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Identifying Sales-Influencing Touchpoints along the Omnichannel Customer Journey

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Abstract

Retailers have started to integrate their online and offline channels in order to increase revenue by creating a superior customer experience. However, they lack an instrument with which to identify the touchpoints that are most influential for customer decision making. Therefore, this study introduces a novel, multi-method approach that utilizes combined data-collection and data-analyses procedures that help retailers to identify and meaningfully cluster relevant touchpoints along the customer journey. Results indicate, among others, that retailers can benefit from abandoning the classic, within-company perspective and cluster their touchpoints according to the customers' perspective. Furthermore, our approach enables retailers to infer the most important sales-influencing touchpoints. Here, findings indicate that retailers should be selective in providing the right touchpoints for their customers, as some of them can have a direct or indirect negative impact on sales. Retailers can use these insights to support their touchpoint-selection and thus decision-making process through thought provoking impulses.

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Keywords: Omnichannel; Touchpoints; Customer Journey, Sales.

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1. Introduction

Retailers face a significant challenge in staying competitive with e-commerce, as retail revenue peaked in 2001 [1, 2] and e-commerce revenue has been rising since then [3]. Additionally, social distancing measures resulting from the COVID-19 pandemic have escalated these challenges even further [4]. In order to safeguard against e-commerce competitors, many retailers started to target their customers across online and offline channels individually, with every channel being treated as isolated from the other [5]. However, as many retailers begin to adopt customer experience as the centre of their business models, it becomes evident that treating channels as isolated from one another does not offer a satisfactory customer experience [6, 7]. Hence, retailers decided to merge their online and offline channels to create a seamless and superior customer experience, simultaneously across all their channels [8]. This approach is called 'omnichannel retailing' and, as demonstrated by previous studies, this new form of experience indeed can enhance customers' attitude towards retailers and consequently can increase retail revenue [6, 9–12]. However, when combining online and offline channels, the number of potential contact points between retailers and customers (hereafter: touchpoints) increases considerably [8]. This is problematic, as retailers are unable to influence many of these touchpoints by themselves (e.g., independent content on third-party social media pages, such as product reviews of customers on YouTube) [8, 13]. Retailers are only capable of managing and steering their brand-owned touchpoints, which are defined as customer contact points designed and managed by retailers only (e.g., advertising, corporate websites, in-store displays, etc.) [8]. As stated by Grewal and Roggeveen [14], although being a fundamental part of every customer journey, retailers lack an instrument with which to identify and group brand-owned touchpoints, which are the most influential for customers' purchasing decisions. In particular, identifying the monetary impact of a touchpoint has thus far remained notoriously difficult to determine and previous studies elaborate on this problem solely in the context of e-commerce [15, 16]. However, these previous approaches are not transferable to omnichannel retailers since customers' interactions with offline touchpoints are infamously difficult to track.

Therefore, the objective of this study is to highlight a novel approach with which omnichannel retailers can utilize a combination of different research procedures (e.g., touchpoint identification workshop, customer survey) to identify relevant touchpoints and to cluster them both from a company and a customer perspective (based on customer habits). This approach helps to identify gaps between these two viewpoints and to make touchpoint management more effective. Furthermore, the aim of this study is to identify the strongest sales-influencing touchpoints. By applying Bayesian Multiple Regression (BayS-MR), this research is able to determine which of the brand-owned touchpoints have a positive, neutral, or even negative impact on sales. Consequently, this study addresses the following research questions:

RQ I: How can touchpoints be clustered from the managerial and customer perspective? Are there any differences?
RQ II: Which touchpoints have the strongest (positive or negative) influence on the purchase decision of customers?

This paper is structured as follows: First, the paper presents the methods and data we used to create a complete overview of potentially sales-influencing touchpoints, in Section 2. Hereafter, we present the results from our statistical analyses in Section 3. Consequently, in Section 4, we discuss the strengths, weaknesses, and opportunities that our approach offers, answer the proposed research questions, and outline future research opportunities. Section 5 provides the conclusion of the paper.

2. Methodology

To identify sales-influencing touchpoints along the omnichannel customer journey, we first use a corporate touchpoint identification workshop to identify and cluster all the brand-owned touchpoints of a retailer. Second, we use an online survey in combination with the statistical method of Confirmatory Factor Analyses (CFA) to cluster the brand-owned touchpoints from a customer perspective. This allows us to compare company and customer point of view, allowing us to identify possible mismatches in company resource allocation and thus provides a basis for interpreting the results of the upcoming BayS-MR. Third, we use sales and survey data in combination with a BayS-MR to identify the most sales-influencing brand-owned touchpoints. Using the knowledge gained from the survey in sequence with the BayS-MR, we can interpret why certain touchpoints have a positive, neutral, or negative impact on sales.

In the following section, we provide the steps we followed to collect and analyse the multi-source data. All data originate from a major Austrian fashion retailer who adopted an omnichannel retail strategy.

2.1 Corporate Touchpoint Identification Workshop

To identify all brand-owned touchpoints of the fashion retailer we carried out a workshop specifically designed to identify brand-owned touchpoints [17]. In the workshop we used a combination of the creative techniques, World Café [18] and Channel CARDS [19], to extract as much knowledge about touchpoints from the retailer's employees (including top managers) until we reached a state of data saturation. Data saturation describes a state at which no additional knowledge about a topic can be generated [20]. In the context of the workshop, this represents the best-possible overview of brand-owned touchpoints. The state of data saturation is verified by the Cohen's Kappa statistic and our workshop reached a Cohen's Kappa value of 0.76, which, according to Landis and Koch [21], represents a substantial agreement and thus a state of data saturation. As proposed by the workshop design, we followed up with a practical approach using multiple focus groups supported by the creative techniques instant word clouds as well as instant polls to cluster the overview of touchpoints from a company perspective. This procedure revealed 145 touchpoints (in the form of words, e.g., 'Retail Store', 'TV Spots'), which were clustered into twelve main categories ('Events', 'Classical Media', 'Cooperation', 'Online Advertising', 'Out of Home', 'Point of Sale', 'Public Relations', 'Print Advertising', 'Customer Relationship Management', 'Service', 'Social Media', 'Website') by the group of employees and top managers of the retailer.

2.2 Customer survey

We then used the identified touchpoints in a subsequent online survey, to identify the most recognized touchpoints from a customer perspective. In this online survey, participants were first asked when they brought a product from the fashion retailer the last time (options: 'In the past 3/6/9/12 months', 'More than 12 months ago', 'Never'). Following, they were presented with the 12 previously identified main touchpoint categories and were asked to rate how often they came into contact with the touchpoint categories. This was measured on a 5-point Likert scale (range: 1 = 'Not at all' to 5 = 'Very often'). For every main category in which participants did not answer 'Not at all', they were shown a follow-up question presenting all touchpoints of this main category. Consequently, participants were asked to rate how often they recognized specific touchpoints on a 5-point Likert scale (range: 1 = 'Not at all' to 5 = 'Very often').

The sequence of the main categories as well as of touchpoints in each category was randomized to avoid order bias. We also asked participants standard demographic questions and their contact details as well as (if applicable) personal loyalty card number to allow the retailer to match the survey data to customer sales data. The questionnaire was implemented with Questback.

We distributed the survey to 76,948 registered customers of the fashion retailer between mid-November and mid-December 2020. Of the participants, 1,487 successfully completed the survey. From these, we only analysed questionnaires of those individuals for whom the retailer was able to provide a detailed sales history - including online and offline sales. For our analyses, as suggested in literature [22], we further only selected customers who had made a purchase within the last three months in order to keep recall bias at a minimum and to ensure that the customers' memory of used touchpoints was reliable. Screening for outliers, we z-standardised the cumulative sales values (money spent in the last three months) and excluded cases at a cut of point of 1.96. Lastly, we excluded participants whose answers were incomplete. N = 243 participants remained, who were further analysed in this study. The participants mean age was 47.8 years ($\sigma = 9.704$), with 102 being male (42%) and 141 being female (58%). 75 (30.8%) participants had a net household income of less than €3,000, 83 (37.8%) between €3,000 and €4,999, 26 (10.7%) above €5,000, and 59 (24.3%) preferred not to state their net household income. From the participants, 18 (8.6%) had at least a high school degree, 151 (62.1%) had an apprenticeship or associates degree, 56 (23.1%) had a degree on a university level, and 18 (7.4%) had other education.

2.3 Analysis

To cluster the recognized touchpoints from a customer point of view, we looked for patterns concerning consumers' brand-owned touchpoint perception by using CFA. Additionally, we analysed the direct impact of touchpoint perception on customer sales value (i.e., money spent in the last three months) using BayS-MR. We decided to use a combination of CFA and BayS-MR, as opposed to, e.g., semi-structured interviews with customers, since we want to base our results not on individual customer opinions, but instead on the comprehensive customer data set provided by the retailer. As such, the CFA provides value from an aggregated point of view and the BayS-MR from a touchpoint-specific point of view. CFA, as part of Structural Equation Modelling, has been used especially in social science and particularly the marketing context, to model the relation between latent and observed variables [23]. Therefore, this study uses CFA to illustrate which clusters of touchpoints customers recognize along their customer journey and thus are typically jointly used by customers before making a purchase. In contrast, BayS-MR is regularly used in practice for A/B testing [24, 25]. It is agreed that it is an efficient way to identify the strongest predictors of a data set [26–28]. As such, it is regarded as great improvement compared to more traditional regression approaches such as stepwise regression [26]. Therefore, this study uses a BayS-MR to analyse the direct effect of individual touchpoints on customers' sales value. CFA was performed using the IBM SPSS Amos 27 structural equation modelling software as it is the industry leading tool for performing such analysis [29]. For the BayS-MR, we used the open-source statistical tool JASP 0.14.1 because of its easy accessibility and profound output of Bayesian results [30].

3. Results

The results section is divided into two parts. First, we present the results of our CFA (see Tab. 1 and Tab. 2) by highlighting the each identified touchpoint cluster. Second, we present the four best models (when compared to a Null-Model) of the performed BayS-MR (see Tab. 3) and give an overview of the most sales-influencing brand-owned touchpoints (see Tab. 4).

3.1 Confirmatory Factor Analysis

An exploratory factor analyses was first used to extract the underlying structure of the identified 145 touchpoints (i.e., touchpoint categories) from the customer perspective. The Bartlett-Test ($\chi^2 = 20293.879$, df = 6441, $p < .001$) as well as the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO = .837) indicated that the identified touchpoints are suitable for a factor analysis. Hence, we performed a principal component analysis with varimax rotation. Based on the scree plot and theoretical considerations, we chose a 7-factor solution explaining 46.04% of the variance. The extracted factors (i.e., touchpoint clusters) were: 'Point of Sale (POS)', 'Cooperation's (CP)', 'Service (SV)', 'Website (WEB)', 'Classical Media (CM)', 'Social Media (SOM)', and 'Customer Relationship Management (CRM)'.

Moving forward, we used confirmatory factory analysis (CFA) to reassess the identified structure. An overview of the factors and underlying touchpoints can be found in Table 1. The table shows which touchpoints were typically recognized by customers. The model fitted the data adequately ($\chi^2 = 794.5$, df = 443, RMSEA = 0.57, CFI = 0.911, SRMR = 0.594) [31, 32]. Construct validity and reliability were also established as indicated by adequate Cronbach's alpha coefficients (range: 0.753 – 0.924), sufficient item to construct loadings (range: 0.516 – 0.899), and composite reliability (range: 0.757 – 0.886). Average variance extracted (AVE) ranged between 0.539 and 0.668 and were above the desired threshold of 0.5. Only the factors 'Cooperation' (CP) (0.421) and 'Classic Media (CM) (0.338) were below. However, as stated by Fornell & Larcker [33], an AVE of less than 0.5 can still be regarded as adequate if composite reliability is above 0.6, which was true for all factors. Discriminate validity was also established as the square root of all AVE values exceeded the corresponding correlations for all factor pairs [33] (see Tab. 2).

To complete our analyses, we used a structural equation model to test if the found factors have a direct effect on sales value. The structural model fits the data adequately ($\chi^2 = 813.6$, df = 443, RMSEA = 0.55, CFI = 0.912, SRMR = 0.584). Results indicate that only the touchpoint cluster 'CP' showed a significantly negative effect on sales value (B = -99.4, S.E. = 39.058, p = 0.011). It has to be mentioned that the factor CRM was close to being significant (B = 28.735, S.E. = 15.336, p = 0.061).

Table 1. Measurement Descriptives.

Factors	Standardized Loading
Point of Sale (POS) α = 0.924, CR = 0.858, AVE = 0.668	
Retail Assortment	0.899
Retail Sales personnel	0.861
Retail Payment options	0.804
Retail Receipts	0.802
Retail Store	0.846
Cooperation (CP) α = 0.758, CR = 0.781, AVE = 0.421	
Club offers	0.756
Cooperations with retailer	0.734
Presentations from retailer	0.647
Google maps entries	0.556
Give away	0.516
Service (SV) α = 0.847, CR = 0.853, AVE = 0.539	
Product testing	0.790
Bike measurement	0.780
Running analysis	0.670
Rental stations	0.652
Bike workshop	0.766
Website (WEB) α = 0.901, CR = 0.886, AVE = 0.666	
Website assortment	0.899
Website payment options	0.923
Search function on website	0.833
Product descriptions on website	0.558
Classic Media (CM) α = 0.753, CR = 0.757, AVE = 0.388	
TV Spots	0.494
Advertisements in Magazines	0.741
Advertisements in newspapers	0.582
Advertisements in catalogues	0.675
Advertisements on posters	0.593
Social Media (SOM) α = 0.868, CR = 0.875, AVE = 0.587	
Facebook	0.883
Videos on social media	0.794
Offers on social media	0.835
Instagram	0.620
Social Media competitions	0.666
Customer Relationship Management (CRM) α = 0.816, CR = 0.827, AVE = 0.618	
Loyalty card	0.846
E-mail newsletter	0.643
Post newsletter	0.852
Note: α: Cronbach's alpha, CR: Composite reliability, AVE: Average variance extracted. All loadings are significant at $p < 0.001$.	

Table 2. Measurement Model - Descriptive Statistics and Correlation Matrix.

Factor	Mean	SD	CP	SOM	CRM	CM	WEB	SV	POS
CP	1.32	0.64	**0.649**						
SOM	1.53	0.95	0.429	**0.766**					
CRM	1.78	1.19	0.309	0.306	**0.786**				
CM	2.33	1.08	0.432	0.263	0.431	**0.623**			
WEB	2.15	1.19	0.235	0.264	0.193	0.323	**0.816**		
SV	1.36	0.80	0.461	0.196	0.197	0.417	0.060	**0.734**	
POS	2.99	1.28	0.261	0.169	0.244	0.342	0.265	0.350	**0.818**

Note: Figures on the highlighted diagonal represent the square root of the average variance extracted of the representative factor.

3.2 Bayesian Multiple Regression

We performed a BayS-MR with the 145 identified touchpoints as dependent and the sales value generated as independent variable. As prior for the regression coefficients we used the Jeffreys-Zellner-Siow prior with an r scale of 0.354, as this is the most recommended prior in literature [34, 35]. Prior model probability was set to uniform as we regarded all touchpoints as equally likely to influence the sales value of a customer and this options presents the most neutral choice [36].

Results of the BayS-MR showed multiple models were more likely to predict the direct influence of specific touchpoints on sales than a Null model, which states that the independent variables do not predict the dependent variable (see Tab. 3). More specifically, the best-calculated model was 10,739 times more likely to predict the dependent variable (No: 1, R^2 = 0.162, BF10 = 10,739) compared to the Null model. According to Lee and Wagenmakers [37], this presents extreme evidence that the independent variables are able to predict the dependent variable.

Table 3. Model Comparison.

No.	Model with touchpoints	P(M|data)	BF M	BF 10	R^2
0	Null model	6.277e -8	0.033	1.000	0.000
1	Cooperation with retailer + Cooperation with partner store + Search engine advertising + Digital signage outdoor + Parking spots + POS TV + Warranty services	6.741e -4	353.684	10,739	0.162
2	Cooperation with retailer + Cooperation with partner store + Search engine advertising + Digital signage outdoor + Parking spots + Warranty services	6.068e -4	318.349	9,667	0.151
3	Cooperation with retailer + Cooperation with partner store + Search engine advertising + Digital signage outdoor + POS Assortment + Warranty services	3.162e -4	165.821	5,036	0.146
4	Cooperation with retailer + Cooperation with partner store + Search engine advertising + Digital signage outdoor + Warranty services	3.014e -4	158.072	4,801	0.135

Note: Table displays the four best models and the Null model, P(M) is uniform at 1.907e -6

Table 4. Posterior Summary.

Touchpoints	BF inclusion	Posterior Mean	SD	95% Credible Interval		Influence on Sales Value
				Lower	Upper	
Warranty services	403.940	47.401	13.238	22.116	73.796	Positive
Parking spots	1.103	1.782	6.103	0.000	19.883	Probably positive
POS Assortment	0.771	1.356	5.578	0.000	18.219	
POS Receipts	0.492	0.580	3.530	0.000	6.110	
Employees	0.494	0.532	3.233	0.000	0.869	
Company vehicles	0.601	-1.513	7.499	0.000	1.173	
Cooperation with partner store	1.150	4.556	14.955	-0.189	54.978	
Cooperation with fitness studios	0.593	2.108	10.888	-2.991	21.476	
Post newsletter	0.645	0.952	4.730	-4.216	4.020	No effect
Banner advertising	0.492	-0.762	4.450	-5.600	0.000	Probably negative
Google maps entry	0.573	-1.227	6.543	-6.401	0.000	
Cinema advertisement	0.588	-2.946	14.442	-8.070	0.628	
Tablet assisted sales	0.623	-1.702	7.868	-18.636	0.000	
POS TV	0.845	-2.092	7.894	-24.994	1.540	
Exclusive webstore brands	1.176	-3.537	9.551	-33.274	0.000	
Search engine advertising	1.582	-5.281	11.726	-35.983	0.000	
Cooperation with retailer	2.110	-13.546	21.759	-65.342	1.150	
Digital signage outdoor	24.194	-36.945	14.559	-67.511	-8.175	Negative

Note: Touchpoints with a credibility interval of 0.00 (lower) - 0.00 (upper) are not displayed.

Additionally, the BayS-MR was able to identify a set of touchpoints that were most likely to influence the sales value of a customer (see Tab. 4). Table 4 displays the average monetary impact of a touchpoint on sales value (Posterior Mean) as well as a 95% credibility interval in which the monetary impact will fall. For touchpoints with a 95% credibility interval above 0 this influence was positive. Below 0 the influence was negative. Those with a credibility interval containing 0 but with the lower end being 0 or slightly under 0 and the higher end being well above 0, made the influence probably positive. The aforementioned case vice versa made it probably negative. A credibility interval containing 0 with equal lower and upper distribution did not have an effect [35]. The strength of these effects was interpreted by evaluating the posterior mean of each touchpoint. For example, the posterior mean of the 'Warranty services' touchpoint showed that an increase of one Likert point in warranty service recognition increased the sales value of a customer, on average and across all models, by €47.40. Every model containing 'Warranty service' as predictor is 403.94 more likely to predict sales value (BF inclusion = 403.94). Contrary, an increase in recognition of the touchpoint 'Digital signage outdoor' worth one Likert point will decrease the average sales value of a customer by €36.95, meaning that when a customer recognizes this touchpoint, it has a negative impact on their expenditures. Every model containing 'Digital signage outdoor' as predictor was 24.194 more likely to predict sales value (BF inclusion = 24.194).

4. Discussion

Reflecting on our first research question, results indicate that the seven touchpoint clusters most recognized by customers are: 'Point of Sale', 'Cooperation', 'Service', 'Website', 'Classic Media', 'Social Media' and, 'Customer Relationship Management'. In the initial touchpoint identification workshop conducted with the retailer, however, twelve main categories were identified by the retailer's employees (including top managers). This means that the retailer does follow another logic than its customers do when organizing the brand-owned touchpoints. However, especially the way managers group touchpoints has an impact on how they coordinate them (e.g., communicating a unified marketing message within a specific category) [38, 39]. This implies that omnichannel activities can lack efficiency and effectiveness since the same marketing messages can be communicated in a seemingly homogeneous group of touchpoints, while customers typically tend to use touchpoints that (according to the retail managers) belong to different touchpoint clusters. For the specific retailer analysed, we argue that the customer-based clusters represent the most important points of interest the retailer can use to interact with customers in a consistent way. Therefore, in line with Grewal and Roggeveen [14], the retailer should especially care for their optimal design and integration into the retailer's customer journey. Looking from a different perspective, if a specific touchpoint, in which the retailer puts a lot of effort, is not part of a customer-based cluster, the retailer should readjust his promotion strategy of this touchpoint, as it seems not to be recognized by customers. Clearly, the existence of these customer-based clusters may not be directly transferable to all other retailers. However, we argue that the approach of combining a touchpoint identification workshop with a customer survey can lead to insightful results by identifying potential gaps between the managers' and customers' viewpoint concerning touchpoints recognition and usage.

Looking at our second research question concerning touchpoints' influences, the BayS-MR was able to identify specific touchpoints that influence the sales value of a customer. Moreover, it identified possible model combinations of those touchpoints, which have a high likelihood of describing the influence of a specific set of touchpoints on the sales value of a customer. Similar results have been reported in the realm of e-commerce for online touchpoints only [15, 16]. However, our study could show that the value of brand-owned omnichannel touchpoints is likewise determinable. In particular, the BayS-MR could identify one touchpoint with a *definitely positive* influence on sales value ('Warranty service') and one touchpoint with a *definitely negative* influence on sales value ('Digital signage outdoor'). In addition, the BayS-MR could identify seven touchpoints with a *probably positive*, one with no, and nine with a *probably negative* effect on sales value. Additionally, the performed structural equation model could identify one statistically significant negative influence of the cluster 'Cooperation' on sales value. However, from a retailer perspective all these effects must be put into context. For example, it could be possible that customers with a high sales value often make use of the warranty service, which could indicate high product returns because of poor product quality. Conversely, the touchpoint 'Warranty Service' could generate a feeling of security in customers who buy many products because of the availability of a warranty service in general. In addition, the negative influence of cooperations ('CP') should not entice the retailer to abandon all his retail cooperations. Instead, the retailer should evaluate why this factor in particular reduces customer sales value and what can be done to improve the perception of this factor. The information provided by the BayS-MR about the influence of specific touchpoints on sales value can be especially very beneficial in such evaluation. As such, it becomes evident that, for this specific retailer, in particular touchpoints that impose opinions on customers (mostly marketing communication channels) have a negative impact on sales value, while service channels are having a positive impact. In accordance with Gatignon [40], a plausible explanation would be that customers do not like to be manipulated, but enjoy the services provided by the retailer.

Summarizing, we argue that CFA and BayS-MR can both support omnichannel retailers in their decision-making process for touchpoint grouping and selecting the most influential touchpoints out of a diverse set. However, retailers should be aware that the specific reasons a touchpoint influences customer sales value remains a debateable question that needs to be answered by every retailer individually.

As with all research, our study comes with limitations that can be venues for future research. It has to be noted that most of the data we used was collected manually via a workshop with employees, a survey of customers and sales data set from the omnichannel retailer. Naturally, these data come with uncertainty regarding data quality and accuracy. In particular, our study does not distinguish between customers only recognizing or actively using a touchpoint, which, depending on point of view, might lead to different implications when discussing the impact of a touchpoint on sales value. Similarly, we could not track the sequence or buying phase in which customers encountered the touchpoints, thus the identified sales value of a touchpoint has to be understood as an average value aggregated across all buying phases and touchpoint sequences. In the future, this problem could be mitigated by sophisticated tracking tools that are able to track customers along their online and offline journey precisely. Future research might therefore replicate our analyses with the use of big data and more precise customer tracking tools, possibly using artificial intelligence to evaluate the sales value of touchpoints. Additionally, our analysis is based on the data of one retailer only. It has to be pointed out that, for this retailer, the general touchpoint recognition (see Tab. 2) was low (mean = 1.92), which could impact the explanatory power of the performed analyses. Future studies might elaborate which result such analyses yields for retailers from different branches with higher touchpoints recognition. A possible final outcome of these future studies could be the unification of automatic touchpoint tracking and evaluation with the help of artificial intelligence into a customer relationship management tool that can automatically adjust a retailers' advertising strategy.

5. Conclusion

In this study, we used a combination of a touchpoint identification workshop, a customer survey, and CFA to identify the most recognized touchpoint clusters from a company and customer perspective. Our results indicate that retailers (12 clusters) and their customers (7 clusters) perceive groups of touchpoints differently. The retailer needs to pay special attention to the clusters perceived by customers, as they represent the most direct connection to the customer. Additionally, we used sales data and BayS-MR to identify from a company perspective most sales influencing brand-owned touchpoints. We could identify one *positive*, seven *probably positive*, one *neutral*, eight *probably negative*, and one *negative* touchpoint having a direct influence on customer sales value. The insights regarding these touchpoints can be used by retailers in the channel-choice and integration and thus decision-making process as they provide a reliable statistical base of discussion that can lead to thought provoking impulses.

To conclude, as the power of e-commerce rises and omnichannel retailers try to remain competitive by improving their customer experience, the need for accurate tracking tools that can estimate the sales value of omnichannel customer journeys together with their underlying touchpoints rises. This study can serve as a thought-provoking impulse when developing such tools and it will be rewarding to see how future tracking technologies might improve the concept of this paper.

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References

[1] US Census Bureau (2018) "Department store sales (excluding leased departments) in the United States from 1992 to 2016 (in billion U.S. dollars)." Available at: https://www.statista.com/statistics/197712/annual-department-store-sales-in-the-us-since-1992/ [accessed 30.07.2021].

[2] ICSC (2018) "Sales growth of department stores in Western Europe from 2012 to 2017, by country." Available at: https://www.statista.com/statistics/911107/department-store-sales-growth-western-europe/ [accessed 30.07.2021].

[3] Statista (2021) "eCommerce - Worldwide | Statista Market Forecast." Available at: https://www.statista.com/outlook/dmo/ecommerce/worldwide?currency=eur [accessed 17.05.2021].

[4] Nicola, Maria, Zaid Alsafi, Catrin Sohrabi, Ahmed Kerwan, Ahmed Al-Jabir, and Christos Iosifidis, et al. (2020) "The socio-economic implications of the coronavirus pandemic (COVID-19): A review." *Int J Surg* **78** 185–193.

[5] Anderl, Eva, Ingo Becker, Florian von Wangenheim, and Jan H. Schumann (2016) "Mapping the customer journey: Lessons learned from graph-based online attribution modeling." *International Journal of Research in Marketing* **33 (3)**: 457–474.

[6] Parise, Salvatore, Patricia J. Guinan, and Ron Kafka (2016) "Solving the crisis of immediacy: How digital technology can transform the customer experience." *Business Horizons* **59 (4)**: 411–420.

[7] Melero, Iguácel, F. Javier Sese, and Peter C. Verhoef (2016) "Recasting the Customer Experience in Today's Omni-channel Environment." *Universia Business Review* **(50)**: 18–37.

[8] Lemon, Katherine N., and Peter C. Verhoef (2016) "Understanding Customer Experience Throughout the Customer Journey." *Journal of Marketing* **80 (6)**: 69–96.

[9] Eriksson, Niklas, Carl-Johan Rosenbröijer, and Asle Fagerstrøm (2018) "Smartphones as decision support in retail stores – The role of product category and gender." *Procedia Computer Science* **138** 508–515.

[10] Zimmermann, Robert, Andreas Auinger, and René Riedl (2019) "Smartphones as an Opportunity to Increase Sales in Brick-and-Mortar Stores: Identifying Sales Influencers Based on a Literature Review.", in Nah FF-H, Siau K, editors. *HCI in Business, Government and Organizations. eCommerce and Consumer Behavior*, Cham, Springer International Publishing.

[11] Bradley, Joseph, James Macaulay, Kathy O'Connell, Kevin Delaney, Anabelle Pinto, and Joel Barbier (2015) "Winning the New Digital Consumer with Hyper-Relevance.: In Retail, Insight Is Currency and Context Is King." Available at: https://www.startitup.sk/wp-content/uploads/2015/11/ioe-retail-whitepaper.pdf [accessed 21.07.2021].

[12] Juaneda-Ayensa, Emma, Ana Mosquera, and Yolanda Sierra Murillo (2016) "Omnichannel Customer Behavior: Key Drivers of Technology Acceptance and Use and Their Effects on Purchase Intention." *Front Psychol* **7** 1117.

[13] Rosenbaum, Mark S., Mauricio L. Otalora, and Germán C. Ramírez (2017) "How to create a realistic customer journey map." *Business Horizons* **60 (1)**: 143–150.

[14] Grewal, Dhruv, and Anne L. Roggeveen (2020) "Understanding Retail Experiences and Customer Journey Management." *Journal of Retailing* **96 (1)**: 3–8.

[15] Xu, Lizhen, Jason A. Duan, and Andrew Whinston (2014) "Path to Purchase: A Mutually Exciting Point Process Model for Online Advertising and Conversion." *Management Science* **60 (6)**: 1392–1412.

[16] Li, Hongshuang, and P. K. Kannan (2014) "Attributing Conversions in a Multichannel Online Marketing Environment: An Empirical Model and a Field Experiment." *Journal of Marketing Research* **51 (1)**: 40–56.

[17] Zimmermann, Robert, and Andreas Auinger (2020) "Identifying Brand-Owned Touchpoints Along the Digital Retail Customer Journey – A Practical Approach.", in Gronau N, Heine M, Poustcchi K, Krasnova H, editors. *WI2020 Community Tracks,* GITO.

[18] Brown, Juanita, and David Isaacs (2007) "Das World Café: Kreative Zukunftsgestaltung in Organisationen und Gesellschaft." Heidelberg, Auer.

[19] foryouandyourcustomers.com (2018) "ChannelCARDS for Your Multichannel Business - foryouandyourcustomers." Available at: https://foryouandyourcustomers.com/magazine/channelcards/?lang=en [accessed 31.07.2021].

[20] Saunders, Benjamin, Julius Sim, Tom Kingstone, Shula Baker, Jackie Waterfield, and Bernadette Bartlam, et al. (2018) "Saturation in qualitative research: exploring its conceptualization and operationalization." *Qual Quant* **52 (4)**: 1893–1907.

[21] Landis, J. R., and Gary G. Koch (1977) "The Measurement of Observer Agreement for Categorical Data." *Biometrics* **33 (1)**: 159–174.

[22] Leva, Marco, and Cristina Ziliani (2018) "Mapping touchpoint exposure in retailing." *IJRDM* **46 (3)**: 304–322.

[23] Palomo, Jesus, David B. Dunson, and Ken Bollen (2008) "Bayesian Structural Equation Modeling.", in Lee S-Y, editor. *Handbook of latent variable and related models*, Amsterdam [etc.], Elsevier.

[24] Blake, Arnold "Bayesian A/B testing — a practical exploration with simulations." *Towards Data Science* (2019), 25 November 2019 Available at: https://towardsdatascience.com/exploring-bayesian-a-b-testing-with-simulations-7500b4fc55bc [accessed 17.05.2021].

[25] Michaeli, Idan (2021) "Frequentist vs. Bayesian approach in A/B testing." Available at: https://www.dynamicyield.com/lesson/bayesian-testing/ [accessed 17.05.2021].

[26] Smith, Gary (2018) "Step away from stepwise." *J Big Data* **5 (1)**: 146.

[27] Koehrsen, Will "Introduction to Bayesian Linear Regression - Towards Data Science." *Towards Data Science* (2018), 2018 Available at: https://towardsdatascience.com/introduction-to-bayesian-linear-regression-e66e60791ea7 [accessed 17.05.2021].

[28] Wagenmakers, Eric-Jan, Maarten Marsman, Tahira Jamil, Alexander Ly, Josine Verhagen, and Jonathon Love, et al. (2018) "Bayesian inference for psychology. Part I: Theoretical advantages and practical ramifications." *Psychon Bull Rev* **25 (1)**: 35–57.

[29] Arbuckle, J. L. (2021) "Amos (Version 27.0)." Chicago, IBM SPSS.

[30] JASP Team (2020) "JASP (Version 0.14.1).".

[31] Little, Todd D., and Rex B. Kline, editors (2016) "Principles and practice of structural equation modeling." New York, London, The Guilford Press.

[32] Coughlan, Joseph, Daire Hooper, and Michael Mullen (2008) "Structural Equation Modelling: Guidelines for Determining Model Fit." *Electronic Journal of Business Research Methods* **6 (1)**: 53–60.

[33] Fornell, Claes, and David F. Larcker (1981) "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error." *Journal of Marketing Research* **18 (1)**: 39.

[34] Andraszewicz, Sandra, Benjamin Scheibehenne, Jörg Rieskamp, Raoul Grasman, Josine Verhagen, and Eric-Jan Wagenmakers (2015) "An Introduction to Bayesian Hypothesis Testing for Management Research." *Journal of Management* **41 (2)**: 521–543.

[35] Heo, Ihnwhi, and Rens van de Schoot (2020) "Tutorial: Advanced Bayesian regression in JASP.".

[36] Hoeting, Jennifer A., David Madigan, Adrian E. Raftery, and Chris T. Volinsky (1999) "Bayesian model averaging: a tutorial." *Statist. Sci.* **14 (4)**.

[37] Lee, Michael D., and Eric-Jan Wagenmakers (2014) "Bayesian cognitive modeling: A practical course." Cambridge, United Kingdom, New York, Cambridge University Press.

[38] Liu, Lucy, and Adela J. McMurray (2004) "Frontline leaders." *Jnl Euro Industrial Training* **28 (2/3/4)**: 339–352.

[39] Zimmermann, Robert, and Andreas Auinger (2021) "Managerial and Departmental Differences in the Perceived Influence of Brand-Owned Touchpoints on Brand Perception - Case Study." *Procedia Computer Science* **181 (1)**: 157–165.

[40] Gatignon, Hubert (2016) "Manipulating Consumers is Not Marketing." Available at: https://knowledge.insead.edu/customers/manipulating-consumers-is-not-marketing-4662 [accessed 21.07.2021].