M = 4.88). They are driven by utilitarian motives. Convenience seekers had above average rates of full-time employment (57.8%) and degree-level education (35%).

7. Limitations

This study is based on single case data; therefore, further research is needed to verify the generalizability of the results of this research. Furthermore, a longitudinal study regarding clusters, as mentioned and proposed by Christodoulides et al. [21], would contribute further to existing literature and could possibly identify interesting changes in shopping motives and customer needs over time. In addition, the social propagation of offers can play an important role not only in changes in clusters over time but also in the time of day offers are issued [9, 13]. Further research regarding this idea and any differences between the clusters found in our research could be analyzed.

A further limitation of this research is the high price levels in Switzerland, and Swiss citizens' high income and purchasing power [60]. This could potentially bias the utilitarian and hedonistic buying motives, as Swiss customers' price sensitivity may be different from those of customers elsewhere. Lastly, Switzerland is a rather small country, potentially biasing the convenience aspects of online shopping when compared to larger countries, and as Amazon ships only certain products to the Swiss market, shopping behavior may be biased regarding shopping on daily deal platforms.

8. Implications and conclusion

Our study has research implications for the segmentation of the special e-commerce form of daily deal platforms. In contrast to Kruzka [3], we found that daily deal shoppers are motivated by both hedonistic and utilitarian motives, with four clusters showing an emphasis on hedonistic values. Research results suggest that for the recreational cluster, amusement is important but privacy concerns are prevalent, too. Therefore, actions targeted at augmenting amusement perceptions must not compromise privacy. Furthermore, this segment is female, and so actions should preliminarily target this gender.

The mobile shopper cluster is, from a monetary viewpoint, a relevant group, with 57.6% of customers spending above 1,000 USD a year. As they are highly interested in bargains and location-based offers, customizing offers presented to them based on their location and providing a mobile (responsive) website are advisable. Furthermore, the traditionalist cluster shows low spending amounts and is especially concerned with privacy. As this cluster spends the least time online, the website's navigation, guidance, and reassurance measures (e.g., trust seals, explicitly highlighting privacy policies) are of particular importance.

Bargain hunters constitute a cluster especially motivated to save money, but in a way that allows them to experience amusement in the process. Actions such as highlighting savings and combining shopping with a gamification approach are worth investigating for this cluster. Moreover, the largest cluster is the socializers, and these shoppers enjoy virtual, social communication. Website elements supporting and enhancing this form of communication are recommended. Social login functionality, sharing of daily deal offers via social media, and participation in communities such as customer clubs or loyalty programs are possible options to meet the needs of this cluster (a model for analyzing social influence on purchasing decisions within this cluster is provided by [52]).

Convenience seekers constitute the smallest cluster. They are highly driven by utilitarian motives and characterized by the lowest values of amusement; thus, a hassle-free, fast service approach is recommended, focusing on ease of use. In addition, it could be worthwhile to implement functionality that helps these customers save time shopping online, such as smart filtering functionalities, personalized offers, e-mail alert functions, easy checkout shopping functionality, and same-day delivery or pickup, as most shoppers in this group work full time.

Tangible benefits can be expected from adapting the functionality and design of the website according to the needs of each cluster. This will enhance customers' online shopping experience and lead to loyalty and positive word-of-mouth behavior [61], which in turn can both be especially valuable for the socializer cluster and contribute to the success of the platform or website as a whole. The identified clusters and their characteristics can provide guidance in implementing website functionality, features, and design.

From a managerial point of view, a solid segmenting, targeting, and positioning approach is advised, as the six identified clusters differ substantially, especially regarding amusement and convenience needs and privacy concerns. Therefore, providing each segment with different versions of the website is advisable, as this is technically possible (e.g., dynamic website adaption, so-called morphing websites [62]) and would meet the needs of the segments more precisely and thus provide higher levels of perceived value for each cluster. The identified clusters further provide guidance for managerial decisions such as prioritizing marketing measures and allocating marketing budgets to these measures with respect to the clusters found in this research.

Although not discussed in this paper, the influence of context (e.g., time and quantity restraints) and minute design details such as the color of the price with respect to gender (see Puccinelli et al. [63]) and its effect on customers' shopping experiences are important and should therefore be considered with great care by daily deal platform providers.

7. References

[1] C. R. Allred, S. M. Smith, and W. R. Swinyard, "E-shopping lovers and fearful conservatives: a market segmentation analysis," International Journal of Retail & Distribution Management, vol. 34, 2006, pp. 308-333.

[2] R. DeNale and D. Weidenhamer. (2015, 14.03.2016). Quarterly Retail E-Commerce Sales 4th Quater 2015. Available: https://www.census.gov/retail/mrts/www/data/pdf/ec_current.pdf

[3] A. Kruszka, "Why did I just buy that? A Look at Impulse Buying in the Atmosphere of Daily Deals," Capstone Work, American University, Washington D.C, 2012.

[4] A. Herow, "Shopping on Daily Deal Websites: How Numbers of Previous Purchases Make a Difference in Product Purchase Intentions," Auckland University of Technology, Auckland, 2013.

[5] Statista, "Digital coupons and deals - Statista Dossier," Statista, New York, NY2016.

[6] Marketyze. (2015, June 2016). Flash Sales/Daily Deals and Pricing Intelligence. Available: http://www.marketyze.com/2015/flash-salesdaily-deals-pricing-intelligence/

[7] T. Lang. (2015, 12.04.2016). Die umsatzstärksten Schweizer Onlinshops 2015. Available: http://blog.carpathia.ch/2015/09/15/umsatz-onlineshops-schweiz-2015/

[8] M. Kukar-Kinney, A. C. Scheinbaum, and T. Schaefers, "Compulsive buying in online daily deal settings: An investigation of motivations and contextual elements," Journal of Business Research, vol. 69, pp. 691-699, 2016.

[9] M. Ye, T. Sandholm, C. Wang, C. Aperjis, and B. A. Huberman, "Collective attention and the dynamics of group deals," 2012, p. 1205.

[10] E. Boon, R. Wiid, and P. DesAutels, "Teeth whitening, boot camp, and a brewery tour: a practical analysis of 'deal of the day'," Journal of Public Affairs, vol. 12, 2012, pp. 137-144.

[11] J. W. Byers, M. Minzenmacher, M. Potamias, and G. h. a. o. a. v. Zervas. (2011). A Month in the Life of Groupon. Available: http://arxiv.org/abs/1105.0903v1

[12] K. Jung and B. Y. Lee, "Online vs. Offline Coupon Redemption Behaviors," 2010, vol. 9, 2010-12-01 2010.

[13] J. W. Byers, M. Mitzenmacher, and G. Zervas, "Daily Deals: Prediction, Social Diffusion, and Reputational Ramifications," in WSDM'12, Seattle, Washington, USA, 2012, pp. 543-552.

[14] B. G. Edelman, S. Jaffe, and S. D. Kominers, "To Groupon or Not to Groupon: The Profitability of Deep Discounts," Harvard Business School, Cambridge, 2011.

[15] U. M. Dholakia. (2011, What Makes Groupon Promotions Profitable for Businesses? Available: http://ssrn.com/abstract=1790414

[16] U. M. Dholakia. (2012, June 2016). How Businesses Fare with Daily Deals as They Gain Experience: A Multi-

Time Period Study of Daily Deal Performance Available: http://ssrn.com/abstract=2091655
[17] Y. Cai, M. Mahdian, A. Mehta, and B. Waggoner, "Designing Markets for Daily Deals," in WINE 2013, Y. Chen and N. Immorlica, Eds., ed Berlin Heidelberg: Springer-Verlag, pp. 82–95, 2013.
[18] U. M. Dholakia, "Daily Deal Fatigue or Unabated Enthusiasm? A Study of Consumer Perceptions of Daily Deal Promotions," S. E. Kimes, Ed., 1.09.2011 ed. SSRN: SSRN, 2011, p. 27.
[19] S. J. Chen and T. Z. Chang, "A descriptive model of online shopping process: some empirical results," International Journal of Service Industry Management, vol. 14, 2003, pp. 556-569.
[20] T. L. Childers, C. L. Carr, J. Peck, and S. Carson, "Hedonic and utilitarian motivations for online retail shopping behavior," Journal of Retailing, vol. 77, 2001, pp. 511-535.
[21] G. Christodoulides, N. Michaelidou, and N. T. Siamagka, "A typology of internet users based on comparative affective states: evidence from eight countries," European Journal of Marketing, vol. 47, 2013, pp. 153-173.
[22] B. J. Babin, W. R. Darden, and M. Griffin, "Work and/or Fun: Measuring Hedonic and Utilitarian Shopping Value," Journal of Consumer Research, vol. 20, 1994, pp. 644-656.
[23] C. Demangeot and A. J. Broderick, "Exploring the experiential intensity of online shopping environments," Qualitative Market Research: An International Journal, vol. 9, 2006, pp. 325-35.
[24] L. Sin and A. Tse, "Profiling Internet Shoppers in Hong Kong," Journal of International Consumer Marketing, vol. 15, 2002, pp. 7-29.
[25] W. R. Swinyard and S. M. Smith, "Why people (don't) shop online: A lifestyle study of the Internet consumer," Psychology & Marketing, vol. 20, Jul 2003, pp. 567-597.
[26] D. H. Doty and W. H. Glick, "TYPOLOGIES AS A UNIQUE FORM OF THEORY BUILDING: TOWARD IMPROVED UNDERSTANDING AND MODELING," Academy of Management Review, vol. 19, 1994, pp. 230-251.
[27] W. W. Hill, S. E. Beatty, and G. Walsh, "A segmentation of adolescent online users and shoppers," Journal of Services Marketing, vol. 27, 2013, pp. 347-360.
[28] A. K. Kau, Y. E. Tang, and S. Ghose, "Typology of online shoppers," Journal of Consumer Marketing, vol. 20, 2003, pp. 139-156.
[29] C. Dennis, C. Jayawardhena, L. Tiu Wright, and C. Dennis, "Consumers online: intentions, orientations and segmentation," International Journal of Retail & Distribution Management, vol. 35, 2007, pp. 515-526.
[30] BFS. (2015, 14.03.2016). Haushalte und Bevölkerung - E-commerce-Ausgaben der Haushalte [Excel Sheet]. Available:
http://www.bfs.admin.ch/bfs/portal/de/index/themen/16/04/key/approche_globale.indicator.30108.301.html
[31] Y. T. Wong, S. Osman, A. Said, and L. Paim, "A typology of personal factor attributes among shoppers," Journal of Fashion Marketing and Management: An International Journal, vol. 18, 2014, pp. 394-412.
[32] P.-L. To, C. Liao, and T.-H. Lin, "Shopping motivations on Internet: A study based on utilitarian and hedonic value," Technovation, vol. 27, 2007, pp. 774-787.
[33] C. M. Lim, R. Runyan, and Y.-K. Kim, "Segmenting luxe-bargain shoppers using a fuzzy clustering method," International Journal of Retail & Distribution Management, vol. 41, 2013, pp. 848-868.
[34] C. Zuccaro and M. Savard, "Hybrid segmentation of internet banking users," International Journal of Bank Marketing, vol. 28, 2010, pp. 448-464.
[35] M. I. El-Adly, "Shopping malls attractiveness: a segmentation approach," International Journal of Retail & Distribution Management, vol. 35, 2007, pp. 936-95.
[36] C. Mathwick, "Understanding the online consumer: A typology of online relational norms and behavior," Journal of Interactive Marketing, vol. 16, 2002, pp. 40-55.
[37] B. Seegebarth, S. H. Behrens, C. Klarmann, N. Hennigs, and L. L. Scribner, "Customer value perception of organic food: cultural differences and cross-national segments," British Food Journal, vol. 118, 2016, pp. 396-411.
[38] A. J. Rohm and V. Swaminathan, "A typology of online shoppers based on shopping motivations," Journal of Business Research, vol. 57, 2004, pp. 748-757.
[39] S. Gilboa, "A segmentation study of Israeli mall customers," Journal of Retailing and Consumer Services, vol. 16, 2009, pp. 135-144.
[40] M. Frasquet, I. Gil, and A. Molla, "Shopping-centre selection modelling: a segmentation approach," The International Review of Retail, Distribution and Consumer Research, vol. 11, 2001, pp. 23-38.
[41] K. A. Passyn, M. Diriker, and R. B. Settle, "Images Of Online Versus Store Shopping: Have The Attitudes Of Men And Women, Young And Old Really Changed?," Journal of Business & Economics Research (JBER), vol. 9, 2011, pp. 99-110.
[42] C. Smith. (2015, 3.06.2016). The surprising facts about who shops online and on mobile. Available: http://www.businessinsider.de/the-surprising-demographics-of-who-shops-online-and-on-mobile-2014-6?r=US&IR=T
[43] E. M. Tauber, "Why Do People Shop?," Journal of Marketing, vol. 36, 1972, pp. 46-49.
[44] E. C. Hirschman and M. B. Holbrook, "Hedonic Consumption: Emerging Concepts, Methods and Propositions," Journal of Marketing, vol. 46, 1982, p. 92-101.
[45] R. Wilson, Strategic Marketing Management: Planning, Implementation, and Control. Oxford: Butterworth-Heinemann, 1992.
[46] R. R. Dholakia and O. Uusitalo, "Switching to electronic stores: consumer characteristics and the perception of shopping benefits," International Journal of Retail and Distribution Management, vol. 30, 2002, pp. 459-469.
[47] M. Wolfinbarger and M. Gilly, "Shopping Online for Freedom, Control, and Fun," California Management Review, vol. 43, 2001, pp. 34-55.
[48] P. Sorce, V. Perotti, and S. Widrick, "Attitude and age differences in online buying," International Journal of Retail and Distribution Management, vol. 33, 2005, pp. 122-132.
[49] M. Lingenfelder and P. Loevenich, "Identifikation und Auswahl von Zielgruppen im E-Commerce: Ergebnisse einer empirischen Untersuchung," Marketing Zeitschrift für Forschung und Praxis, vol 25, 2003, pp. 119-131.

[50] N. Donthu and A. Garcia, "The Internet Shopper," Journal of Advertising Research, 1999, pp. 52-58,.
[51] M. A. Morganosky and B. J. Cude, "Consumer response to online grocery shopping," International Journal of Retail & Distribution Management, vol. 28, 2000, pp. 17-26.
[52] Y. A. Kim and J. Srivastava, "Impact of social influence in e-commerce decision making," in ICEC07, Minneapolis, MN, US, 2007, pp. 293-301.
[53] G. Hutcheson and N. Sofroniou, The multivariate social scientist. London: Sage, 1999.
[54] J. F. Hair, R. E. Andersin, R. L. Tatham, and W. C. Black, Multivariate Data Analysis with Readings. New York, NY: Macmillan, 1992.
[55] P. Eckstein, Angewandte Statistik mit SPSS: praktische Einführung für Wirt-schaftswissenschaftler. Wiesbaden: Gabler, 2004.
[56] J. H. Ward, "Hierarchical grouping to optimize an objective function," Journal of the American Statistical Association, vol. 58, 1963, pp. 236-244.
[57] J. McQueen, "Some methods for classification and analysis of multivariate observations," in Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, 1967, pp. 281–297.
[58] G. Punj and D. W. Stewart, "Cluster Analysis in Marketing Research: Review and Suggestions for Application," Journal of Marketing Research, vol. 20, 1983, pp. 134-148.
[59] M. N. Khalid, "CLUSTER ANALYSIS – A STANDARD SETTING TECHNIQUE IN MEASUREMENT AND TESTING," Journal of Applied Quantitative Methods, vol. 6, 2011, pp. 46-58.
[60] OECD, "OECD Economic Surveys: Switzerland 2015," OECD Publishing, ReportNovember 2015.
[61] A. Bilgihan, J. Kandampully, and T. Zhang, "Towards a unified customer experience in online shopping environments," International Journal of Quality and Service Sciences, vol. 8, 2016, pp. 102-119.
[62] J. R. Hauser, G. L. Urban, G. Liberali, and M. Braun, "Website Morphing," Marketing Science, vol. 28, 2009, pp. 202-223.
[63] N. M. Puccinelli, R. Chandrashekaran, D. Grewal, and R. Suri, "Are Men Seduced by Red? The Effect of Red Versus Black Prices on Price Perceptions," Journal of Retailing, vol. 89, 2013, pp. 115-125.