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Are you still online or are you already mobile? – Predicting the path to successful conversions across different devices

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ABSTRACT

As digitalization increases, retail firms must invest in online and mobile commerce to attract customers to their website or mobile store. Since the type of device used to access marketing channels influences conversions, this research examines the different impacts of different devices such as desktop computers, tablets, and smartphones on the success of various marketing channels. We find customer experience (CX) to be important in improving attribution outcomes (e.g., conversion rates) by combining clickstream and survey data to understand consumers' decision processes. Therefore, this paper also conceptualizes and measures perceptions of CX of clickstream-data participants. We identify the central implications of using each device.

1. Introduction

Due to rapid evolutions in technology, interactions between customers and retail firms have fundamentally changed (Grewal et al., 2017). Customer nowadays have evolving expectations of retailers because of reduced information asymmetries, past experiences, higher levels of customer orientation, or the multiplication of media outlets (e.g., Kumar, 2018). Retailers are interested in how customer behavior is changing as a result of the adoption of different devices for shopping purposes in both the online and mobile contexts (Kannan and Li, 2017; Souiden et al., 2018). Whereas the online context is mainly represented by desktop computers, customers increasingly use smartphones and tablets as primary devices for shopping in the mobile context (Criteo, 2018). Thus, retail firms are challenged by high levels of diversity and complexity in customer journey configurations across different devices used by customers (Harris et al., 2018). As a consequence, both scholars and practitioners are shifting their primary focus to the allocation of investments to attract customers to online or mobile stores, respectively (e.g., Marketing Science Institute, 2016; 2018).

Since the effect of marketing channels (e.g., display advertising) on conversions is expected to differ across different devices, research has been encouraged to include tablets and smartphones in attribution modeling (Kannan and Li, 2017; Lemon and Verhoef, 2016; Souiden et al., 2018). Thus, the first objective of this research is to *understand the effectiveness of various marketing channels across desktop, tablet, and smartphone devices in enhancing retailers' performance of marketing channel budget allocation*. Against this background, user-specific clickstream data was collected from a retailer that runs both an online and a mobile store. The paper implements an existing attribution model (Anderl et al., 2016) that tracks customer behavior at device level.

The variety of shopping devices not only challenges retailers, it also fundamentally alters customers' experience (CX) perceived during the path to purchase (e.g., Marketing Science Institute, 2016; 2018). Therefore, research is encouraged to examine attribution not just from a technological point of view, but also how human factors play an important role (Rodríguez-Torrico et al., 2017). To address this issue, Lemon and Verhoef (2016) suggested that future research should combine clickstream and survey data to enable the underlying decision processes of customers to be described. In order to improve attribution outcomes, such as higher conversion rates, creating and delivering positive CXs becomes critical (Giovanis and Athanasopoulou, 2018; Grewal et al., 2017; Souiden et al., 2018). In this context, previous research has not considered CX as a separate construct (Verhoef et al., 2009), thus, it is still unclear which factors influence perceptions of CX and how CX is related to important behavioral outcomes (Lemon and Verhoef, 2016; Piotrowicz and Cuthbertson, 2014). Consequently, the second objective of this research is to *understand underlying choice processes of clickstream-data participants in enhancing both customers´ short-term CX (conversions) and long-term CX (behavioral outcomes)*. Hence, the paper addresses the following research questions: *What are the differences with regard to the success of various marketing channels across desktop, tablet, and smartphone devices? Which determinants of CX*

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Table 1
Comparison of recent research on marketing channel budget allocation with the present study.

	Context	Attribution model	Data	Conversions and non-conversions?	Integration of offline channels?	Integration of online channels?	Integration of mobile channels?	Combined with survey data?
Anderl et al. (2016)	Various industries	First- and higher-order Markov walks	Individual level	Yes	No	Yes	No	No
Kireyev et al. (2016)	Bank	Persistence modeling technique	Aggregate level	No	No	Yes	No	No
de Haan et al. (2016)	Five product categories	Structural vector autoregressive model	Category-level	No	Yes	Yes	No	No
Abhishek et al. (2015)	Typical stages of the conversion funnel	Hidden Markov model	Individual level	No	No	Yes	No	No
Li and Kannan (2014)	Online channels	Bayesian model	Individual level	Visit and purchase stage	No	Yes	No	No
This study	Fashion retailer	First- and higher-order Markov walks	Individual level	Yes	No	Yes	Yes	Yes

contribute most to conversions across desktop, tablet, and smartphone devices? How is CX related to important outcomes such as satisfaction, repurchase intention, or word-of-mouth?

Against this background, we expand the CX construct and use a measurement scale that includes affective, behavioral, cognitive, and social dimensions. As a result, this research extends recent literature on marketing channel budget allocation by (1) including mobile devices into attribution modeling (2) combining clickstream data and survey data (see Table 1).

The remainder of this paper is structured as follows: First, we present our attribution model development and the conceptual model of CX. Second, we provide an overview of our data. Third, we present and discuss the empirical findings. Finally, we outline the limitations of our study, and the implications for managers and further research. Fig. 1 summarizes the methodological approach of this research as well as the contributions to the literature.

2. Conceptual framework

2.1. Development of the attribution model

Since standard online advertising metrics (e.g., cost per acquisition) or simple heuristics (e.g., last-click attribution) cannot account for synergy or dynamic effects of various marketing channels (Anderl et al., 2016; Kireyev et al., 2016), academic research and practitioners have shifted focus to attributing the credit for one conversion to a range of marketing channels simultaneously. To analyze customer journeys and to derive an attribution model, we present a graph-based Markovian framework based on approaches proposed by Archak et al. (2010) and Anderl et al. (2016). This approach was chosen because Markov models illustrate dependencies between sequences of observations of a variable of interest. Therefore, customer journeys can be represented by their sequential nature (e.g. Anderl et al., 2016; Li and Kannan, 2014). In our model, customer journeys are constructed as chains in directed Markov graphs that are defined by a set of states:

$$S = \{s_1, \ldots, s_n\}$$

and a transition matrix W with edge weights:

In this base model, every state S corresponds to one channel of the marketing mix. In addition, each Markov chain contains three special states: START (added to the first channel of each customer journey), CONVERSION (connected to each channel that leads to a successful conversion), and NULL (added to nonconversions and after each CONVERSION state). The transition probability w_{ij} results from the probability that contact with channel i is followed by contact with channel j, where i and j can also be the same channel.

Since base models only take the last channel of a customer journey into account, all further information about channel interactions are neglected. With regard to this limitation, Anderl et al. (2016) introduced higher-order models in which the probability of state S depends on the last k states:

$$P(X_t = s_t X_{t-1} = s_{t-1},\ X_{t-2} = s_{t-2}, \ldots,\ X_1 = s_1)$$
$$= P(X_t = s_t X_{t-1} = s_{t-1},\ X_{t-2} = s_{t-2}, \ldots,\ X_{t-k} = s_{t-k}).$$

Higher-order Markov chains outperform attribution heuristic models (e.g., last-click and first-click attribution) and simple logit models related to the robustness and the predictive accuracy of attribution results (Anderl et al., 2016; Li and Kannan, 2014). With respect to the order (k) of Markov chains, the predictive accuracy increases with the order, while robustness decreases. With this trade-off in mind, we chose a second-order Markov chain as our attribution model because decision-supporting models should deliver stable and reproducible results. Thus, the probability of the future state S depends on the present state and the preceding state.

Based on the collected data, we can develop an attribution model

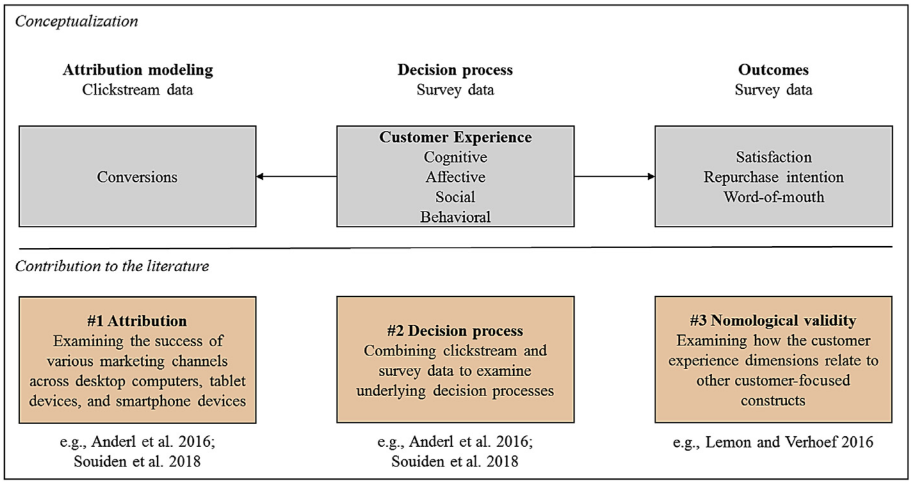


Fig. 1. Methodological approach and contribution to the literature.

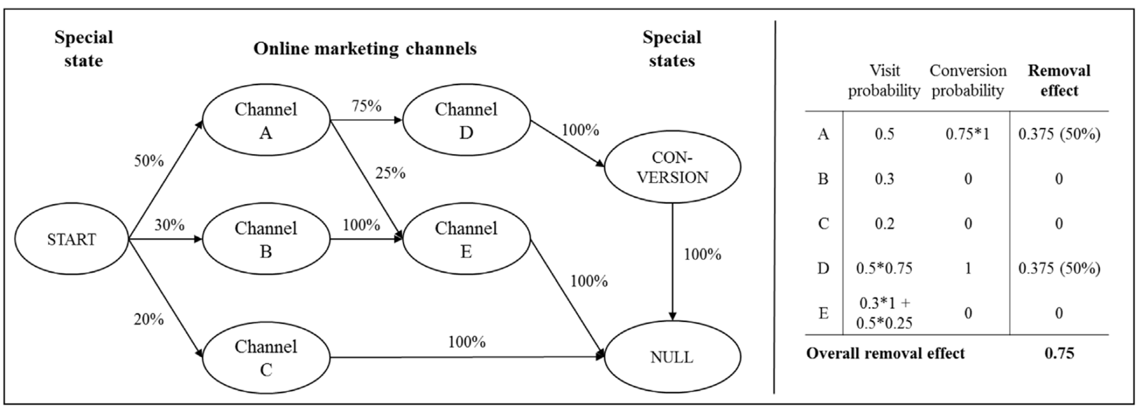


Fig. 2. Exemplary calculation of the removal effect.

that is tailored to the retailer by using the removal effect (RE). The RE represents the change in conversion rate if a channel is removed from the attribution model or from the Markov graph, respectively (Anderl et al., 2016). Thus, retailers can derive the accurate value of each channel. Referring to Archak et al. (2010), the RE of a channel is calculated by multiplying the visit probability (passing the channel on a random walk from the START state) and the eventual conversion probability (reaching the CONVERSION state from the channel). RE can take values from zero to the total conversion rate. We report them as a percentage rate of the sum of the entire RE. Fig. 2 illustrates the calculation of the RE.

2.2. Conceptualization of CX

CX is defined as customer's multidimensional response to a retailer's offerings and actions during the entire customer journey, encompassing pre-purchase, purchase, and post-purchase stages (Lemon and Verhoef, 2016). In a retailing context, literature suggests that the construct of CX encompasses *cognitive, affective, behavioral,* and *social* dimensions (e.g., Verhoef et al., 2009). Although related CX measurements have been developed over the years, a measurement to assess the online and mobile context is still lacking. Integration of factors that cover the nature of electronic and mobile commerce is essential because different customers are likely to express different expectations and preferences regarding the CX (Souiden et al., 2018). A modified conceptualization of CX allows us to examine customer's perceptions regardless of the used device, fitting the context of our study.

For instance, mobile devices, and to some extent desktop computers, allow customers to shop without temporal and spatial constraints. This ‘ubiquitous availability’ of services is perceived favorably by customers because it successfully bridges offline and online retailing environments (Hubert et al., 2017). In this context, retailers are encouraged to provide service in a variety of online channels and to establish social touchpoints (Hallikainen et al., 2018). Although social media offers new means of interaction, retailers have to be aware that they are losing some control over those interactions and conversations (Grewal et al., 2017). Thus, modifications mainly refer to our behavioral and social dimensions of CX.

The cognitive dimension of CX encompasses situations of problem solving and creativity during the customer journey (Brakus et al., 2009). In this context, customers engage in an effort to search for information related to the product or service, to compare alternatives, or to find a better price (Kleijnen et al., 2007). According to the Technology Acceptance Model, the intention to adopt smartphones for searching tasks is affected by ease of use and usefulness perceptions. While the ubiquitous availability of mobile services increases the ease of use perceptions of customers (Hubert et al., 2017), customers’ perceptions of usefulness could be impacted negatively by the smaller displays and input buttons compared to desktop and tablet computers (Xu et al., 2017). Additionally, in line with cognitive load theory, smartphones represent an environment of increased cognitive load while performing searching tasks (Ayers and Paas, 2012). Since smartphones are mostly used on the move, recent research has shown that mobile users who perform multiple tasks at the same time are characterized by limited attentional capacity and decreased cognitive resources (Blom et al., 2017; Grewal et al., 2018). Thus, we propose that the importance of cognitive CX for decision making decreases with smaller screen sizes and increased portability of the device. Hence.

H1. Perceptions of cognitive CX contribute most to conversions for desktop users and least to conversions for smartphone users (desktop > tablet > smartphone).

The affective dimension of CX encompasses feelings and emotions towards a retailer, as well as previous experiences with the brand (Brakus et al., 2009). Compared to desktop and tablet computers, smartphones are more portable and personal in nature (Grewal et al., 2018). The 'go-mobile transformation' has provided retailers with additional opportunities to interact with their customers on a more personalized and frequent basis (Lamberton and Stephen, 2016). According to cognitive load theory, smartphone users in particular are keen to reduce complexity during the path to purchase (Ayers and Paas, 2012). With limited information available, smartphone users rely heavily on affective components of CX in order to substitute all necessary information to make an informed purchase (Grewal et al., 2018). Due to reasons of limited cognitive capacity and a stronger relationship with the brand, smartphone users are most likely to purchase well-known products and services of familiar retailers (Blom et al., 2017). Thus, we propose that the importance of the affective component of CX for decision-making increases with the portable and personal nature of the device. Hence.

H2. Perceptions of affective CX contribute most to conversions for smartphone users and least to conversions for desktop users (smartphone > tablet > desktop).

The behavioral component of CX is defined as the extent to which customers can control the timing, content, and sequence of a purchase (Kleijnen et al., 2007). Thus, it refers to customers' flexibility to access the (mobile) store at any time and from any place (Florenthal and Shoham, 2010). In this context, the ubiquitous availability of mobile services (Hubert et al., 2017) enhances users of the smartphone channel to fulfill their purchase purposes more efficiently compared to those using other channels. This is because mobile services provide customers with real-time, on-demand access to services, exploiting the time and efficiency utilities of the mobile channel (Kleijnen et al., 2007). As a result, smartphones provide the greatest level of control over the timing and sequence of purchase since they enable users to do business at times and places that would not normally be possible with desktop (or tablet) computers (Wang et al., 2015). Thus, we propose that the importance of behavioral CX for decision making increases with the mobility of the device. Hence.

H3. Perceptions of behavioral CX contribute most to conversions for smartphone users and least to conversions for desktop users (smartphone > tablet > desktop).

The social dimension of CX encompasses the impact of interpersonal communications in social and community networks on decision making (Florenthal and Shoham, 2010; Hallikainen et al., 2018). Due to rising digitalization, customers increasingly rely on third-party information sources (Lemon and Verhoef, 2016), and social responses today are increased by customer-to-customer interactions through various social media platforms (Souiden et al., 2018). The emergence of social media as a pervasive and likely permanent marketing medium was fostered by the widespread adoption of Internet-connected smartphones (Lamberton and Stephen, 2016). In this interconnected world, it is crucial to be constantly available and always responsive (Grewal et al., 2017). According to the Technology Acceptance Model, smartphones are the most convenient devices through which to engage with other customers at any time and in any place. Thus, we propose that the 'social presence' increases with higher levels of device portability and personalization. Hence.

H4. Perceptions of social CX contribute most to conversions for smartphone users and least to conversions for desktop users (smartphone > tablet > desktop).

Since recent research has not yet shown the nomological network of the construct, there is still a question as to how CX relates to major constructs in customer management and marketing (Lemon and Verhoef, 2016). In general, satisfaction represents one of the most important customer outcomes since it is supposed to affect behavioral intentions directly, but also to operate as a key mediating variable, linking behavioral intentions to perceptions of CX (Brady et al., 2005). In this context, literature suggests that for satisfied customers, a trigger occurs in the post-purchase stage that results in customer loyalty, expressed through repurchase behavior and positive recommendations (Lemon and Verhoef, 2016). In line with discussion, recent research has shown that positive experiences within the path to purchase positively affect not only current satisfaction perceptions, but also future (re) purchase and positive word-of-mouth intentions because of strong carryover effects (e.g., Giovanis and Athanasopoulou, 2018). With regard to the construct of CX, marketing and retailing literature frequently did not consider it as a separate construct and neglected it in the favor of, for instance, service quality (e.g., Blut et al., 2015; Miranda et al., 2018; Parasuraman et al., 1988; Verhoef et al., 2007). In addition, prior research questioned how an improved CX justifies investments, or how CX influences firm performance in terms of market metrics and/or financial metrics (Lemon and Verhoef, 2016; Piotrowicz and Cuthbertson, 2014). Conceptually, superior perceptions of CX are assumed to lead to improved perceptions of satisfaction, repurchase intention, and word-of-mouth (Verhoef et al., 2009). Since no strong CX scales have been developed, the conceptual considerations lack empirical evidence (Lemon and Verhoef, 2016). Related constructs, such as brand experience or customer experience quality, show positive impacts on behavioral outcomes. In detail, the brand experience scale provided by Brakus et al. (2009) is positive related to both satisfaction and loyalty. Furthermore, the customer experience quality scale provided by Maklan and Klaus (2011) encompasses four dimensions (peace of mind, outcome focus, moments of truth, and product experience) which displayed positive associations with customer satisfaction (except for moments of truths), loyalty, and word-of mouth. Thus, on the basis of prior behavioral outcome research and analogous to results of related constructs to CX, we expect that CX impacts major behavioral outcomes through a direct and indirect route. Hence.

H5. Perceptions of (a) cognitive, (b) affective, (c) behavioral, and (d) social CX contribute directly to satisfaction and indirectly to repurchase intention and word-of-mouth via satisfaction.

3. Data collection

3.1. Clickstream data

The development of the attribution model is based on user-specific clickstream data provided by a fashion retailer in Germany (observation period: September 29, 2016 to October 29, 2016). The fashion retailer is a specialized retailer selling leather products for women and men. This context was chosen because the fashion segment represents the largest product category and expenditures on online (mobile) advertisement are highest (de Haan et al., 2016). Participants did not receive a compensation to participate in the study.

Data collection occurred at the cookie level, since cookies are the industry standard for multichannel tracking (Anderl et al., 2016); this enabled us to identify individual devices. Each time a user visited the retailer's online or mobile store during the observation period, detailed information about the source of the click and an accurate timestamp were tracked.

One the one hand, a click can represent a direct behavioral response to an advertising exposure, or, on the other hand, results from the user

Table 2
Description of marketing channels.

Marketing channel	Contact origin	Description (adapted from Anderl et al., 2016)
Direct type-in (DIR)	Customer-initiated	Consumers access advertiser's (mobile) store directly by entering the URL, or by locating a bookmark, favorite, or shortcut.
Search engine advertising (SEA)	Customer-initiated	Consumers search for a keyword and receive sponsored search results, also known as paid search.
Search engine optimization (SEO)	Customer-initiated	Consumers search for a keyword and receive organic search results ranked by the search algorithm.
Referrer (REF)	Customer-initiated	Covers all traffic forwarded by external content websites by including a text link. In our data set, referrer includes coupon websites that are customer-initiated.
Display (DIS)	Firm-initiated	Display advertising, also known as banner advertising, entails embedding a graphical object with the advertising message into a website.
Social media (SM)	Firm-initiated	Comprises a set of advertising platforms belonging to the field of social media. In our data set, the advertiser uses targeted Facebook ads.
Newsletter (NL)	Firm-initiated	Encompasses sending marketing messages toward potential customers using e-mail.

entering the retailer's (mobile) website directly. The retailer considered in this study operates a total of seven marketing channels, as described in Table 2: 'direct type-in,' 'search engine advertising (SEA),' 'search engine optimization (SEO),' and 'referrer' represent customer-initiated channels (CIC) whereas 'display,' 'newsletter,' and 'social media' represent firm-initiated channels (FIC). Additionally, the fashion retailer runs several retail stores. Since we only record users' internet activity, we are not able to exclude online-offline cross-channel effects.

The clickstream data revealed customer journeys based on the click pattern of individual customers across all operated marketing channels across desktop computers, tablets, and smartphones. The marketing channels are for both desktop computers and mobile devices the same.

As seen in Table 3, the composition of assessed journeys using desktop computers and mobile devices, including tablets and smartphones, are almost even (mobile devices: 50.80%). Across all devices, the majority of tracked journeys represent a one-click journeys. On average, assessed customer journeys using a tablet or smartphone device are more than one click shorter than journeys with a desktop device. Thus, the probability of a successful conversion is twice as high when the customer journey is executed with a desktop computer.

3.2. Survey data collection and measurement reliability

The data were collected with the help of the fashion retailer, who invited a random sample of its customers to participate. To be invited to the study, customers had to make a purchase during the observation period. After completing a successful conversion, participants were invited via e-mail to participate in the survey and were asked to answer the questions with respect to their most recent shopping experience. The consideration of only successful conversions allows us to examine which determinants of CX contribute most to purchase decisions across different devices. For each participating customer, the device used and the last two touchpoints of the customer journey were identified from the clickstream data. The final sample consists of 230 participants with a mean age of 44.25 years (SD = 14.26). The sample consists of 62.6% females. The composition of devices in the survey data corresponds to the composition of successful conversions in the clickstream data: desktop computers (survey: 64.8%; clickstream: 62.5%), tablets (survey: 17.8%; clickstream: 17.8%), and smartphones (survey: 17.4%; clickstream: 19.7%).

Since there is no dedicated measurement of CX in mobile environments, we adapted scales from Brakus et al. (2009) to cover the cognitive and affective dimensions, and from Florenthal and Shoham (2010) to cover the social and behavioral dimensions. The outcomes were measured with established scales derived from Fornell (1992) and Zeithaml et al. (1996). To measure the constructs, seven-point Likert scales with the anchors 1 (strongly disagree) to 7 (strongly agree) were used.

Table 3
Description of the clickstream data.

	Desktop	Tablet	Smartphone
No. of journeys	40,251	17,554	23,998
Average length	3.81 clicks	2.51 clicks	2.45 clicks
One-click journeys	23,739 (58.98%)	10,729 (61.12%)	13,986 (58.28%)
No. of conversions	2249	641	707
Conversion rate (%)	5.59	3.65	2.95

Further, we used both AVE-SV and heterotrait-monotrait (HTMT) techniques in conjunction to provide the most stringent assessment of discriminant validity (see Table 4, Panel A) (Voorhees et al., 2016). According to the Fornell and Larcker (1981) criterion, the result of the test for discriminant validity was satisfactory. With respect to the HTMT ratio of correlations, one ratio exceeds the suggested value of 0.90 (Henseler et al., 2015). Since the *repurchase intention-satisfaction ratio* does not exceed the value of 1.0, it is not interpreted as discriminant validity violation (Voorhees et al., 2016).

As seen in Table 4 (Panel B), all constructs showed Cronbach's alpha scores exceeding the threshold value of 0.70 (Nunnally, 1978), composite reliability scores exceeding the threshold value of 0.60 (Bagozzi and Yi, 1988), and average variance extracted scores exceeding the threshold value of 0.50 (Fornell and Larcker, 1981).

To reduce the risk of a potential common method bias in advance, the design of the questionnaire was adjusted accordingly. For instance, respondent anonymity was ensured, independent and dependent variables were separated into different sections, and the survey contained reverse coded items (Kortmann, 2014). Additionally, we conducted a post hoc test of the data assessing common method bias with Harman's single-factor test (Harman, 1967). The test reveals that the first factor reveals only 29.35% of the total variance, while four factors with eigenvalues greater than one accounted for 71.26% of the variance. Thus, it is not likely that common method bias is present since neither a single factor emerged from the exploratory factor analysis of all survey items, nor one general factor accounted for the majority of the variance.

4. Results and discussion

4.1. Attribution results

First, we compare the attribution results of our proposed framework with the attribution model currently used by the fashion retailer—namely 'last indirect click.' Last indirect click represents a modified heuristic approach of the last-click attribution and credits the whole conversion to the last channel that is not 'direct type-in.' We use a second-order Markov model for comparison and calculate the mean RE of all states containing channel i as the last channel. To enable a comparison, the model results are presented as percentage values. Second, we compare the purchase propensity of various marketing channels across different devices at channel level, as well as for channel sequences.

Table 4
Panel A. Correlations and heterotrait-monotrait ratios among latent constructs.

	1	2	3	4	5	6	7
1 Affective CX	**.83**						
2 Behavioral CX	.59 [.79]	**.80**					
3 Cognitive CX	.44 [.54]	.26 [.30]	**.93**				
4 Social CX	.44 [.63]	.62 [.84]	.13 [.24]	**.78**			
5 Repurchase intention	.35 [.37]	.35 [.35]	.07 [.06]	.40 [.42]	**.85**		
6 Satisfaction	.35 [.35]	.35 [.37]	-.02 [.04]	.35 [.36]	.80 [.92]	**.91**	
7 Word-of-mouth	.36 [.37]	.33 [.35]	-.00 [.03]	.35 [.35]	.74 [.86]	.79 [.88]	**.91**

Note: Bold numbers on the diagonal show the square root of the AVE; numbers below the diagonal represent construct correlations [HTMT ratios].

4.1.1. Channel-level attribution

As seen in Table 5, attribution heuristics such as last indirect click can lead to incorrect conclusions because some channels are overestimated while others are underestimated.

These structural differences apply consistently across all devices. In this context, the results confirm those from previous research studies (e.g., Abhishek et al., 2015; Anderl et al., 2016; Li and Kannan, 2014), which also found structural differences between attribution heuristics and Markov models, but in a different way.

For instance, the last-indirect-click attribution approach assigns less credit to the channel direct type-in. This is reasonable, since this heuristic attribution model ignores the channel direct type-in as the last channel of successful customer journeys. Therefore, this model only assigns credit to the channel direct type-in if the customer journey was a one-click journey. In this context, last-indirect-click attribution assigns more overall credit to firm-initiated marketing channels (FIC) and underestimates the overall contribution of customer-initiated marketing channels (CIC). These results differ from other heuristic attribution approaches, such as first click or last click, which tend to underestimate FIC since display and social media advertising may be underrepresented by one-click heuristics (e.g., see Anderl et al., 2016; Li and Kannan, 2014).

As also seen in Table 5, CIC (direct type-in, search engine advertising [SEA], search engine optimization [SEO], and referrer) account for the majority of conversions across all devices (desktop: 87.90%, tablet: 83.43%, and smartphone: 93.64%). Thus, the results of previous studies are confirmed and the importance of these channels for marketing success across all devices is highlighted (e.g., Anderl et al., 2016). However, the actual contributions by channel vary substantially across desktop, tablet, and smartphone devices.

Table 5
Attribution results in comparison to 'last indirect click'.

Marketing channel	Desktop		Tablet		Smartphone	
	LIC (%)	MG (%)	LIC (%)	MG (%)	LIC (%)	MG (%)
DIR	12.25	34.63	13.64	39.62	17.57	38.95
SEA	33.57	28.35	37.06	29.38	43.88	36.35
SEO	30.70	19.66	22.33	12.81	23.16	14.63
REF	9.03	5.26	5.74	1.62	5.45	3.71
DIS	12.47	10.92	19.84	16.27	5.45	5.46
SM	1.23	0.72	0.61	0.15	3.95	0.52
NL	0.75	0.46	0.78	0.15	0.54	0.38
Customer-initiated	85.55	87.90	78.77	83.43	90.06	93.64
Firm-initiated	14.45	12.10	21.23	16.57	9.94	6.36

LIC = Last indirect click; MG = Markov Graph 2nd order.

For instance, the RE of the channel 'SEA' is comparatively higher for smartphones (36.35%) than for desktop computers (28.35%), or tablets (29.38%). This is reasonable since smartphones are associated with screen-size constraints (Kaatz et al., 2017), which limit the presentation of search results to the very first items. Accordingly, smartphone users searching for a keyword are likely to click sponsored search results more frequently than nonsponsored results. Consequently, organic search results gain importance with increasing display size, and

Table 4
Panel B. Measurement reliability of latent constructs.

Dimension	Item		Reference	Cronbach's	CR	AVE
Cognitive		*During the last purchase process …*	Adapted from Brakus et al. (2009)	.891	.925	.862
	COG1	… I engaged in a lot of thinking.				
	COG2	… I engaged in situations of problem solving.				
	COG3	… my curiosity was stimulated.*				
Behavioral			Adapted from Florenthal and Shoham (2010)	.770	.845	.646
	BEH1	… I was able to access the store at any time.				
	BEH2	… I was able to access the store from any location.				
Social	BEH3	… I had real-time access to the services.	Adapted from Florenthal and Shoham (2010)	.735	.822	.611
	SOC1	… I conducted a helpful discussion in social networks.				
	SOC2	… I had an interpersonal dialogue with other customers.				
	SOC3	… I socialized with other customers.				
Affective		*My last purchase decision …*	Adapted from Brakus et al. (2009)	.804	.868	.688
	AFF1	… was induced by positive sentiments for this retailer.				
	AFF2	… was affected by strong emotions for this retailer.				
	AFF3	… was affected by previous experiences with this retailer.				
Satisfaction	SAT1	I was satisfied with this retailer.	Fornell (1992)	.893	.933	.824
	SAT2	The retailer was getting close to the ideal retailer.				
	SAT3	The retailer met my needs.				
Repurchase intention	RPI1	I intend to use this retailer within the next few years.	Zeithaml et al. (1996)	.803	.884	.717
	RPI2	I consider this retailer to be my first choice for future transactions.				
	RPI3	I consider doing more business with this retailer in the coming months.				
Word-of-mouth	WOM1	I say positive things about this retailer to other people.	Zeithaml et al. (1996)	.896	.936	.829
	WOM2	I recommend this retailer to someone who seeks my advice.				
	WOM3	I encourage friends and others to do business with this retailer.				

*Item has been excluded because of low factor loading.

contribute most to desktop computers (SEO: 19.66%). Since the highest RE of the marketing channels ‘referrer,’ ‘social media,’ and ‘newsletter’ can also be assigned to desktop computers, the desktop channel seems to induce casual browsing behavior, which results in more impulsive purchases and a wider diversity of products and services (Xu et al., 2017). In contrast, mobile devices are particularly suitable for purchases that do not require an extended information search, such as purchases of well-known products from well-known brands (Wang et al., 2015).

Furthermore, the direct type-in channel shows a higher RE for tablet and smartphone devices, although this channel accounts for the most conversions across all devices. With regard to smartphones, the number of direct visits to the mobile store may be increased by omni-channel behaviors. The ‘go-mobile transformation’ has contributed to add ubiquitous services that are perceived favorably by mobile users (Hubert et al., 2017), who particularly take advantage of the simultaneous usage of integrated channels to provide seamless shopping experiences (Beck and Rygl, 2015; Kuksov and Liao, 2018).

With regard to tablet computers, the importance of the direct type-in channel for successful conversions may result from spillover effects generated by FIC. In particular, ‘display advertising’ (RE_{Tablet} = 16.27%) stimulates customers early in the customer journey (Abhishek et al., 2015), activating their search behavior (Kireyev et al., 2016). Since supposed spillover or carryover effects cannot be derived on the basis of channel-level attribution, we now introduce channel sequences for desktop, tablet, and smartphone devices to illustrate the interplay of channels.

4.1.2. Interplay of channels

As seen in Table 6, the results show for almost all channel sequences across all devices the highest RE after the ‘START’ state, representing the large number of one-click journeys in the data set.

When neglecting one-click journeys, almost all marketing channels across each device show the highest purchase propensity when the preceding channel is followed by a direct type-in. Therefore, the direct type-in channel benefits most from both spillover and carryover effects.

Second, the results indicate that CIC increasingly generate trends for same-channel sequences because direct type-in and SEA in particular promise high levels of customization and accessibility (Florenthal and Shoham, 2010). In contrast, FIC show few trends for same-channel sequences, except for tablet devices (e.g., display > display, RE = 3.76%). Referring to Godfrey et al. (2011), an explanation for this might be that the ideal point of firm-initiated contact varies between the devices examined. Third, in line with this discussion, spillover effects from FIC to FIC are virtually nonexistent across all devices. Thus, the shift of the ideal point after subsequent firm-initiated contact is equivalent to a cross-channel reactance, which is even greater than the same-channel reactance.

Finally, spillover effects from FIC to CIC occur mainly for tablet (7.36%) and desktop computers (6.97%), but not for smartphones (3.12%). As seen in Table 6 (Panel A, Panel B), retailers are especially able to increase direct visits to the store through display advertising across desktop and tablet computers.

4.2. Survey results

First, in order to describe the underlying decision processes of clickstream-data participants who completed a purchase, we employ analysis of variance to derive differences between device groups with regard to their CX perceptions. In this way, H1–H4 are tested.

As seen in Fig. 3 (Panel A), perceptions of the cognitive dimension of CX are highest for desktop users (mean: 3.69), followed by tablet (mean: 3.23) and smartphone (mean: 2.84) users. While the difference in mean between desktop computers and smartphones is significant ($\Delta = 0.85$; $F = 3.67$; $p < .04$), differences between the other channel groups are only visible by tendency. Therefore, H1 is partially supported. This result strongly supports the clickstream data by demonstrating that desktop users expend significantly higher effort on their path to purchase compared to smartphone users. Accordingly, this explains the fact that the average customer journey is one click longer for desktop users, as revealed from the clickstream data (see Table 3).

In contrast, purchase decisions of smartphone users are mainly impacted by affective CX perceptions (Fig. 3, Panel B). Again, the difference in mean between smartphones and desktop computers is significant ($\Delta = 0.87$; $F = 5.54$; $p < .01$), while differences between the other channel groups are only visible by tendency. Therefore, H2 is supported partially. However, this result is in line with clickstream data, as it demonstrates that smartphone users are most likely to purchase well-known products or services from well-known brands (Wang et al., 2015).

Additionally, as indicated by the clickstream data, smartphone users' direct visits to retailers’ mobile stores may be fostered by omni-channel behaviors. Since behavioral CX perceptions (Fig. 3, Panel C) contribute most to conversions for smartphones (smartphone vs. desktop: $\Delta = 0.82$; $F = 5.04$; $p < .01$), it can be speculated that smartphone users particularly appreciate the increased mobility, which allows them to engage in commerce at any time and at any place (Wang et al., 2015) so that they are able to benefit from the simultaneous use of fully integrated channels (Beck and Rygl, 2015; Kuksov and Liao, 2018). Nevertheless, H3 is only partially supported since the differences in mean between the other channel groups are only visible by tendency.

With regard to the social dimension of CX (Fig. 3, Panel D), no significant differences between perceptions of device groups were found ($F = 1.63$; $p = .20$). Therefore, the impact of social and community touchpoints during the customer journey affects the.

Purchase propensity of desktop, tablet, and smartphone users equally. Thus, H4 is not supported.

Second, in order to test the impact of CX dimensions on customer-focused outcome constructs we take advantage of structural equation modeling using the SmartPLS 3 software package. In this way, H5a–d are tested. PLS-SEM was applied for several reasons concerning the research objective and data characteristics. With regard to the research objective, PLS-SEM is preferable since (1) the primary goal was to explain the variance of customer-focused outcome constructs and closely

Table 6
Panel A. Attribution results for marketing channel sequences (desktop computer).

Current marketing channel	Preceding marketing channel							
	START (%)	DIR (%)	SEA (%)	SEO (%)	REF (%)	DIS (%)	SM (%)	NL (%)
Direct type-in (DIR)	9.96	9.78	4.84	6.01	1.07	2.33	0.31	0.17
Search engine advertising (SEA)	18.50	1.66	5.51	1.68	0.17	0.68	0.00	0.02
Search engine optimization (SEO)	14.60	1.42	2.57	0.31	0.20	0.39	0.04	0.04
Referrer (REF)	1.13	1.85	0.92	0.98	0.50	2.90	0.09	0.00
Display (DIS)	4.40	1.31	1.13	0.87	0.24	0.24	0.00	0.02
Social Media (SM)	0.33	0.11	0.07	0.13	0.04	0.00	0.04	0.00
Newsletter (NL)	0.13	0.20	0.00	0.11	0.02	0.00	0.00	0.00

Table 6
Panel B. Attribution results for marketing channel sequences (tablet computer).

Current marketing channel	Preceding marketing channel							
	START (%)	DIR (%)	SEA (%)	SEO (%)	REF (%)	DIS (%)	SM (%)	NL (%)
Direct type-in (DIR)	10.97	11.63	7.73	3.46	0.59	4.86	0.00	0.37
Search engine advertising (SEA)	17.97	3.31	5.60	1.25	0.15	1.10	0.00	0.00
Search engine optimization (SEO)	9.13	0.96	1.55	0.15	0.15	0.88	0.00	0.00
Referrer (REF)	1.03	0.00	0.00	0.44	0.00	0.15	0.00	0.00
Display (DIS)	7.81	2.36	1.84	0.52	0.00	3.76	0.00	0.00
Social Media (SM)	0.15	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Newsletter (NL)	0.15	0.00	0.00	0.00	0.00	0.00	0.00	0.00

related to it, (2) the exploratory nature of the research objective (e.g., Gefen et al., 2011; Hair et al., 2012; Reinartz et al., 2009). With regard to data characteristics, PLS-SEM was chosen because (3) it can handle both reflective and formative measures unrestrictedly (Hair et al., 2012), (4) newly developed constructs were used (e.g., Richter et al., 2016; Sarstedt et al., 2016), and (5) the sample had the same size as recent studies using PLS (Hair et al., 2012) and the number of observations was lower than 250 (Reinartz et al., 2009). In this context, the minimum sample size for PLS-SEM was exceeded (Barclay et al., 1995; Hair et al., 2011).

As seen in Table 7, the results support three of the four dimensions of CX. Since the behavioral component of CX is not related to any outcome variable, H5c is not confirmed. In contrast, H5a, H5b, and H5d are fully supported. Satisfaction is positively impacted by affective CX ($\beta = 0.27$, $p < .01$) and social CX ($\beta = 0.19$, $p < .05$), while cognitive CX has a negative impact on satisfaction ($\beta = -0.18$, $p < .05$). These dimensions explain 21% of the variance of satisfaction. With regard to the other outcome variables, satisfaction impacts repurchase intention ($\beta = 0.74$, $p < .01$) and word-of-mouth ($\beta = 0.73$, $p < .01$) positively. Overall, 64.7% of the variance in repurchase intention and 62.7% of the variance of word-of-mouth are explained.

To test mediation effects, a reconsidered approach of Baron and Kenny (1986) provided by Zhao et al. (2010) was used which, for instance, excludes the first step of the causal step approach, since there is no need for a significant zero-order effect of the independent variable on the mediator variable (Preacher and Hayes, 2008; Shrout and Bolger, 2002; Zhao et al., 2010). In the first step, the significance of the indirect effect is determined. If the indirect effect is not significant, then there is no mediation effect. In the second step, if the indirect effect is significant, the type of mediation is determined. A nonsignificant direct effect indicates an indirect-only type of mediation, former known as full mediation (Baron and Kenny, 1986). In the case of a significant direct effect, the directions of both the mediated effect ($a \times b$) and direct effect (c) determine either there is a complementary mediation (same direction) or a competitive mediation (opposite directions). As also seen in Table 7, satisfaction mediates the relationships between the dimensions of CX (cognitive, affective, and social) and the outcomes (repurchase intention and word-of-mouth) either in an indirect-only or complementary way (Zhao et al., 2010). Since the affective and social components of CX contribute positively to customer-focused outcomes, the importance of branding in digitally empowered retail environments is highlighted (e.g., see Erdem et al., 2016). In contrast, cognitive CX is negatively related to satisfaction, repurchase intention, and word-of-mouth. Therefore, retailers have to be aware that the provided benefit of the purchase exceeds the customer's effort during the customer journey. If retailers fail to do so, desktop users in particular are likely to switch retailer and spread negative word-of-mouth based on dissatisfaction.

5. Conclusion

5.1. Contributions to the literature

As indicated in Table 1, our research advances the literature in several ways and addresses multiple shortcomings of prior research. This research was motivated by three research questions, which structure this section:

What are the differences with regard to the success of various marketing channels across desktop, tablet, and smartphone devices?

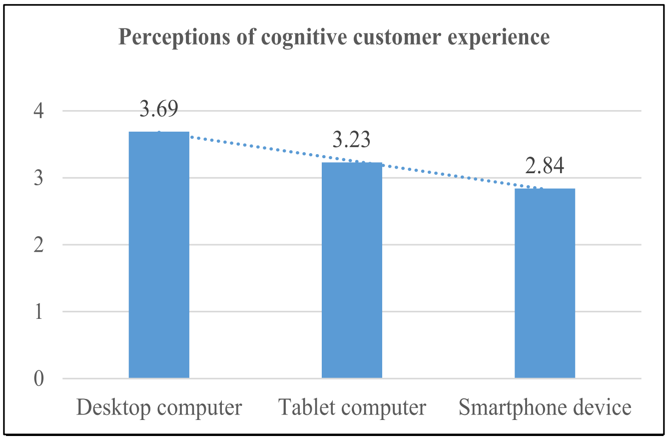
The current study contributes to the discipline by considering mobile devices in attribution modeling. Thereby, we identified the impact of mobile devices on conversions and were able to examine the probability of success of different marketing channels dependent on the device. In summary, desktop users should be approached by marketing channels which induce casual browsing behavior (e.g., newsletter, social media, referrer, SEO). In contrast, mobile users are more likely to use marketing channels that do not require an extended information search, such as SEA or direct visits to familiar stores.

Which determinants of CX contribute most to conversions across desktop, tablet, and smartphone devices?

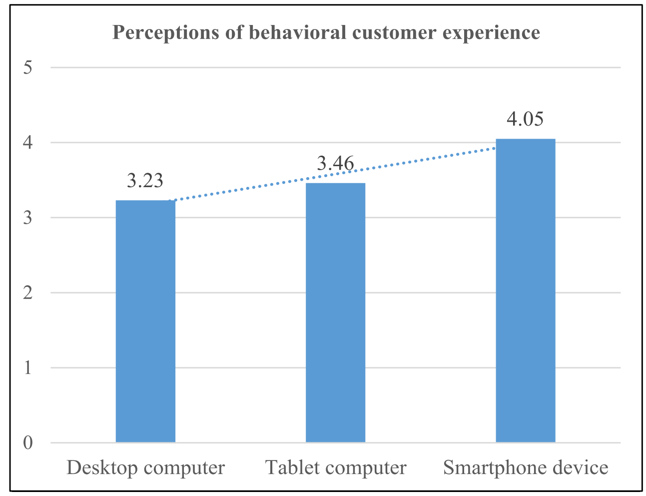
We advance the literature by combining clickstream data with survey data to explain the underlying decision processes of customers. In this context, we expand the CX construct and adapted a new measurement scale from established references that includes affective, behavioral, cognitive, and social dimensions. We examined the CX perceptions of customers who made a successful purchase during the observation period, and were able to derive differences related to the importance of CX dimensions for successful conversions between

Table 6
Panel C. Attribution results for marketing channel sequences (smartphone device).

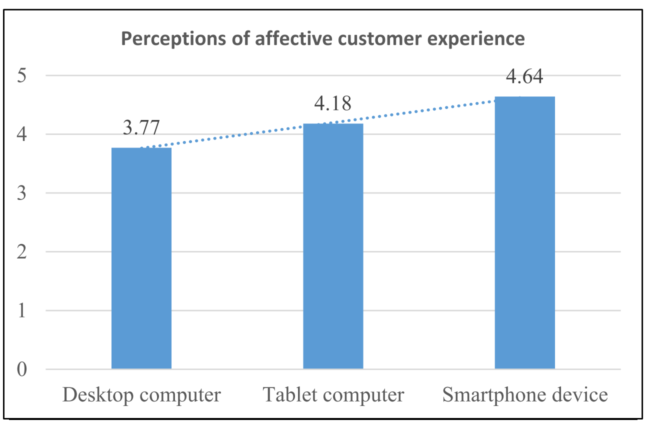
Current marketing channel	Preceding marketing channel							
	START (%)	DIR (%)	SEA (%)	SEO (%)	REF (%)	DIS (%)	SM (%)	NL (%)
Direct type-in (DIR)	11.70	11.90	7.02	5.33	1.17	1.50	0.20	0.13
Search engine advertising (SEA)	21.65	2.47	8.78	2.28	0.20	0.91	0.00	0.07
Search engine optimization (SEO)	9.88	1.56	2.73	0.07	0.26	0.07	0.07	0.00
Referrer (REF)	1.11	0.78	0.78	0.52	0.33	0.13	0.00	0.07
Display (DIS)	1.30	1.50	0.91	0.39	0.07	1.30	0.00	0.00
Social Media (SM)	0.46	0.00	0.00	0.00	0.00	0.00	0.07	0.00
Newsletter (NL)	0.00	0.26	0.07	0.00	0.07	0.00	0.00	0.00



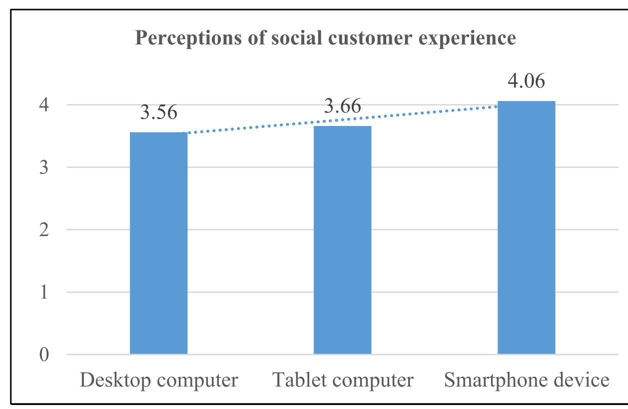
Comparison of device groups	Difference in mean	p-value
Smartphone vs. desktop computer	Δ = -.85	p < .05
Smartphone vs. tablet computer	Δ = -.39	n.s.
Desktop computer vs. tablet computer	Δ = .46	n.s.



Comparison of device groups	Difference in mean	p-value
Smartphone vs. desktop computer	Δ = .82	p < .01
Smartphone vs. tablet computer	Δ = .59	n.s.
Desktop computer vs. tablet computer	Δ = -.23	n.s.



Comparison of device groups	Difference in mean	p-value
Smartphone vs. desktop computer	Δ = .87	p < .01
Smartphone vs. tablet computer	Δ = .46	n.s.
Desktop computer vs. tablet computer	Δ = -.41	n.s.



Comparison of device groups	Difference in mean	p-value
Smartphone vs. desktop computer	Δ = .50	n.s.
Smartphone vs. tablet computer	Δ = .40	n.s.
Desktop computer vs. tablet computer	Δ = -.10	n.s.

Fig. 3. Panel A. Results for cognitive CX dependent on the device. **Panel B.** Results for affective CX dependent on the device. **Panel C.** Results for behavioral CX dependent on the device. **Panel D.** Results for social CX dependent on the device.

desktop, tablet, and smartphone devices. Our research reveals that desktop users' purchase decisions are mainly driven by cognitive components of CX, whereas smartphone users mainly rely on affective and behavioral experiences. In contrast, tablet users are more likely to determine their purchase decision on the basis of an overall experience. The social dimension of CX influences purchase decisions across devices equally.

How is CX related to important outcomes such as satisfaction, repurchase intention, or word-of-mouth?

The research shows how the dimensions of CX are related to other customer-focused constructs, such as satisfaction, repurchase intention, and word-of-mouth. The results demonstrate that affective and social components of CX are positively related to those outcomes, whereas the cognitive dimension of CX has a negative direct impact on satisfaction and negative indirect effects on repurchase intention as well as word-of-mouth via satisfaction. The behavioral dimension of CX is not related to the outcomes.

5.2. Managerial implications for the focal firm

Based on the results, we can provide several suggestions for the focal firm. In general, the attribution model presented offers the exact value for each channel for each device. This information can help the focal fashion retailer distribute its marketing budget more efficiently. Additionally, the focal firm can react to the behavior of customers in order to improve purchase propensity, since the retailer knows the probability of successful conversion for each channel sequence for each device. Most importantly, our research can help the focal fashion retailer to better understand the perceptions and expectations of its customers, as well as the consequences of CX.

Furthermore, the clickstream data reveal that desktop users still account for the majority of conversions (62.5%), although the composition of journeys taken via desktop computers and mobile devices is almost even (mobile devices: 50.80%). Therefore, journeys taken using desktop computers obtain higher conversion rates. This may be due to

Table 7
Results of structural equation modeling.

		Direct effects		Indirect effects		Type of mediation
		β	*p-value*	*β*	*p-value*	
Cognitive customer experience	→ Repurchase intention	.054	n.s.	-.135	< .05	indirect-only
	→ Satisfaction	-.182	< .05			
	→ Word-of-mouth	-.042	n.s.	-.132	< .05	indirect-only
Affective customer experience	→ Repurchase intention	.021	n.s.	.202	< .01	indirect-only
	→ Satisfaction	.270	< .01			
	→ Word-of-mouth	.115	n.s.	.197	< .01	indirect-only
Behavioral customer experience	→ Repurchase intention	-.013	n.s.	.093	n.s.	no-effect nonmediation
	→ Satisfaction	.126	n.s.			
	→ Word-of-mouth	-.028	n.s.	.094	n.s.	no-effect nonmediation
Social customer experience	→ Repurchase intention	.133	< .05	.138	< .05	complementary
	→ Satisfaction	.185	< .05			
	→ Word-of-mouth	.064	n.s.	.136	< .05	indirect-only
Satisfaction	→ Repurchase intention	.744	< .001			
	→ Word-of-mouth	.733	< .001			

R-square: satisfaction = 0.210; repurchase intention = 0.655; word-of-mouth = 0.635.

Table 8
Implications for the focal fashion retailer.

	Desktop users	Smartphone users	Tablet users
Customer-initiated channels	*'Search engine optimization (SEO)' and 'Referrer'* The fashion retailer is advised to (a) improve search engine marketing compromising SEO combined with keyword advertising and (b) extend its presence on coupon and/or price-comparison websites	*'Direct type-in' and ' Search engine advertising (SEA)'* Since both marketing channels benefit most from one-click journeys, as well as from carryover effects, the fashion retailer is encouraged to improve interactivity perceptions of both its mobile store and named marketing channels	*'Direct type-in' and 'SEA'* The fashion retailer is advised to induce direct visits to the mobile store through 'display advertising'
Firm-initiated channels	*'Display advertising'* The customer-initiated channel 'referrer' can be induced by spillover effects from 'display advertising'	*'Controlled usage'* The fashion retailer is encouraged to (a) make controlled usage of firm-initiated contacts after a direct visit or a sponsored search that does not lead to a successful conversion, and (b) provide personalized content of high relevance	*'Same-channel sequences'* Ideal point of firm-initiated contacts is highest—the fashion retailer is advised to employ same-channel sequences of firm-initiated channels (especially 'display advertising'), but not to make use of cross-channel sequences
Customer experience	*'Cognitive'* The fashion retailer is advised to ensure that the benefit of the purchased product or service exceeds the effort of the path to purchase (e.g. in the form of a sufficient discount) to avoid dissatisfied customers	*'Affective' and 'Behavioral'* The fashion retailer is advised to (a) facilitate and speed communications among their customers, (b) adapt omni-channel concepts, and (c) reduce cognitive effort of its customers in order to reduce complexity	*'Provide a holistic experience'* Since the tablet device seems to be a hybrid of desktop computers and smartphone devices, the fashion retailer is encouraged to consider all dimensions of customer experience

several reasons: A practical explanation for the low conversion rates may be the fact that the fashion retailer's mobile store is not responsive. In order to optimize the mobile store for different viewing contexts and to ensure the mobile store's convenience, information quality, and aesthetics (Kaatz et al., 2017), we advise the focal retailer to implement a responsive design. A theoretical explanation for different conversion rates might be that focusing on conversions on single devices in isolation, as per our study, usually leads to an overestimation of conversions attributed to nonmobile devices (de Haan et al., 2018). Currently, mobile customers do not appear to be as profitable as desktop customers; however, focusing on the latter alone neglects the profitability of future customers, as well as the changing marketing landscape driven by technological improvements such as tablet and smartphone devices (e.g., de Haan et al., 2018; Grewal et al., 2018). Subsequently, Table 8 provides guidelines based on the most important implications found for each device.

5.3. General managerial implications

Furthermore, local insights gained enable us to set standards globally. As mentioned by Anderl et al. (2016), the use of higher-order Markov models as well as the combination of clickstream and survey data enables to generalize prior findings indicating that (1) mobile users rely most on direct visits to the mobile store (e.g., Lee et al., 2018), (2) desktop users have to be adequately rewarded with regard to their cognitive effort of the path to purchase (e.g., Li and Kannan, 2014), and (3) social touchpoints have an increasingly greater impact on purchase decisions across all users (e.g., Shen and Sengupta, 2018). Those empirical generalizations can provide valuable guidance to managers (Kamakura et al., 2014) that subsequently refer to the highlighted key results.

With regard to smartphone users, as indicated by both clickstream and survey data, managerial focus should concentrate on reducing smartphone users' cognitive effort on the path to purchase by increasing direct visits to the mobile store since direct type-ins are empirically associated with the most purchases (Lee et al., 2018).

First, retailers with both online and offline operations are advised to use their brick-and-mortar stores as showrooms (Kuksov and Liao, 2018; Rodríguez-Torrico et al., 2017) by implementing price matching guarantees (Jing, 2018; Kireyev et al., 2017) or click-and-collect concepts (Beck and Rygl, 2015; Jing, 2018). Second, at macro-level, online retailers are encouraged to implement an upmarket repositioning strategy, namely raising the levels of service quality offered by the mobile store to foster mobile device user's sense of reliability of the store (Lee et al., 2018).

With regard to desktop users, as indicated by both clickstream and survey data, managers have to be aware that the benefits of the purchase exceed the efforts of the path to purchase. On the one hand, to reduce the latter, retailers are advised to aim optimization of organic search results by, for instance, estimating customer content preferences from online search queries (Liu and Toubia, 2018) and design an effective web page (Bleier et al., 2019). On the other hand, managers are encouraged to particularly reward desktop users with sufficient discounts or smallest price guarantees, because they perceive their time used, physical energy spend, or cognitive effort during the path to purchase as fairer basis for marketing budget allocation (Shaddy and Shah, 2018).

Across all devices, as demonstrated by the survey data, the social dimension of CX is able to positively impact future buying behavior of customers. Thus, managerial priority should be to facilitate and speed oral communications among their customers (Erdem et al., 2016). Driven by such an interaction focus, retailers benefit from an increased self-brand connection (Shen and Sengupta, 2018), which finally will positively influence future purchase decisions of customers (e.g., Hallikainen et al., 2018).

In spite of this discussion, customers still have to be treated as individuals, while technology should be used to predict their behavior. Hence, to better satisfy customer needs, retailers are encouraged to implement a customer-centric focus. Following the approach of this research, marketing practices should be built around distinct customer groups (Crecelius et al., 2019), segmented according to the device used, since this research highlights specific behaviors dependent on the device. Hence, based on individual customer preferences, retailers are encouraged to recommend newly developed products or high involvement products on desktop devices, whereas habitual and well-known products should be advertised on mobile devices.

5.4. Limitations and further research

Our research has several limitations that could be addressed in future studies. First, the attribution model and measurement of the perceptions of CX are only valid for one industry. Even though the fashion market represents a huge sector, future research is encouraged to replicate our results in other industry and retail contexts, since previous studies have shown that the industry context as well as the retailing context impacts the success of marketing channels (Anderl et al., 2016; Li and Kannan, 2014).

Second, although the questionnaire was designed to avoid common method bias in advance, and Harman's single factor test indicated that the results are unlikely to be subject to substantial common method variance, it is impossible to address common method bias in single-informant studies (Guide and Ketokivi, 2015). Thus, future research is encouraged to use multiple data sources to reduce the risk of common method bias.

Third, although we examined the contribution of different devices to marketing success, our results do not reveal the influence on conversions and CX when multiple devices are used across the customer journey. Therefore, future research is encouraged to focus on cross-device usage during the path to purchase. In this context, researchers should examine contextual drivers of conversions. In order to help explain when devices are used and when interdependencies between devices occur, location and time of day seem to be factors that deserve further exploration (de Haan et al., 2018; Xu et al., 2017).

Fourth, since the fashion retailer runs several retail stores, we are not able to exclude online–offline cross-channel effects. In this context, both the clickstream and survey data indicate that smartphone users in particular enact omni-channel behaviors during their path to purchase. Hence, one of the most important themes for future research is to examine how mobile devices and mobile services can be integrated into both online and offline operations (Souiden et al., 2018).

Fifth, the HTMT ratio between satisfaction and repurchase intention violates the HTMT$^{.90}$ criterion (Henseler et al., 2015), but since the ratio does not exceed the value of 1.0 (Voorhees et al., 2016), the elimination of items and merging of constructs was waived (Henseler et al., 2015).

Finally, the present research examined the consequences of CX. However, since CX matters in all stages of the customer journey, researchers are encouraged to examine the determinants of CX in the pre-purchase, purchase, and post-purchase stage across different devices or device combinations, respectively.

References

Abhishek, K.H., Hosanagar, K., Fader, P., 2015. Media Exposure through the Funnel: A Model of Multistage Attribution. Working Paper. Carnegie Mellon University, Pittsburgh.

Anderl, E., Becker, I., von Wangenheim, F., Schumann, J., 2016. Mapping the customer journey: lessons learned from graph-based online attribution modeling. Int. J. Res. Mark. 33 (3), 457–474.

Archak, N., Mirrokni, V., Muthukrishnan, S., 2010. Mining advertiser-specific user behavior using adfactors. In: Rappa, M., Jones, M. (Eds.), Proceedings of the 19th International Conference on World Wide Web. ACM, pp. 31–40.

Ayers, P., Paas, F., 2012. Cognitive load theory: new directions and challenges. Appl. Cognit. Psychol. 26, 827–832.

Bagozzi, R.P., Yi, Y., 1988. On the evaluation of structural equation models. J. Acad. Mark. Sci. 16, 74–94.

Barclay, D.W., Higgins, C.A., Thompson, R., 1995. The partial least squares approach to causal modeling: personal computer adoption and use as illustration. Technol. Stud. 2 (2), 285–309.

Baron, R.M., Kenny, D.A., 1986. The moderator-mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. J. Personal. Soc. Psychol. 51 (6), 1173–1182.

Beck, N., Rygl, D., 2015. Categorization of multiple channel retailing in multi-, cross-, and omni-channel retailing for retailers and retailing. J. Retail. Consum. Serv. 27, 170–178.

Bleier, A., Harmeling, C.M., Palmatier, R.W., 2019. Creating effective online customer experiences. J. Mark. 83 (2), 98–119.

Blom, A., Lange, F., Hess Jr., R.L., 2017. Omnichannel-based promotions' effects on purchase behavior and brand image. J. Retail. Consum. Serv. 39, 286–295.

Blut, M., Chowdhry, N., Mittal, V., Brock, C., 2015. E-Service-Quality: a meta-analytic review. J. Retail. 91 (4), 679–700.

Brady, M.K., Knight, G.A., Cronin, J.J., Hult, G.T.M., Keillor, B.D., 2005. Removing the contextual lens: a multinational multi-setting comparison of service evaluation models. J. Retail. 81 (3), 215–230.

Brakus, J.J., Schmitt, B.H., Zarantonello, L., 2009. Brand experience: what is it? How is it measured? Does it affect loyalty? J. Mark. 73 (3), 52–68.

Crecelius, A.T., Lawrence, J.M., Lee, J.-Y., Lam, S.K., Scheer, L.K., 2019. Effects of channel members' customer-centric structures on supplier performance. J. Acad. Mark. Sci. 47 (1), 56–75.

Criteo, 2018. Global Commerce Review: EMEA, Q2 2018. Available at. https://www.criteo.com/wp-content/uploads/2018/09/18_GCR_Q2_Report_EMEA.pdf, Accessed date: 19 December 2018.

de Haan, E., Kannan, P.K., Verhoef, P.C., Wiesel, T., 2018. Device switching in online purchasing: examining the strategic contingencies. J. Mark. 82 (5), 1–19.

de Haan, E., Wiesel, T., Pauwels, K., 2016. The effectiveness of different forms of online advertising for purchase conversion in a multiple-channel attribution framework. Int. J. Res. Mark. 33 (3), 491–507.

Erdem, T., Keller, K.L., Kuksov, D., Pieters, R., 2016. Understanding branding in a digitally empowered world. Int. J. Res. Mark. 33 (1), 3–10.

Florenthal, B., Shoham, A., 2010. Four-mode channel interactivity concept and channel preferences. J. Serv. Mark. 24 (1), 29–41.

Fornell, C., 1992. A national customer satisfaction barometer: the Swedish experience. J. Mark. 56 (1), 6–21.

Fornell, C., Larcker, D.F., 1981. Evaluating structural equation models with unobservable variables and measurement error. J. Mark. Res. 18 (1), 39–50.

Gefen, D., Rigdon, E.E., Straub, D., 2011. 's comments: an update and extension to SEM guidelines for administrative and social science research. MIS Q. 35 (2), III–XIV.

Giovanis, A.N., Athanasopoulou, P., 2018. Consumer–brand relationships and brand loyalty in technology-mediated services. J. Retail. Consum. Serv. 40, 287–294.

Godfrey, A., Seiders, K., Voss, G.B., 2011. Enough is enough! The fine line in executing multichannel relational communication. J. Mark. 75 (4), 94–109.

Grewal, D., Ahlbom, C.-P., Beitelspacher, L., Noble, S.M., Nordfält, J., 2018. In-store mobile phone use and customer shopping behavior: evidence from the field. J. Mark. 82 (4), 102–126.

Grewal, D., Roggeveen, A.L., Runyan, R.C., Nordfält, J., Vazquez Lira, M.E., 2017. Retailing in today's world: multiple channels and other strategic decisions affecting firm performance. J. Retail. Consum. Serv. 34, 261–263.

Guide, V.D.R., Ketokivi, M., 2015. Notes from the editors: redefining some methodological criteria for the journal. J. Oper. Manag. 37 (4), v–viii.

Hair, J.F., Ringle, C.M., Sarstedt, M., 2011. PLS-SEM: indeed a silver bullet. J. Mark. Theory Pract. 19 (2), 139–152.

Hair, J.F., Sarstedt, M., Ringle, C.M., Mena, J.A., 2012. An assessment of the use of partial least squares structural equation modeling in marketing research. J. Acad. Mark. Sci. 40 (3), 414–433.

Hallikainen, H., Alamäki, A., Laukkanen, T., 2018. Individual preferences of digital touchpoints: a latent class Analysis. J. Retail. Consum. Serv Article in Press. https://doi.org/10.1016/j.jretconser.2018.07.014.

Harman, H.H., 1967. Modern Factor Analysis. University of Chicago Press, Chicago, IL.
Harris, P., Riley, F.D.O., Hand, C., 2018. Understanding multichannel shopper journey configuration: an application of goal theory. J. Retail. Consum. Serv. 44, 108–117.
Henseler, J., Ringle, C.M., Sarstedt, M., 2015. A new criterion for assessing discriminant validity in variance-based structural equation modeling. J. Acad. Mark. Sci. 43 (1), 115–135.
Hubert, M., Blut, M., Brock, C., Backhaus, C., Eberhardt, T., 2017. Acceptance of smartphone-based mobile shopping: mobile benefits, customer characteristics, perceived risks, and the impact of application context. Psychol. Market. 34 (2), 175–194.
Jing, B., 2018. Showrooming and webrooming: information externalities between online and offline sellers. Market. Sci. 37 (3), 469–483.
Kaatz, C., Brock, C., Blut, M., 2017, December. Developing a conceptualization of mobile service quality. In: Proceedings of ICIS 2017, Seoul, Republic of Korea.
Kamakura, W., Kopalle, P.K., Lehmann, D.R., 2014. Empirical generalizations in retailing. J. Retail. 90 (2), 121–124.
Kannan, P.K., Li, H., 2017. Digital marketing: a framework, review and research agenda. Int. J. Res. Mark. 34 (1), 22–45.
Kireyev, P., Kumar, V., Ofek, E., 2017. Match your own price? Self-matching as a retailer's multichannel pricing strategy. Market. Sci. 36 (6), 908–930.
Kireyev, P., Pauwels, K., Gupta, S., 2016. Do display ads influence search? Attribution and dynamics in online advertising. Int. J. Res. Mark. 33 (3), 475–490.
Kleijnen, M., de Ruyter, K., Wetzels, M., 2007. An assessment of value creation in mobile service delivery and the moderating role of time consciousness. J. Retail. 82 (1), 33–46.
Kortmann, S., 2014. The mediating role of strategic orientations on the relationship between ambidexterity-oriented decisions and innovative ambidexterity. J. Prod. Innov. Manag. 32 (5), 666–684.
Kuksov, D., Liao, C., 2018. When showrooming increases retailer profit. J. Mark. Res. 55 (4), 459–473.
Kumar, V., 2018. A theory of customer valuation: concepts, metrics, strategy, and implementation. J. Mark. 82 (1), 1–19.
Lamberton, C., Stephen, A.T., 2016. A thematic exploration of digital, social media, and mobile marketing research's evolution from 2000 to 2015 and an agenda for future research. J. Mark. 80 (6), 146–172.
Lee, J.-Y., Fang, E., Kim, J.J., Li, X., Palmatier, R.W., 2018. The effect of online shopping platform strategies on search, display, and membership revenues. J. Retail. 94 (3), 247–264.
Lemon, K., Verhoef, P., 2016. Understanding customer experience throughout the customer journey. J. Mark. 80 (6), 69–96.
Li, H., Kannan, P., 2014. Attributing conversions in a multichannel online marketing environment: an empirical model and a field experiment. J. Mark. Res. 51 (1), 40–56.
Liu, J., Toubia, O., 2018. A semantic approach for estimating consumer content preferences from online search queries. Market. Sci. 37 (6), 930–952.
Maklan, S., Klaus, P., 2011. Customer experience: are we measuring the right things? Int. J. Mark. Res. 53 (6), 771–792.
Marketing Science Institute, 2016. Research Priorities 2016–2018. Available at. https://www.msi.org/uploads/articles/MSI_RP16-18.pdf, Accessed date: 19 December 2018.
Marketing Science Institute, 2018. Research Priorities 2018–2020. Available at. https://www.msi.org/uploads/articles/MSI_RP18-20.pdf, Accessed date: 19 December 2018.
Miranda, S., Tavares, P., Queiró, R., 2018. Perceived service quality and customer satisfaction: a fuzzy set QCA approach in the railway sector. J. Bus. Res. 89 (8), 371–377.
Nunnally, J.C., 1978. Psychometric Methods. McGraw Hill, New York.
Parasuraman, A., Zeithaml, V.A., Berry, L.L., 1988. SERVQUAL—a multiple-item scale for measuring consumer perceptions of service quality. J. Retail. 64 (1), 12–40.
Piotrowicz, W., Cuthbertson, R., 2014. Introduction to the special issue information technology in retail: toward omnichannel retailing. Int. J. Electron. Commer. 18 (4), 5–16.
Preacher, K.J., Hayes, A.F., 2008. Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behav. Res. Methods 40 (3), 879–891.
Reinartz, W.J., Haenlein, M., Henseler, J., 2009. An empirical comparison of the efficacy of covariance-based and variance-based SEM. Int. J. Res. Mark. 26 (4), 332–344.
Richter, N.F., Sinkovics, R.R., Ringle, C.M., Schlägel, C., 2016. A critical look at the use of SEM in international business research. Int. Mark. Rev. 33 (3), 376–404.
Rodríguez-Torrico, P., San-Jose Cabezudo, R., San-Martín, S., 2017. Tell me what they are like and I will tell you where they buy. An analysis of omnichannel consumer behavior. Comput. Hum. Behav. 68 (C), 465–471.
Sarstedt, M., Hair, J.F., Ringle, C.M., Thiele, K.O., Gudergan, S.P., 2016. Estimation issues with PLS and CBSEM: where the bias lies!. J. Bus. Res. 69 (10), 3998–4010.
Shaddy, F., Shah, A.K., 2018. Deciding who gets what, fairly. J. Consum. Res. 45 (4), 833–848.
Shen, H., Sengupta, J., 2018. Word of mouth versus word of mouse: speaking about a brand connects you to it more than writing does. J. Consum. Res. 45 (3), 595–614.
Shrout, P.E., Bolger, N., 2002. Mediation in experimental and nonexperimental studies: new procedures and recommendations. Psychol. Methods 7 (4), 422–445.
Souiden, N., Ladhari, R., Chiadmi, N.-E., 2018. Editorial—new trends in retailing and services. J. Retail. Consum. Serv Article in Press. https://doi.org/10.1016/j.jretconser.2018.07.023.
Verhoef, P., Langerak, F.L., Donkers, B., 2007. Understanding brand and dealer retention in the new car market: the moderating role of brand tier. J. Retail. 83 (1), 97–113.
Verhoef, P., Lemon, K., Parasuraman, A., Roggeveen, A., Tsiros, M., Schlesinger, L., 2009. Customer experience creation: determinants, dynamics and management strategies. J. Retail. 85 (1), 31–41.
Voorhees, C.M., Brady, M.K., Calantone, R., Ramirez, E., 2016. Discriminant validity testing in marketing: an analysis, causes for concern, and proposed remedies. J. Acad. Mark. Sci. 44 (1), 119–134.
Wang, R., Malthouse, E.C., Krishnamurthi, L., 2015. On the go: how mobile shopping affects customer purchase behavior. J. Retail. 91 (2), 217–234.
Xu, K., Chan, J., Ghose, A., Pil Han, S., 2017. Battle of the channels: the impact of tablets on digital commerce. Manag. Sci. 63 (5), 1469–1492.
Zeithaml, V.A., Berry, L.L., Parasuraman, A., 1996. The behavioral consequences of service quality. J. Mark. 60 (2), 31–46.
Zhao, X., Lynch, J.G., Chen, Q., 2010. Reconsidering Baron and Kenny: myths and truths about mediation analysis. J. Consum. Res. 37 (3), 197–206.