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Multichannel consumer behaviors in the mobile environment: Using fsQCA and discriminant analysis to understand webrooming motivations☆

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ABSTRACT

This study examines how different motivations determine three types of webrooming: traditional webrooming, webrooming extended to include mobile devices, and multidevice webrooming. The examination uses information-processing and uncertainty-reduction theories and fsQCA and discriminant analysis methods. The data derived from a convenience sample obtained through personal and online surveys. The results from the discriminant analysis indicate a significantly positive effect of information attainment on explaining all behaviors, and price comparison orientation and empowerment for mobile-related behaviors. The fsQCA findings show various motivational configurations for each webrooming behavior. In almost all, both information-processing and uncertainty-reduction motivations exist that support the importance of the underlying theories in explaining webrooming. Furthermore, empowerment is more relevant in behaviors where mobile device usage is always present. This study enriches the theoretical body of the webrooming construct, and the results can guide marketing and multichannel managers in developing differentiated strategies that address consumers' webrooming-specific needs.

1. Introduction

The proliferation of mobile channel formats in retailing has extended channel choices beyond traditional catalogue, store, and online channels, which make consumer multichannel behaviors more complex. Multichannel consumers are those that use multiple channels during the purchase process (Frasquet, Mollá, & Ruiz, 2015). Taking advantage of channel-specific attributes (Verhoef, Neslin, & Vroomen, 2007), consumers switch and combine recent and traditional channels during their purchase processes to better satisfy their shopping needs and to obtain a seamless and interchangeable shopping experience (Verhoef, Kannan, & Inman, 2015). This switching poses challenges to retailers as cross-channel behaviors by multichannel consumers can lead to cross-channel free-riding (i.e., researching products through the channel of Firm A and purchasing through another channel of Firm B) (Chou, Shen, Chiu, & Chou, 2016). To develop effective multichannel customer management strategies that cater to consumer-specific needs and retain them throughout their decision-making, understanding consumers and what determines their channel choice is the crucial first phase (Neslin et al., 2006).

Showrooming consists of searching for product information offline and purchasing online (Verhoef et al., 2015). Due to its popularity, several studies have started developing a systematic understanding of the construct and its specific underlying drivers (e.g., Gensler, Neslin, & Verhoef, 2017; Rapp, Baker, Bachrach, Ogilvie, & Beitelspacher, 2015). However, webrooming, which consists of searching for product information online and purchasing offline (Flavián, Gurrea, & Orús, 2016), is the most prevalent cross-channel behavior. For electronic product purchases (e.g., laptops/mobile phones/televisions), 44% of European consumers confirm the practice of webrooming against 9% of showroomers (Google Consumer Barometer, 2015). Also, European consumers that purchase in-store because of Internet information tend to spend four times more than those purchasing online for retail products in general, with sales through this cross-channel behavior expected to continue to dominate by 2020 (Forrester, 2015).

Despite being the most important cross-channel behavior, webrooming lacks a theoretically structured treatment in the multichannel literature. Previous studies have focused on identifying various multichannel behaviors and characterizing them with the same set of channel usage motivations (e.g., Schröder & Zaharia, 2008). However, recent studies argue that as a specific multichannel behavior, more directed theories and associated motivations may better explain

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webrooming with potentially higher explanatory influence (e.g., Flavián et al., 2016). Adding to the paucity of studies focusing on webrooming and its motivations, the introduction of more online channel formats is influencing channel decisions and imposing new unexplored behaviors that warrant further understanding (Lemon & Verhoef, 2016). For example, in Europe, 71% of consumers are now smartphone users, 36% are tablet users, 74% are computer users, and 71% are multidevice users (Google Consumer Barometer, 2017), but the evaluation of multichannel motivations in an increasing mobile context, extremely important nowadays, is lacking in the current literature (Park & Lee, 2017). Thus, the development of structured theoretical knowledge on what specifically motivates webrooming and how it differs with mobile usage has become increasingly necessary.

As such, the present study examines how specific motivations explain different webrooming behaviors in today's retail environment. It investigates and compares which motivations lead to the adoption of webrooming in a traditional setting, when the mobile channel is included to expand the webrooming construct, and when consumers are multidevice users. The study complements and advances the theoretical foundation of Flavián et al. (2016) by proposing and testing specific motivations that may help explain the webrooming behavior and aid the development of multichannel strategies. Flavián et al. (2016) rely on information-processing and uncertainty-reduction theories to argue that consumers expend effort and resources searching online and purchasing offline to satisfy their need for information and reduce the uncertainty related with the purchase. Built on this view, the current conceptual framework proposes and tests information attainment, price comparison, and empowerment, based on information-processing theory, and need for touch, risk aversion, and choice confidence, based on uncertainty-reduction theory, as possible webrooming motivations. Other motivations might determine cross-channel usage, such as shopping enjoyment or offline retailer loyalty (e.g., Gensler et al., 2017; Konuş, Verhoef, & Neslin, 2008). However, we propose and test the specific motivations above, which have not yet been tested in the webrooming context, due to their important theoretical relation to the theories underlying the conceptual framework of Flavián et al. (2016).

The webrooming motivations are examined using discriminant analysis (DA) and fuzzy-set qualitative comparative analysis (fsQCA). The DA is a correlational technique that is adequate for analyzing phenomena when dependent variables are categorical (Hair, Anderson, Tatham, & Black, 1995). However, contrary to regression-based approaches, fsQCA allows complex configurational analyses where we can assess causal asymmetry, equifinality, multifinality, and conjunctural causation (Ragin, 2008; Woodside, 2018). To the best of our knowledge, this is the first study to both systematically examine motivational antecedents of webrooming behaviors and use this methodological approach, contributing to the extension of the multichannel literature at a theoretical, empirical, and methodological level. Chou et al. (2016) apply fsQCA in a multichannel setting, but they do not address webrooming specifically and their results are compared to structural equation modeling, thus supporting the innovative approach of this study.

The findings indicate that fsQCA allows a more nuanced and comprehensive view of the motivations that determine each webrooming behavior. The DA shows that information attainment is related to all types of webrooming behaviors and that price comparison and empowerment are important for behaviors that include mobile devices. On the other hand, fsQCA denotes multiple motivational configurations for each behavior where, in almost all, both information-processing and uncertainty-reduction motivations are present. Empowerment is also prevalent for behaviors that include mobile devices, specifically multidevice webrooming.

The paper is organized as follows: after the introduction, we present the literature review. We then describe the methodological procedures and results. Then, we provide a discussion of the findings, conclusions, theoretical and managerial implications, limitations, and suggestions for future research.

2. Literature review

2.1. The webrooming construct: theoretical background

Webrooming is the search for product-related information on the Internet and consequent purchase in-store (Flavián et al., 2016). Traditionally, the Internet has been accessed through personal computers (PCs) and laptops which, like physical stores, are channels. From a consumer-centric perspective, channels are mediums through which consumers search for information, purchase, or both (Konuş et al., 2008; Verhoef et al., 2007). Although webrooming is the most prevalent cross-channel behavior, few empirical studies explicitly examine it. Verhoef et al. (2007), for example, indirectly model cross-channel behaviors by examining the benefits and costs that determine each choice of search and purchase channel and subsequently consider cross-channel synergies. Frasquet et al. (2015) identify various cross-channel behaviors, including webrooming, but characterize them based on the same set of motivations for channel usage. Both do not consider motivations that specifically drive webrooming. To narrow this research gap, this study explicitly examines the factors that affect the webrooming behavior.

Flavián et al. (2016) propose a conceptual foundation for studying webrooming. Although they do not analyze specific motivations, the authors suggest that consumers combine online searching with offline purchasing to fulfill information-processing and uncertainty-reduction needs. Webrooming is a specific form of research shopping (Verhoef et al., 2015) which is, by definition, the consumer's propensity to search in one channel and purchase through another (Verhoef et al., 2007). The research process itself implies consumer engagement at some level of cognitive effort (Flavián et al., 2016), which according to information-processing theory (Bettman, 1979) includes attention, perception, memory, meaning, and importantly search and processing of information on product attributes (Puccinelli et al., 2009; Solomon, Bamossy, Askegaard, & Hogg, 2006). The effort is also physical as consumers dislocate themselves in-store to evaluate and purchase the product (Frasquet et al., 2015). As a result, consumers learn from their efforts in the research process. Individuals driven by control and empowerment may be increasingly stimulated by the research process, as more information allows increased choices and the maximization of benefits (Heitz-Spahn, 2013).

Consumers may also dedicate cognitive and temporal resources to researching online and physical effort purchasing offline to reduce purchase-related uncertainty (Flavián et al., 2016). Theories on the reduction of uncertainty (Berger & Calabrese, 1975; Kramer, 1999) state that the experience of uncertainty is an important motivational factor that results in information seeking as the means to reduce the perceived uncertainty. Depending on informational needs, consumers combine channels in their decision-making to arrive at individualized knowledge, which increases the overall perceived certainty of the decision (Schul & Mayo, 2003). The uncertainty that leads to the adoption of webrooming can arise from factors related to the product, channel, or individual. For example, complex and high involvement purchases require an extensive search for information, which can be aided with complementarity in online-offline channels (Voorveld, Smit, Neijens, & Bronner, 2016). Regarding the channel, Internet characteristics may also influence consumers to switch to the offline channel to confirm information and to purchase due to information overload (Chen, Shang, & Kao, 2009), transaction and privacy risks (Frasquet et al., 2015), or concerns on the vendor's online reputation (Chou et al., 2016). At an individual level, studies find that self-affirmation positively affects physical store patronage prior to purchase, as it increases the need to physically and thoroughly inspect products and guarantees confidence in the choice (Balasubramanian, Raghunathan, & Mahajan, 2005).

2.2. Webrooming in the mobile environment

More recently, mobile devices have become specific online channels for purchase-related activities (Shankar et al., 2016). The addition of this channel allows more formats for Internet access by the consumer (PCs/laptops, mobile devices, or both) to search for information. As such, this study extends the definition of traditional webrooming to also include mobile device usage at the search level (referred to as extended webrooming) and analyzes the motivations that determine this webrooming. Since mobile devices potentially enhance cross-channel synergies (Lemon & Verhoef, 2016), the study further examines the variations in motivations for multidevice webrooming (i.e., consumers using both PCs/laptops and mobile devices).

Of mobile properties, ultra-portability and wireless connection are particularly relevant because they provide ubiquitous information and transactions (Shankar & Balasubramanian, 2009). The unrestricted physical and temporal access to information substantially increases the mobile channel's potential as an interactive online decision aid compared to traditional online search, especially within stores (Rapp et al., 2015). Aware of possible information asymmetries by retailers that affect consumers' trust in salespeople, mobile devices are used to immediately access other sources of information that allow increased control over the purchase process (Spaid & Flint, 2014). As such, information-processing needs may assume a greater role in extended webrooming and even more in multidevice webrooming, as the mobile channel is always present. Consumers still purchase offline, exerting a physical effort, which may imply an equally important uncertainty-reduction strategy among webrooming behaviors.

2.3. Webrooming motivations

The examination of motivations is central to understand consumer behaviors (Solomon et al., 2006). To examine what influences consumers' decision to webroom, the study builds on and complements the theoretical foundation of Flavián et al. (2016) by deriving, proposing, and testing specific motivations that may explain the different webrooming behaviors. The basis for our proposition on motivations is the theoretical relation they have to information-processing and uncertainty-reduction theories in the webrooming context.

2.3.1. Information-processing motivations

Flavián et al.'s (2016) information-processing focus leads us to test whether information attainment, price comparison orientation, and empowerment are potentially important motivations that may affect webrooming. Information attainment is the consumer's need for information regarding product attributes (Noble, Griffith, & Weinberger, 2005). This information contributes to cognitive structures that affect decision-making and increase the consumers' evaluative ability regarding products (Alba & Hutchinson, 1987).

Price comparison orientation refers to the consumer's need for comparable knowledge regarding product prices (Heitz-Spahn, 2013) where consumers can achieve savings (Konuş et al., 2008). Due to the significant increase in deal-seeking following the last global economic crisis, several authors have determined that the need for economic management is one of the most dominant drivers for combining online and offline channels, highlighting the importance of analyzing price separately from other product dimensions (e.g., Spaid & Flint, 2014).

Further, consumer empowerment is the consumer's ability to control their choices in the decision process (Neghina, Bloemer, van Birgelen, & Caniëls, 2017). Control, which is gained through assimilating and processing information, decreases the imbalances in consumers' relational and informational power with retailers and increases their sense of fairness and negotiation capacity in the purchase (Spaid & Flint, 2014).

Aiming to arrive at the best possible decision (Puccinelli et al., 2009), webroomers desire information that enhances their product-related knowledge (price and attributes) and provide control over decision-making (Flavián et al., 2016). The low search costs of the Internet (Verhoef et al., 2007), and the possibility to confirm information and purchase in-store allow these information-processing needs to be more easily satisfied. As such, we propose that information attainment, price comparison orientation, and empowerment contribute to explain webrooming. Due to the ubiquity of mobile devices, which allow remote information access and processing (Shankar & Balasubramanian, 2009), these motivations are expected to be particularly salient for webrooming including the mobile channel (more for multidevice webroomers) compared to those employing traditional online search channels.

2.3.2. Uncertainty-reduction motivations

Consistent with the uncertainty-reduction proposition of Flavián et al. (2016), the study considers need for touch, perceived risk, and confidence as potentially relevant motivations associated with uncertainty reduction that may influence webrooming. Need for touch is the consumer's preference for information that can be obtained through physically manipulating objects (Peck & Childers, 2003). The tactile information reinsures consumers' previous judgements and positively affects search-process satisfaction and post-choice behavior (Flavián et al., 2016).

Perceived risk refers to consumers' uncertainty regarding the potentially negative consequences that could result from purchases (Chou et al., 2016). This study only considers the risk that is related to the online channel. The theft of identity or banking information, reputation concerns of the retailer, and delivery unfulfillment of online purchases (Chou et al., 2016; Schröder & Zaharia, 2008) are among the reasons leading to risk avoidance.

Confidence is a mentally formed state of certainty that represents both a motivation and a goal (Flavián et al., 2016). The need for confidence directly influences consumers' information-processing and decision-making (Tormala, Rucker, & Seger, 2008), which affects the reduction of uncertainty.

Although the Internet provides informational benefits, some of its inherent characteristics increase uncertainty. For consumers that need to physically inspect products before purchase, perceive security and transaction risks online, or search for high levels of choice confidence overall, the increased physical effort of going to the store to observe and purchase the product may be important in satisfying their needs. Combining online and offline channels provides transparency (Brynjolfsson, Hu, & Rahman, 2013), which can reduce uncertainty. As such, we propose that need for touch, perceived risk, and confidence contribute to explain webrooming. However, within webrooming, no differences are expected between mobile device users and users of traditional online search channels for these specific motivations. The need for touch and confidence apply regardless of the online channel, and the perception of risk refers to the Internet as a whole.

3. Method

3.1. Data collection

This study assumes an exploratory approach. The target population are 18-year-old individuals or older, living in Portugal, that have bought electronic products in-store in the last year. Product selection was based on the predomination of webrooming in this product category (Google Consumer Barometer, 2015). If more than one purchase was made, the most recent one was stressed to increase the likelihood of recall and to decrease selective memory. A convenience sample of 263 respondents was obtained from personal and online surveys. The personal survey was administered to staff and students with various educational degrees from a Portuguese university. To obtain a more diverse sample and to decrease representativeness issues, the online survey was sent by email to the teachers and other students of post-graduate, masters, doctoral, and executive courses at the same university, and through Facebook to the authors' personal contacts. Personal interviews with 17 participants recruited to pre-test the questionnaire verified the questions' understandability. Data collection occurred during December of 2017. Although the personal survey had a 100% response rate, the eligibility of participation and consequent response and nonresponse rates are typically unknown in online surveys where population frames cannot be clearly identified (Couper, 2000). To decrease the unwillingness to respond and to increase the quality of the response, anonymity and confidentiality were guaranteed and the scientific purpose of the study was reinforced.

Within the sample, 52.5% of the respondents were male, 68.1% were 35 years old or younger, 68.8% had an undergraduate or master's degree, 63.5% had a monthly net income of 1000€ or less; and regarding occupation, 29.7% were students, 44.9% were employed, and 9.1% were self-employed. Regarding the product that was purchased, 35.0% of respondents purchased a smartphone, 16.6% a television, and 15.2% a PC/laptop. The remaining individuals purchased other electronic products (e.g., sound systems, smartwatches, cameras, tablets, etc.). Despite sampling limitations, the nonresponse error was estimated by comparing early and late respondents on dependent, independent, and demographic variables (Armstrong & Overton, 1977). An equal size of 50% of first and last respondents was used to maintain the statistical power of the comparison (Collier & Bienstock, 2007). We found no differences between the types of respondents in almost all variables.

3.2. Measures

This study adapted measures from the literature (see Appendix A) for the independent variables (conditions). A five-point Likert scale that ranged from strongly disagree (1) to strongly agree (5) was used to measure each item. Information attainment (*inform*) was adapted from Noble et al. (2005), price comparison orientation (*price*) from Heitz-Spahn (2013), consumer empowerment (*empow*) from Neghina et al. (2017), need for touch (*touch*) from Peck and Childers (2003), perceived risk (*risk*) from Chou et al. (2016), and choice confidence (*conf*) from Flavián et al. (2016). The Cronbach's alpha coefficients for the measures are all above 0.70, which indicates good internal reliability (Hair et al., 1995). Moreover, we used a confirmatory factor analysis (CFA) to assess the measures' quality. The CFA model showed an overall acceptable fit ($\chi_{(155)}{}^2 = 380.88, p < 0.001$; χ^2/df = 2.46; CFI = 0.90; TLI = 0.88; SRMR = 0.057; RMSEA = 0.075) according to Hair et al. (1995). Each item loads in only one latent variable, evidencing its unidimensionality (Ping, 2004). The composite reliability (CR) is larger than 0.70, and the average variance extracted (AVE) is > 0.50 (Appendix A), which displays very good reliability for all measures (Fornell & Larcker, 1981). For each latent variable, the loadings are high (0.61–0.91) and significant (p = 0.001), confirming convergent validity (Anderson & Gerbing, 1988). The correlations between the latent variables (0.035–0.775) are lower than the AVE square root (0.715–0.854), except for empowerment and choice confidence by a small difference, which demonstrates discriminant validity (Fornell & Larcker, 1981).

For the dependent variables (outcomes), a categorical classification approach was used to assign individuals (see Gensler et al. (2017) for a showrooming example). Individuals that bought in-store were asked whether they searched for information prior to purchase, and, if so, their degree of usage of the (i) physical store, (ii) mobile device, and (iii) PC/laptop to search using a three-point scale: did not use this channel (1), used this channel few times (2), and used this channel many times (3). Depending on their answers, individuals were classified in different webrooming behaviors.

Table 1
Summary data for dependent (outcomes) and independent (conditions) variables.

Dependent variables (outcomes)	Frequency	Percentage (%)
Model 1 (n = 108): *webt*		
1 - No webrooming	37	34.26
2 - *Webt* with low PC/laptop usage	11	10.18
3 - *Webt* with high PC/laptop usage	60	55.56
Model 2 (n = 263): *webext*		
1 - No webrooming	37	14.07
2 - *Webext* with low usage of PC/laptop, mobile, or both	19	7.22
3 - *Webext* with high usage of PC/laptop, mobile, or both	207	78.71
Model 3 (n = 172): *webmm*		
1 - No webrooming	37	21.51
2 - *Webmm* with low mobile usage	28	16.28
3 - *Webmm* with high mobile usage	107	62.21
Model 4 (n = 172): *webmpc*		
1 - No webrooming	37	21.51
2 - *Webmpc* with low PC/laptop usage	24	13.95
3 - *Webmpc* with high PC/laptop usage	111	64.54

Independent variables (conditions)	*inform*	*price*	*empow*	*touch*	*risk*	*conf*
Model 1 (N = 108)						
Mean	3.75	3.96	4.08	3.28	4.05	4.20
SD	0.74	0.74	0.51	0.76	0.88	0.50
Calibration values at						
90%	4.333	5.000	5.000	4.167	5.000	5.000
50%	4.000	4.000	4.000	3.333	4.000	4.000
10%	2.667	3.000	3.500	2.167	3.000	3.500
Model 2 (N = 263)						
Mean	3.94	4.20	4.23	3.42	3.95	4.34
SD	0.71	0.73	0.52	0.77	0.97	0.51
Calibration values at						
90%	5.000	5.000	5.000	4.333	5.000	5.000
50%	4.000	4.333	4.000	3.500	4.000	4.250
10%	3.000	3.000	3.600	2.333	2.500	3.750
Model 3 (N = 172)						
Mean	3.90	4.25	4.23	3.53	3.82	4.36
SD	0.79	0.79	0.52	0.78	1.04	0.51
Calibration values at						
90%	5.000	5.000	5.000	4.500	5.000	5.000
50%	4.000	4.500	4.000	3.500	4.000	4.250
10%	3.000	3.000	3.500	2.500	2.000	3.750
Model 4 (N = 172)						
Mean	3.90	4.25	4.23	3.53	3.82	4.36
SD	0.79	0.79	0.52	0.78	1.04	0.51
Calibration values at						
90%	5.000	5.000	5.000	4.500	5.000	5.000
50%	4.000	4.500	4.000	3.500	4.000	4.250
10%	3.000	3.000	3.500	2.500	2.000	3.750

3.3. Webrooming variables

The study considers various webrooming behaviors as dependent variables. The first is traditional webrooming (*webt*), with n = 108. To consider only traditional PC/laptop users, mobile users were excluded from the sample (using or not using other channels). The second is extended webrooming (*webext*), with n = 263 (the whole sample). It includes those using one or both online channels, apart from the physical store. For multidevice webrooming, n = 172 was obtained by

Table 2
Discriminant analysis results.

					Group means on the discriminant function[b]		
Independent Variables	Standardized Coefficients	Discriminant Loading[a] (rank)	Univariate F ratio	Hit Ratio	1	2	3
Model 1: *webt*				75.9%	−1.094	−0.219	0.715
inform	0.983	0.743 (1)	21.143*				
price	−0.137	0.221 (2)	1.851				
empow	0.225	0.313 (4)	5.020				
touch	−0.626	−0.320 (5)	4.522				
risk	0.358	0.168 (3)	1.063				
conf	−0.339	0.092 (6)	0.855				
Model 2: *webext*				81.7%	−1.172	−0.265	0.234
inform	0.863	0.930 (1)	27.564*				
price	0.155	0.491 (3)	7.667*				
empow	0.192	0.494 (2)	7.894*				
touch	−0.361	−0.133 (5)	1.330				
risk	0.048	0.022 (6)	0.312				
conf	−0.070	0.319 (4)	4.016				
Model 3: *webmm*				71.5%	−1.016	0.209	0.297
inform	0.820	0.953 (1)	22.203*				
price	0.194	0.590 (2)	9.064*				
empow	0.272	0.559 (3)	7.645*				
touch	−0.182	0.018 (5)	1.493				
risk	−0.035	−0.058 (6)	0.835				
conf	−0.129	0.361 (4)	3.541				
Model 4: *webmpc*				70.3%	−1.020	−0.035	0.348
inform	0.830	0.963 (1)	24.090*				
price	0.220	0.607 (2)	9.596*				
empow	0.155	0.519 (3)	7.672*				
touch	−0.150	0.032 (5)	0.027				
risk	−0.081	−0.094 (6)	0.542				
conf	−0.041	0.391 (4)	4.213				

* p-value < 0.05/6 (6 independent variables).
[a] Correlation between discriminating and standardized canonical discriminating function.
[b] 1, 2, and 3 refer to the classification of groups for each dependent variable in Table 1.

excluding mobile-only and PC/laptop-only users. To check for possible differences, two types of multidevice webrooming were considered: those based on the degree of mobile usage regardless of the degree of PC/laptop usage (*webmm*), and those based on the degree of PC/laptop usage regardless of the degree of mobile usage (*webmpc*).

The four webrooming variables (four models) were coded based on the degree of usage of the considered channels for search in each model (see the three groups of each dependent variable in Table 1). Respondents not searching for information or only using physical stores (few or many times) were classified as non-webroomers in the first group of each model. Those with low usage of the device(s) considered in each model (e.g., low PC/laptop usage in *webt*) were classified in the second group. Finally, high usage of the corresponding device in each model (e.g., high PC/laptop usage in *webt*) were classified in the third group.

4. Discriminant analysis and fuzzy-set qualitative comparative analysis

This study uses discriminant analysis (DA) and fuzzy-set qualitative comparative analysis (fsQCA) to examine the relation between motivations and different types of webrooming behaviors. The methods have different purposes and are guided by different propositions. Integrating complementary methods allows richer analyses as it maximizes the amount of information on specific phenomena, particularly relevant in studies with exploratory focuses (Priola, 2010), which is the case.

DA is a correlational technique that, based on a set of metric independent variables, classifies objects into one of at least two exhaustive and mutually exclusive groups of a categorical dependent variable, and has application and interpretation analogous to regression analysis (Hair et al., 1995). It focuses on linearity, unifinality, causal symmetry, and additive and net effects of competing independent variables (motivations) on the dependent variables (webrooming behaviors) (Woodside, 2018). The net nonoverlapping contribution of individual motivations to explain webrooming behaviors using the DA is enriched by the combinatory analysis of motivations that lead to each behavior provided by fsQCA. Contrary to the DA, fsQCA is a set-theoretic technique that focuses on configurational effects between conditions (motivations) and outcomes (webrooming behaviors) (Ragin, 2008). The method allows equifinality, in which different motivational configurations may lead to the same behavior, and multifinality, where the same motivations can contribute to different behaviors. It also allows asymmetry in condition-outcome relations and recognizes conjunctural causation, in which a causal configuration (i.e., combination of motivations) can be necessary, sufficient, or both to attain the outcome (behavior) while the constituent conditions (motivations) are neither necessary nor sufficient (Ragin, 2008; Woodside, 2018). To the best of our knowledge, fsQCA has only been applied in multichannel research by Chou et al. (2016) but in a distinct context, denoting the importance of the present study.

The DA technique is applied using SPSS (Statistical Package for the Social Sciences) and fsQCA uses fsQCA 3.0 software (www.fsqca.com) for calculations.

4.1. Discriminant analysis

A simultaneous estimation DA is used to examine the net effects of

Table 3
Sufficiency analysis.

Model 1: *webt* = f (*inform, price, empow, touch, risk, conf*)			
Consistency cutoff: 0.77			
Causal Configuration	Raw cov.	Uni. cov.	Cons.
~touch~conf*empow*	0.24	0.03	0.75
*~touch*inform*empow*	0.33	0.06	0.80
*price*risk*~touch*~conf*	0.20	0.03	0.82
*price*risk*inform*empow*	0.37	0.13	0.81
Solution coverage: 0.53			
Solution consistency: 0.77			

Model 2: *webext* = f (*inform, price, empow, touch, risk, conf*)			
Consistency cutoff: 0.84			
Causal Configuration	Raw cov.	Uni. cov.	Cons.
*~touch*risk*	0.34	0.05	0.88
*empow*inform*risk*	0.35	0.02	0.92
*empow*conf*price*	0.38	0.07	0.90
empow~touch*	0.40	0.06	0.90
Solution coverage: 0.63			
Solution consistency: 0.89			

Model 3: *webmm* = f (*inform, price, empow, touch, risk, conf*)			
Consistency cutoff: 0.77			
Causal Configuration	Raw cov.	Uni. cov.	Cons.
*empow*inform*price*	0.41	0.01	0.84
*empow*inform*risk*	0.36	0.01	0.87
*empow*conf*price*	0.43	0.02	0.82
*empow*conf*risk*	0.36	0.01	0.82
empow~touch*	0.41	0.07	0.83
Solution coverage: 0.65			
Solution consistency: 0.82			

Model 4: *webmpc* = f (*inform, price, empow, touch, risk, conf*)			
Consistency cutoff: 0.77			
Causal Configuration	Raw cov.	Uni. cov.	Cons.
*empow*inform*price*	0.42	0.01	0.87
*empow*inform*risk*	0.35	0.01	0.86
*empow*conf*price*	0.43	0.02	0.84
*empow*conf*risk*	0.34	0.01	0.79
empow~touch*	0.40	0.07	0.82
Solution coverage: 0.64			
Solution consistency: 0.82			

Note: "~" represents the absence of a condition and "*" the logical operator AND.
fsQCA 3.0 Software for calculations (www.fsqca.com).

independent variables. The DA assumptions are confirmed in each model except for homogeneity of variances-covariances in Models 1 and 2 (*p*-value < 0.05) and normality (only *touch* in Model 1 is normally distributed). However, the DA method is robust to the violation of assumptions when the dimension of the smallest group is larger than the number of independent variables, and group means are not proportional to variances (Stevens, 1986), which is the case.

For each model, the first discriminant function explains among-group variability between 86.7% and 92.4% and is statistically significant at p-value < 0.001 (Model 1: $\lambda = 0.544$, $\chi_{(12)}^2 = 62.475$; Model 2: $\lambda = 0.788$, $\chi_{(12)}^2 = 61.350$; Model 3: $\lambda = 0.743$, $\chi_{(12)}^2 = 49.485$; Model 4: $\lambda = 0.734$, $\chi_{(12)}^2 = 49.422$). Since the second discriminant functions explain little variance and are not statistically significant ($0.205 \leq$ p-value ≤ 0.440), the analysis centers on the first functions. In all models, the standardized coefficient weights (Table 2) indicate that *inform* has a strong positive and significant effect on each webrooming behavior ($0.820 \leq \beta \leq 0.983$; p-value < 0.01) and *touch* a negative non-significant effect. Except for Model 1, *price* has a significantly positive effect ($0.155 \leq \beta \leq 0.220$; p-value < 0.01) as well as *empow* ($0.155 \leq \beta \leq 0.272$; p-value < 0.01). Furthermore, *conf* has a negative, non-significant effect in all models and *risk* a positive, non-significant effect in Models 1 and 2. The discriminate loadings confirm that *inform* is the most important variable for discriminating between the groups in each webrooming behavior, followed by *price* and *empow* in the last two models. In Model 2, *empow* is the second most important variable and *price* the third. Group means on the discriminant function indicate that *inform*, *price*, and *empow* seem to be the highest for webroomers with high level of corresponding device usage and the lowest for non-webroomers in each model. For example, for traditional webrooming (*webt*), *inform* is higher for those with high PC/laptop usage (group 3 in the last column of Table 2). Hit ratios indicate medium to highly successful classification rates for each model, and cross-validation results confirm 72.2%, 81.4%, 69.8%, and 69.8% correct reclassifications, respectively.

4.2. Fuzzy-set qualitative comparative analysis

4.2.1. Calibration

FsQCA uses the notion of set membership, which requires original data to be transformed into membership score sets that range from zero (fully excluded from the set) to one (fully included in the set) (Ragin, 2008). For each motivational construct, an index score is calculated before calibration by producing the average of each indicator. Three anchors are specified for the calibration process and are based on Campbell, Sirmon, and Schijven (2016): the point of full membership is the 90th percentile of data values, the cross-over point is the 50th percentile of data values, and full non-membership point the 10th percentile of data values. Table 1 indicates the percentile values for calibrating the conditions in each model as well as descriptive statistics. Theoretical anchors (Ragin, 2008) were used to calibrate the membership sets of the webrooming outcome of each model in which cases of the first groups (non-webroomers) were rated as full non-membership, cases of the second groups (webroomers with low corresponding device usage) were rated as the cross-over point, and cases of the third groups (webroomers with high corresponding device usage) were rated as full membership. To avoid dropping cases from the analysis, 0.001 was added to the scores with an exact value of 0.5 (Fiss, 2011).

4.2.2. Analysis of necessary and sufficient conditions

The fsQCA analysis begins with testing the necessary conditions for the presence or absence of outcomes (Schneider & Wagemann, 2010). Causal conditions are necessary if they are always present or absent when the outcome is present or absent (Ragin, 2008). For each outcome of the study (*webt*, *webext*, *webmm*, and *webmpc*) and their absence (~*webt*, ~*webext*, ~*webmm*, and ~*webmpc*), no necessary conditions were verified at a consistency threshold of 0.80 ("almost always necessary") (Ragin, 2000).

Regarding sufficiency, causal conditions are sufficient for the outcome when the set membership value of a condition is less than or equal to the outcome set membership value for each case (Ragin, 2000). The construction of the truth table is the first step in analyzing sufficient conditions, where each case is assigned to a particular row that corresponds to a configuration of causal conditions (Ragin, 2008). Running the fsQCA software resulted in one truth table for each outcome. The reduction of the truth tables uses a recommended threshold of at least 80% of cases in each sample and, to identify which configurations are sufficient to reach each outcome, a consistency threshold of 0.75 or above is applied (Ragin, 2008). The study analyzes the intermediate solution for each outcome (Table 3) since it only considers the causal conditions that are consistent with theoretical knowledge (i.e., easy counterfactuals) (Ragin, 2008). For each configuration and solution outcome, consistency and coverage values allow an informative solution (Fiss, 2011; Ragin, 2008).

The results of Table 3 show that four configurations explain traditional webrooming (*webt*), four explain extended webrooming (*webext*), five explain multidevice webrooming based on mobile usage (*webmm*), and five explain multidevice webrooming based on PC/laptop usage (*webmpc*). *Webt* occurs with low need for touch (*touch*) paired with either low confidence needs (*conf*) and high empowerment (*empow*) or with high information attainment (*inform*) and high *empow*. The behavior also occurs with high price comparison orientation (*price*) and high perceived risk (*risk*) combined with either low *touch* and low *conf*, or high *inform* and high *empow*. *Webext*, on the other hand, occurs when *touch* is low and *risk* is high, or in three other situations where *empow* combines with either (1) high *inform* and high *risk*, (2) high *conf* and high *price*, or (3) low *touch*. The configurations that lead to *webmm* and *webmpc*, which are the same, indicate that high *empow* is needed (but is not sufficient) to achieve both outcomes. The first two configurations show that, besides high *empow*, high *inform* combined with high *price* or high *risk* are required to achieve *webmm* and *webmpc*. The behaviors can also be achieved with high *empow* and high *conf* paired with either high *price* or high *risk*. Moreover, configurations that lead to *webmm* and *webmpc* also combine high *empow* with low *touch*. Note that all configurations in each model indicate that the constituent conditions (motivations) must combine with others to be sufficient. Thus, all conditions in each model are INUS conditions: "an *insufficient* but *necessary* part of a condition which is itself *unnecessary* but *sufficient* for the result" (Mackie, 1965).

The study also examines the causal conditions that lead to the absence of the outcomes (∼*webt*, ∼*webext*, ∼*webmm*, and ∼*webmpc*), as recommended in fsQCA (Schneider & Wagemann, 2010). For each absence, the results of the truth tables indicate that all configurations have consistencies below the acceptable level of 0.75. This denotes causal asymmetry as various configurations lead to the presence of each outcome, but no configurations are consistently associated with their absence.

4.2.3. Robustness check and predictive validity

The study conducts a robustness check of the models by altering the cross-over calibration point (Fiss, 2011). In separate analyses, we subtract and add 0.25 to the 50th percentile value for each outcome and repeat the fsQCA tests. The results indicate small variations in the causal combinations and the number of solutions for the subtraction with no major changes in interpretation. The addition has slightly more variation: one of the six *webt* configurations indicates the presence of ∼*empow*, and ∼*touch* is no longer present in the *webmm* and *webmpc* configurations. These results may be due to the left skewedness of the sample data, which affects the sensitivity analysis.

The examination of predictive validity is also important to assess how well a model predicts its outcome with additional samples (Wu, Yeh, Huan, & Woodside, 2014). We assess predictive validity only for *webext* since it is the most general model (Table 4). The sample is split into an analysis (first subsample) and holdout samples (second subsample). Highly consistent configurations are then obtained for the first subsample, which are subsequently tested using data from the second subsample to examine the predictive ability of these configurations for the second subsample. This procedure is repeated for the second subsample using the data from the first subsample. The results indicate a high predictive ability of the configurations of the first subsample for the second subsample, and vice-versa.

5. Discussion and conclusions

The objective of this study is to examine how information-processing and uncertainty-reduction motivations help explain webrooming behaviors using DA and fsQCA. The DA results indicate that information attainment, price comparison, and empowerment are the most important motivations that contribute to webrooming, all with significantly positive effects. This can be attributed to the Internet's ability to provide large amounts of comparable attribute information (Noble et al., 2005) that can be posteriorly confirmed in-store before purchasing (Flavián et al., 2016). Information attainment, price comparison, and empowerment continue to be important webrooming motivations with fsQCA and are incorporated in high consistency configurations. The number of configurations, however, implies more motivational nuances in each behavior compared to the DA, which denotes the complexity in analyzing multichannel behaviors (Heitz-Spahn, 2013).

The fsQCA findings show that, for each webrooming behavior, most of the configurations combine at least one information-processing and one uncertainty-reduction motivation (except for the first configuration in the last three models). Information attainment, price comparison orientation, empowerment, perceived risk, and confidence, which evidenced significant roles in multichannel behaviors for Noble et al. (2005), Heitz-Spahn (2013), Spaid and Flint (2014), Chou et al. (2016), and Flavián et al. (2016), respectively, are all relevant in explaining webrooming behaviors but combined differently. This finding could not be observed with the DA as solely information attainment, price comparison, and empowerment were significant within the motivations competing to explain the behaviors. Furthermore, the DA found squared canonical correlation coefficients of 42%, 20%, 22%, and 24% for Models 1, 2, 3, and 4, respectively, while the solution coverages for the corresponding outcomes in fsQCA denote higher empirical relevance overall at 53%, 63%, 65%, and 64%. Need for touch, however, showed a negative, non-significant effect in all DA models, and fsQCA accounted for its absence, not presence, in at least one configuration of each outcome. These finding may be due to the product category. Electronic products are considered search not experience products and, as such, product characteristics can be efficiently and objectively accessed through online channels (Frasquet et al., 2015). In general, the results support that three information-processing motivations and two uncertainty-reduction motivations contribute to explain webrooming behaviors but combined differently among themselves.

For webrooming behaviors including mobile device usage (Models 2, 3, and 4), the DA shows that price comparison and empowerment gain importance compared to *webt*. With fsQCA, empowerment is the motivation that stands out in these three behaviors. Particularly in multidevice webrooming where mobile devices are always used, empowerment is present in all configurations leading to the behaviors. This can be due to the ubiquity associated with these devices that allow consumers to instantly search and share product-related information anywhere, satisfying their need for control over shopping experiences (Spaid & Flint, 2014). Also, three configurations are common to the three models, with *empow*inform*risk* being the one with the highest consistency overall. According to Spaid and Flint (2014), empowerment is obtained through information. However, although mobile devices provide remote information and empowerment, consumers account for the risks regarding the reputation of vendors and the security of

Table 4
Analysis of predictive validity for *webext*.

Causal combinations of 1st subsample			Test of causal combinations of 1st subsample using data from 2nd subsample		
Causal Configuration	Raw cov.	Cons.	Causal Configuration	Raw cov.	Cons.
~touch	0.52	0.85	*~touch*	0.53	0.90
*empow*price*	0.46	0.87	*empow*price*	0.48	0.91
*empow*inform*conf*	0.36	0.90	*empow*inform*conf*	0.38	0.96
*empow*inform*risk*	0.34	0.89	*empow*inform*risk*	0.37	0.96
Solution coverage: 0.72			Solution coverage: 0.74		
Solution consistency: 0.85			Solution consistency: 0.90		
Causal combinations of 2nd subsample			**Test of causal combinations of 2nd subsample using data from 1st subsample**		
Causal Configuration	Raw cov.	Cons.	Causal Configuration	Raw cov.	Cons.
*empow*inform*	0.48	0.96	*empow*inform*	0.46	0.89
*empow*risk*	0.48	0.91	*empow*risk*	0.44	0.83
*empow*price*touch*conf*	0.29	0.89	*empow*price*touch*conf*	0.29	0.90
Solution coverage: 0.61			Solution coverage: 0.57		
Solution consistency: 0.92			Solution consistency: 0.84		

transactions online (Chou et al., 2016), thus purchasing in-store. In sum, the results support that information-processing motivations are more relevant for webrooming that includes mobile devices, especially for multidevice users. Uncertainty-reduction motivations have approximately equal results and presences in all models of the DA and fsQCA (in Model 1 of the fsQCA, ~*conf* emerges, but in the configurations with the lowest raw coverage and consistency levels), thus indicating no significant differences between webrooming behaviors.

The results of the study have important managerial and marketing implications. Although individual motivations help in understanding webrooming, the findings indicate that managers should pay attention to combinations of motivations. Besides different webrooming behaviors, consumers combine various information-processing and uncertainty-reduction motivations differently, which has not been considered yet. The various combinations of motivations that we identify can assist managers in designing tailored strategies that address the specific needs of different webrooming groups. For example, most webroomers value and combine product information and empowerment needs through online-offline channel usage. Besides providing accurate, complete, and comparative product information in each channel, managers should focus on transparency and consistency across channels. Multichannel management tools that integrate, process, and manage channels together may reduce pricing, information, branding, and inventory inconsistencies for retailers. Since empowerment heavily relates to mobile devices, managers should also provide fast and easy ways for consumers to obtain product information in-store, such as QR codes or free access to wireless Internet. These options create opportunities for in-store-specific promotions that deepen loyalty. Given that consumers may combine them, strategies that redirect consumers to physical stores based on their risk aversion to online purchases (e.g., promotion of product orders online and transaction conclusion offline with discounts) and their need for confidence (e.g., development of communication strategies emphasizing personalized and professional advice from salespeople to reduce purchase-related uncertainty) may also be important to avoid cross-channel free-riding.

Besides guiding multichannel managers on how to add value for webrooming consumers, the findings significantly contribute to the multichannel literature by developing a systematic understanding of what motivates a relevant behavior which has not been sufficiently explored. Based on information-processing and uncertainty-reduction theories, this study complements the conceptual foundation of Flavián et al. (2016) by deriving and testing specific motivations that may help explain webrooming. It is the first to validate the importance of information attainment, price comparison orientation, empowerment, risk aversion, and confidence in explaining webrooming and highlights the role of empowerment in mobile-mediated webrooming behaviors. This validation is made through testing, also for the first time, both individual and combinatory roles of the proposed motivations using DA and fsQCA. The fsQCA results contribute methodologically by providing support for equifinality and asymmetry of paths that lead to webrooming behaviors, which cannot be accessed only through regression-based methods.

5.1. Limitations and suggestions for further research

The study has limitations that provide suggestions for further research. The sizes of the groups of the dependent variables are disparate, and the use of a convenience sample poses representativeness issues. Thus, for validity concerns, future research should use a representative and more diverse sample through probability sampling. The replication of this study to other product categories, such as experience products, also deserves attention, since motivational differences should exist. Nonetheless, the present results can serve as proxy for search products that imply some level of involvement. The study only considers consumers purchasing in-store with different search behaviors. Further research should compare webrooming to other cross-channel (e.g., showrooming) or Internet-only shopping behaviors to assess the relevance of these motivations in explaining webrooming. Finally, respondents who only use mobile devices comprise 8% of the sample, thus not analyzed separately. However, due to the important growing role of mobile devices in purchase-related behaviors, future studies should analyze motivational differences in webrooming for these consumers.

Appendix A. Measurement scales

Measures and items[a]	Cronbach's α		
	Model 1	Model 2	Models 3 & 4
Information attainment (adapted from Noble et al. (2005))	0.765	0.761	0.822
CR = 0.785; AVE = 0.556			
I often seek out information regarding which brand to buy[b]			
I spend a lot of time looking for information about products and brands before I make a purchase			
I like to have a great deal of information before making a purchase			
I usually seek out product information before making a purchase			
Price comparison (adapted from Heitz-Spahn (2013))	0.718	0.759	0.809
CR = 0.768; AVE = 0.526			
I often compare product prices across retailers to get the lowest price			
I usually find myself price comparison shopping[b]			
I often find myself looking for the exact same product at different outlets to find the lowest price			
It is important for me to have the best price for the product			
Consumer Empowerment (adapted from Neghina et al. (2017))	0.701	0.734	0.708
CR = 0.736; AVE = 0.582			
I try to be well informed to have power over my choices during the purchase process			
I try to have as much control as possible over my choices during the purchase process			
It is important for me to have influence over the outcome of my choice[b]			
Need for touch (adapted from Peck and Childers (2003))[c]	0.874	0.859	0.875
CR = 0.862; AVE = 0.511			
I place more trust in products that can be touched before purchase			
I feel more comfortable purchasing a product after physically examining it			
If I can't touch a product in the store, I am reluctant to purchase it			
I feel more confident making a purchase after touching a product			
The only way to make sure a product is worth buying is to actually touch it			
I would only buy this kind of products if I could handle it before purchase			
Perceived Risk (adapted from Chou et al. (2016))	0.855	0.837	0.856
CR = 0.843; AVE = 0.729			
I am concerned about the security of Internet purchases			
I am concerned about the risk of interception of personal and credit card information in Internet purchases			
I am concerned about the vendor's reputation in Internet purchases[b]			
Choice Confidence (adapted from Flavián et al. (2016))	0.824	0.830	0.829
CR = 0.830; AVE = 0.551			
It is important for me to be confident in my choice of product			
I try to be certain of my choice of product			
I have to believe that my choice of product is the right one			
To purchase the product, I have to be convinced of my choice			

CR: composite reliability; AVE: average variance extracted.
[a] Likert scale of 1 = Strongly disagree; 5 = Strongly agree for all items.
[b] Item deleted.
[c] Focus on the outcome-directed element of the instrumental dimension of need for touch.

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