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Influence of individual characteristics on whether and how much consumers engage in showrooming behavior

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Abstract This article investigates a set of individual characteristics that can explain whether and how much a consumer engages in showrooming behavior. The authors conceptualized and empirically examined certain variables' impact on both showrooming probability as well as the extent of behavior. The variables under consideration include consumers' involvement, prior knowledge, perceived risk, price consciousness, Internet usage, access device usage, and certain demographic variables. The results reveal that involvement and price consciousness significantly explain whether a consumer is a potential showroomer. Further, showrooming frequency is found to be affected by prior knowledge, perceived risk, price consciousness, Internet usage, access devise usage, and age. Some implications are discussed regarding how retailers can handle showrooming.

Keywords Showrooming · E-commerce · Retailing · Zero-inflated Poisson model

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1 Introduction

The number of retailers that adopt multiple channels to deliver their products is continuously growing. Simultaneously, consumers' exposure to a variety of shopping channels has taught them how to adapt their behavior to every phase of the buying process. Consequently, a fraction of consumers use different channels, and sometimes different firms, to accomplish different tasks in this process, which has become a common phenomenon [1]. For example, after recognizing a need, a consumer might search for product information on channel A of firm X, but proceed to buy the product from channel B of firm Y. When product research is conducted at a store but the actual purchase is made online, we refer to such a behavior as "showrooming," which is one example of various patterns of research shopping behaviors [2].

Although no reliable statistics are currently available concerning the exact quantity of consumers who potentially engage in showrooming, this figure is expected to increase annually due to the rapid penetration of mobile devices. Quint, Rogers, and Ferguson [3] postulated that prospective showroomers might comprise 21–45% of the entire consumer population in the United States, the United Kingdom, and Canada. Therefore, showrooming has recently become of great concern among brick-and-mortar retailers, as most perceive the phenomenon as a serious threat, and believe this can transfer their rightful revenues to their online competitors. This perception seems to be correct, as its negative impact on store sales was estimated at approximately US$159 billion in 2012, and was forecast to reach US$689 billion in 2016 [4].

While the threat seems to be even more serious in the near future, the best strategy to combat showrooming remains unexplored. In fact, practitioners have devised several strategies that are potentially effective, yet almost all of them have neither theoretical nor empirical support from academia. Among these rare studies, Rapp et al.'s [5] work suggests that retailers can leverage coping and cross-selling strategies to diminish the damage caused by showrooming. The authors argue that encouraging salespeople to engage showroomers by implementing coping strategies can attenuate the negative consequences on self-efficacy. Further, the intensive implementation of cross-selling targeted toward potential showroomers is expected to mitigate the adverse effects on a salesperson's performance. However, this creates some important questions. How can a retailer direct those strategies at the appropriate customers? Can a retailer, in other words, identify which of his customers are potential showroomers? Equally important is the question: Can a retailer distinguish between occasional and frequent showroomers?

Any strategy to cope with this problem must be efficiently implemented. A retailer must be able to identify customers who are more likely to be showroomers so that he or she can better target an appropriate strategy at a lower cost. Further, a retailer may need to distinguish between occasional and frequent showroomers for two reasons. First, both types of showroomers may create different consequences, while the damage done by the latter is expected to be more severe. Second, a retailer may need to engage occasional showroomers in a manner that differs from that of frequent showroomers.

As a first step to address this issue, this study examines several individual characteristics that can be used to identify showroomers and non-showroomers, as well as occasional and frequent showroomers. The relevant determinants under consideration include consumers' involvement; prior knowledge; perceived risk; price consciousness; Internet usage; access device usage; and such demographic variables as age, gender, and marital status. We used data collected through an online survey to conduct an empirical study to verify the variables' hypothesized effects on the probability that a consumer engages in showrooming, as well as the frequency of that behavior. We discover that involvement and price consciousness significantly govern the probability of whether a consumer is a potential showroomer. Further, the frequency of showrooming is found to be affected by prior knowledge, perceived risk, price consciousness, Internet usage, access device usage, and age.

We organize the remainder of this article as follows: The next section reviews studies related to showrooming. Subsequently, we describe the analysis framework and provide the research hypotheses. We then describe a zero-inflated Poisson model and introduce the data used in the empirical analysis. Finally, we discuss the results and managerial implications for retailers who struggle to combat showrooming.

2 Literature review

Although extensive studies on the topic of multichannel management exist, only a fraction specifically address the issues related to showrooming. Undoubtedly, the one factor that traditional retailers are most concerned with is how to halt showrooming and prevent the draining of revenues to their online competitors. Unfortunately, sparse research addresses this issue. A set of strategies that could possibly be effective in combating showrooming include increasing customer service, frequent shopper programs, price matching, product assortment differentiation, and in-store Internet access restrictions [6–8]. Further, Mehra et al. [7] economic model indicates that product assortment differentiation can help traditional retailers maintain their profitability, while price matching is found to be ineffective. However, the above propositions lack empirical support, and more work must be done to yield more generalizable findings.

An existing research stream aims to explore the consequences of showrooming on store performance. Rapp et al. [5] investigate how a salesperson's perceptions of customers' intensity to engage in showrooming affects his or her self-efficacy and performance. Further, the authors draw from the theory of self-regulation [9] to examine the moderating roles of coping (i.e., approach and avoidance) and cross-selling strategies. Their findings concerning the main effect reveal that perceived showrooming can significantly decrease self-efficacy and performance. However, self-efficacy appears to be unaffected when a salesperson proactively engages in coping strategies. Further, showrooming's negative effect on a salesperson's performance is also found to be insignificant if salespeople have a greater intention to utilize cross-selling strategies.

Another research stream has illuminated the antecedents of this behavior. A study by Verhoef et al. [2] investigates the causes of research shopping, which involves three channels: the Internet, stores, and catalogs. They develop and empirically estimate a model of channel choice for application in the search and purchase stage of the buying process. Channel attributes (i.e., search and purchase attributes) between channel lock-in and synergy effects are used to explain different research shopping patterns. The authors find that the pattern of searching at a store followed by Internet purchasing (i.e., showrooming) can be largely attributed to stores' advantage over the Internet in terms of search attributes or attractiveness. Thus, showrooming may occur when such attribute effects dominate the lock-in, with a lack of cross-channel synergy effects.

The above study suggests that the Internet has disadvantages regarding purchase attributes when compared to a store; therefore, the benefits of online purchasing are not likely to be a reason why consumers engage in showrooming. However, Quint et al. [3] provide contradicting evidence, in that the most important drivers that motivate consumers to engage in showrooming include the lower prices and free shipping offered by online retailers. Other less influential factors include home delivery, an out-of-stock situation in the store, online rewards and incentives, and an absence of sales tax or VAT online. Accordingly, showrooming can be encouraged not only by the dominance of a store's search attributes, but also by the extent of the Internet's purchase attributes.

Online-offline channel integration is also potentially responsible for the occurrence of showrooming. Herhausen et al. [10] posit that channel integration can affect the perceived quality and risks of both stores and the Internet, which eventually leads to an increase in the intention to search and to buy via both channels. Thus, showrooming can be enhanced by channel integration if it causes greater intention to search at a store and buy online. However, as the study does not focus on showrooming, it is not obvious how this behavior would be induced by channel integration relative to other types of research shopping.

Finally, individual characteristics have been shown to explain heterogeneous preferences toward different channels [11]. The factors associated with channel choice include demographic variables [12], the customer lifecycle [13], and channel experience [14]. Although these studies focus on the choice of a purchasing channel, it is natural to assume that some of the variables are associated with showrooming. In fact, such variables as age and gender have been used to describe customers who showroom [6]. However, no comprehensive study to the best of our knowledge has explored individual characteristics' effects on showrooming.

3 Conceptual framework

Showrooming occurs when consumers recognize that any risks associated with a product can only be eliminated through a direct search at a store; however, they instead buy online to pursue a better price. Purchases are sometimes made through mobile devices, such as smartphones, while consumers are still in a store. The need to search at a store is fairly common, and especially for some products that are difficult or impossible to evaluate through sensory attributes or product descriptions provided on commercial websites. Various products, such as appliances and clothing, are examples of categories for which a direct inspection might be conducted.

As showrooming entails both direct inspection at a store and an online purchase, it is plausible to argue that any factor associated with these behaviors is expected to eventually influence the extent to which consumers engage in showrooming. We use this reasoning as a basis for selecting many relevant variables in our empirical study. In fact, this idea is consistent with some findings in literature, which contend that factors enhancing the search behaviors at the offline channel and/or buying behavior at the online channel will increase the likelihood of showrooming [2, 10, 15]. Research on consumer search and online shopping behavior suggests that such potential determinants include individual characteristics, product characteristics, environmental factors, and situational factors. This study focuses on individual characteristics to build testable hypotheses concerning their effects. Figure 1 illustrates our analytical framework.

As the figure reveals, we anticipate showrooming behavior to be affected by a set of consumer characteristics: consumers' involvement; prior knowledge; perceived risk; price consciousness; Internet usage; access device usage; and certain demographic variables, such as age, gender, and marital status. Early studies of consumer behavior have indicated that involvement is associated with the extent to which consumers search for product information [e.g., 18, 21]. A consensus has been derived suggesting that the information search increases with the degree of involvement with a product or purchase decision [24]. Further, prior studies suggested consumers' knowledge about a product category had an inverted

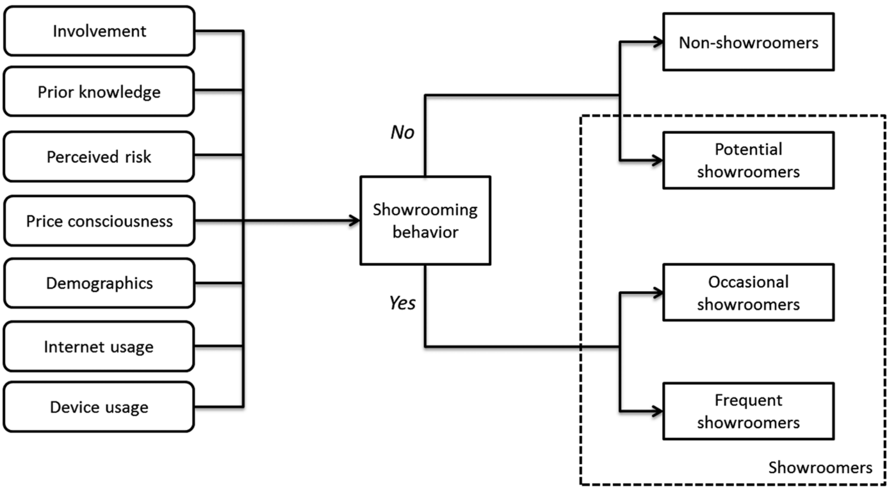

Fig. 1 Conceptual framework

U-shaped impact on information search efforts [24, 28]. Specifically, the information search increases with the degree of prior knowledge up to a threshold, beyond which saturation or a decline in the incremental effect occurs. "Perceived risk" is intended to delineate the risks associated with online shopping. Recent studies by Bhatnagar et al. [37] and Featherman and Pavlou [38] revealed that the risks associated with online purchases lead to a decrease in consumers' intentions to buy products from online providers. Price consciousness can be defined as the degree to which a consumer exclusively focuses on paying low prices [41], which has been shown to affect such consumer decisions as brand and store choice [40, 42]. Thus, we anticipate showrooming behavior will be enhanced by the extent of price consciousness, provided that online stores offer lower prices than those in offline stores. Further, consumers' experience with the Internet has been associated with the ability to search for information concerning products or prices from the Internet, which consequently influences the intention to purchase online [43, 44]. Thus, we expect showrooming behavior to vary among consumers, depending on their Internet usage experience.

Additionally, prior studies also noted the difference in the use of the Internet between males and females [49–51], in which males reportedly browse the Internet longer and more frequently than females. These studies provide a basis for predicting the association between showrooming behavior and gender. Studies also pointed out that in addition to gender, online shopping tendencies and the extent to which consumers collect information regarding a product they consider buying vary with age [37, 52, 54, 55]; this indicates the potential impacts of age on showrooming intensity. Regarding marital status, few studies suggested that married consumers spend less time on product searches and perceive higher risks when buying online [19, 21], which indicates a negative association between this variable and showrooming behavior. Finally, we included the types of devices used to access the Internet, as this is reportedly associated with purchase frequency and volume in online stores [58]. Thus, we anticipate showrooming behavior is affected by device usage.

We intend to use the proposed framework to examine these variables' roles in explaining whether an individual is a showroomer: if this is the case, how much showrooming would he or she engage in. We assume that two consumer segments exist: showroomers and non-showroomers. Showroomers delineate a group of consumers who actually or potentially engage in showrooming behavior, and non-showroomers refer to those who would never engage in showrooming. Consumers who engaged in showrooming from a focal product category at least once during the observation period are regarded as actual showroomers. In contrast, those who have not engaged in showrooming during the same period are considered as either potential showroomers or non-showroomers. These consumers actually purchased from the focal category, but they directly purchased online or purchased from offline stores. Behaviorally, no difference exists between potential showroomers and non-showroomers. However, these groups have different underlying reasons for not engaging in showrooming. Potential showroomers might have engaged in showrooming during that period, but could not do so for some reason, such as a limited time or failure to find better prices from online stores' websites. Non-showroomers, in contrast, have not engaged in showrooming because they perceive little benefit from searching activities at a store and/or buying online.

Further, we expect the intensity of showrooming to vary among actual showroomers. Some consumers would engage in that behavior very frequently (frequent showroomers), while others would do it less frequently (occasional showroomers). Both occasional and frequent showroomers may have different psychological experiences with showrooming. Specifically, frequent showroomers are more likely to perceive showrooming as fitting their motivational orientation in pursuing a certain goal (e.g., buying the right product at the best price). They subsequently become more confident about their actions, and eventually increase their engagement in the goal-pursuing activity [16, 17].

4 Research hypotheses

The aforementioned framework allows us to select specific variables that potentially influence whether and the extent to which a consumer engages in showrooming. However, we lack a theoretical basis to surmise which variable affects which showrooming aspect (i.e., showrooming probability and frequency). Therefore, we leave this as an empirical issue, and hypothesize that each variable influences both aspects.

4.1 Involvement

Prior studies suggest that the amount of search increases with consumers' involvement [18–21]. Two types of involvement are acknowledged as influential: product and purchase involvement. The former refers to an enduring interest or enthusiasm toward a particular product, and the latter refers to the extent of consumers' consciousness about consumption problems resulting from risk perceptions. Each is observed as differently affecting search efforts. Product involvement positively affects the ongoing search, while purchase involvement increases the extent of pre-purchase search behavior [20].

Many researchers have empirically verified involvement's positive effects on the total search effort [22–24]. A major explanation for this is that higher involvement leads to greater product importance, which consequently increases the net benefit of the search as perceived by consumers. This generally applies, given that a search's cost function is fixed. Accordingly, we can anticipate that high-involvement consumers tend to have greater intentions to search for product information at a store; therefore:

H1a Consumers with higher involvement are more likely to engage in showrooming than those with lower involvement.

H1b Among showroomers, consumers with higher involvement tend to engage in showrooming more frequently than those with lower involvement.

4.2 Prior knowledge

Consumer behavior literature conceptualizes prior knowledge as a multidimensional construct encompassing familiarity, expertise, and experience [25, 26]. Brucks [27] further classifies prior knowledge into objective and subjective knowledge. Objective knowledge is what consumers know about a product, and subjective knowledge is what consumers think they know about a product. The influence of prior knowledge on consumers' attitudes and behaviors has attracted considerable attention from researchers in consumer behavior field [28, 29].

Previously, one conflict concerned the effect of prior knowledge on the extent of the search. Some researchers argue that search efforts decrease with prior knowledge, while others claim the opposite. The reasoning behind the former negative effect was that an increase in prior knowledge led to an increase in usable prior information and a decline in choice uncertainty, thus decreasing the search effort [30, 31]. Alternatively, the supporting argument for a positive effect was that prior experiences are often associated with an increase in expertise, which tends to enhance information processing and integration. Therefore, the search effort increases as prior experience increases [25, 32]. However, this conflict seems to have converged to an argument that the relationship is an inverted U-shape [24, 28]. This suggests that the depth of the search increases as prior knowledge moves from low to moderate levels, then decreases as it moves beyond that level. Therefore, we expect that consumers with moderate prior knowledge have a greater intention to search at a store than those with either low or high prior knowledge. Consequently,

H2a Consumers with moderate prior knowledge are more likely to engage in showrooming than those with low or high prior knowledge.

H2b Among showroomers, consumers with moderate prior knowledge tend to engage in showrooming more frequently than those with both low and high prior knowledge.

4.3 Perceived risks in online shopping

The Internet offers several benefits, such as convenience and lower prices, but also poses a certain degree of uncertainty for consumers. The risks associated with online purchases include product performance, financial, and time/convenience risks [33, 34]. Although similar risks can also be encountered at a store, the risks that stem from the Internet are perceived as greater [35, 36]. Intuitively, consumers who perceive the Internet as "high-risk" will be more reluctant to purchase on it. Perceived risks in current literature have been reported to negatively affect consumers' intention to buy using the Internet [37, 38]. Further, Donthu and Garcia [39] find that Internet shoppers are less risk averse than those who buy through other channels. Therefore, we expect a negative effect of perceived risk to have a negative effect, as follows:

H3a Consumers with lower perceived risk are more likely to engage in showrooming than those with higher perceived risk.

H3b Among showroomers, consumers with lower perceived risk tend to more frequently engage in showrooming than those with higher perceived risk.

4.4 Price consciousness

Amongst all the variables being considered, price consciousness may be the one that has obvious effects. As suggested by Quint et al. [3], financial benefits offered by online retailers have been the main reason for consumers to showroom. Thus, we can expect that a large portion of showroomers are price-sensitive consumers. These consumers generally have lower acceptable prices [40] and perceive lower costs of traveling to several stores to search for the best alternatives [41]. Further, it is also suggested that price-conscious consumers are less loyal to any one particular store, and will buy where the best price is offered [42]. In summary, price-conscious consumers are more likely to spend time searching for product information or better prices; therefore:

H4a Price-conscious consumers are more likely to engage in showrooming than those who are less price-conscious.

H4b Among showroomers, price-conscious consumers tend to engage in showrooming more frequently than those who are less price-conscious.

4.5 Internet usage

Positive correlations between Internet usage and online shopping behavior have been confirmed in many studies [43, 44]. Possible explanations include frequent Internet users' better ability to discover online vendors or search for products on the Internet. Further, frequent users may have greater expertise in accomplishing purchasing tasks because, for instance, they have a better knowledge of how to utilize interactive decision aids [45]. Additionally, Internet usage can be associated with positive subjective experiences or enjoyment [46], which in turn leads to a conversion of browsing into purchasing [47, 48].

H5a Consumers who spend more time using the Internet are more likely to engage in showrooming than those who spend less time.

H5b Among the showroomers, consumers who spend more time using the Internet tend to engage in showrooming more frequently than those who spend less time.

4.6 Gender

Literature has documented gaps in the Internet usage and attitudes toward online shopping between men and women. A survey conducted by the Roper Center for Public Opinion Research [49] reports that women are less interested in the Internet than men. This might be why women use the Internet less frequently than men [50]. Other studies reveal that men tend to spend a longer time using the Internet than women [51].These gender differences in Internet-related attitudes and usage may magnify the differences in consumers' perceptions of online shopping risks [52]. Specifically, women perceive higher risks on the Internet than men; therefore, they are more reluctant to purchase from online vendors. Although these gaps may vanish in the future, we argue that it is still relevant to assume that men have a greater intention to buy online; therefore:

H6a Men are more likely to engage in showrooming than women.

H6b Among showroomers, men tend to engage in showrooming more frequently than women.

4.7 Age

Older consumers tend to be less open to life style changes [53], while younger consumers have been reported to more pervasively adopt electronic shopping [54]. Liebermann and Stashevsky [52] support this argument, and further suggest that older consumers perceive higher risks when buying online than younger consumers. However, recent studies have found the opposite results concerning these effects, causing a less obvious relationship between age and online shopping intention [15].

On the other hand, age negatively correlates with the intention to search at a store. Bhatnagar et al. [37] argue that older consumers may have more experience with a product, and therefore, find little need to feel or touch a product or be assured by a salesperson. An experimental study by Cole and Balasubramanian [55] reveals that elderly subjects are less likely than younger subjects to intensely search and select an appropriate product. Positive correlations between age and income can also be responsible for the negative effect of age, as older consumers would bear a greater opportunity cost of the time to travel to a store.

H7a Younger consumers are more likely to engage in showrooming than older consumers.

H7b Younger consumers tend to engage in showrooming more frequently than older consumers.

4.8 Marital status

A few studies suggest that marital status has no significant effect on the intention to purchase online [54]. A study by Bhatnagar et al. [37] reports mixed results, in that married consumers are found to have higher intentions to buy hardware products online, but not software or home electronics. However, another study notes that married consumers may perceive higher risks when buying online than those who are unmarried [52]. Further, some evidence from the literature on consumer searches indicates that married consumers spend less time searching for product information than single consumers [19, 21]. Thus, it is reasonable to expect that showrooming tends to occur among single consumers.

H8a Married consumers are less likely to engage in showrooming than unmarried ones.

H8b Among showroomers, married consumers tend to engage in showrooming less frequently than those who are unmarried.

4.9 Access device usage

The use of Internet access devices may impact purchase intentions and behavior on the Internet. Consumers' intention to make online purchases is likely to depend on their trust in the benefits offered by Internet retailers; the extent of this trust can be positively influenced by how consumers perceive the technical competence and performance level of the device they use [57]. Another study suggests that the adoption of mobile devices, such as smartphones and tablets, may increase online purchases' frequency and order size [58]. Although these devices have visibility and functionality shortcomings compared to personal computers (PCs), they allow consumers to have an immediate access to electronic commerce (EC) sites from any place. For instance, consumers can immediately navigate prices on the Internet right after inspecting a product at a store. Consequently, consumers who use a mobile device can more easily engage in showrooming. This study we compares the effect of the usage of mobile devices, including smartphones, handheld phones, and tablets, against fixed PCs, such as home or office PCs, web television, and game consoles, to hypothesize the following:

H9a Consumers who primarily use a mobile device to access the Internet are more likely to engage in showrooming than those who use other fixed devices.

H9b Among showroomers, consumers who primarily use a mobile device to access the Internet tend to engage in showrooming more frequently than those who use other fixed devices.

5 Model

The basic premise of this study is that two consumer segments exist that differ in terms of showrooming tendencies. One segment consists of consumers who actually or potentially engage in showrooming behavior (i.e., showroomers). The other is a group of consumers who would never engage in showrooming, as they perceive few benefits from directly searching at stores or buying online (i.e. non-showroomers). Consumers belong to the former if they actually engaged in showrooming at least once during a certain period. However, we are unsure as to whether a consumer who has not engaged in showrooming even once during the same period is a potential showroomer or a non-showroomer. Such a consumer's segment can only be probabilistically stated. Further, the extent to which showroomers engage in that behavior varies across individuals. Accordingly, our analysis intends to test our hypotheses and examine how previously stated individual characteristics can describe whether a customer is a showroomer, and explain whether a showroomer is a frequent or occasional showroomer.

We address this problem by employing a zero-inflated Poisson (ZIP) model [59] in our empirical analysis. This model is appropriate to the current study for the following reasons: First, our analysis' dependent variable is showrooming frequency, which takes non-negative integer values. A ZIP model is well-suited to such a problem as it treats count data as a dependent variable. Second, a ZIP model is a class of finite mixture models that assumes zero-count data as generated from two different populations. This is relevant to our context, in which consumers with zero showrooming frequencies are considered as either potential showroomers or non-showroomers, depending on their characteristics. Additionally, the model is flexible, in that it decreases to an ordinary Poisson regression model when the assumption of different populations does not hold.

First, let c_i be an indicator function that equals one if the consumer i is a non-showroomer, and zero otherwise. The probability that the consumer belongs to the non-showroomer segment is denoted by $p_i = \Pr(c_i = 1)$. During a certain period, consumer i engages in showrooming y_i times. If $c_i = 1$, then $y_i = 0$, with a probability of 1. Regarding the showroomers, we assume that y_i follows a Poisson distribution with parameter λ_i. Accordingly, the probability of observing y_i is provided by the following equation:

$$f(y_i|\lambda_i) = \begin{cases} p_i + (1 - p_i)e^{-\lambda_i} & \text{if } y_i = 0 \\ (1 - p_i)\dfrac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!} & \text{if } y_i > 0 \end{cases} \tag{1}$$

Further, λ_i is parameterized to account for individual characteristics' effects, as follows:

$$\begin{aligned} \log(\lambda_i) = \beta_0 + \beta_1 INV_i + \beta_2 KNOW_i + \beta_3 KNOW_i^2 + \beta_4 PRISK_i + \beta_5 PCON_i \\ + \beta_6 USAGE_i + \beta_7 FEM_i + \beta_8 AGE_i + \beta_9 MAR_i + \sum_{j=10}^{13} \beta_j DEV_{ij} \end{aligned} \tag{2}$$

We use a logit specification here for the probability p_i, which provides a linkage between showrooming probabilities and consumers' characteristics. Specifically,

$$p_i = \frac{\exp(u_i)}{1 + \exp(u_i)}, \tag{3}$$

where u_i represents the deterministic part of the model, and is formulized as follows[1]:

$$\begin{aligned} u_i = \gamma_0 + \gamma_1 INV_i + \gamma_2 KNOW_i + \gamma_3 KNOW_i^2 + \gamma_4 PRISK_i + \gamma_5 PCON_i + \gamma_6 USAGE_i \\ + \gamma_7 FEM_i + \gamma_8 AGE_i + \gamma_9 MAR_i + \sum_{j=10}^{13} \gamma_j DEV_{ij} \end{aligned} \tag{4}$$

[1] Note that our hypotheses imply that each β_j has the opposite sign with the respective γ_j for $j \geq 1$.

The independent variables in Eqs. (2) and (4) are a set of variables previously outlined in the hypothesis section: *INV*, *KNOW*, *PRISK*, *PCON*, *USAGE*, and *AGE* denote consumers' involvement, prior knowledge, perceived risk, price consciousness, Internet usage, and age, respectively, and *FEM* and *MAR* represent dummy variables for female and married consumers. Finally, $DEV = [HOMEPC, HANDPHONE, SMARTPHONE, TABLET]$ is a vector of dummy variables for the types of Internet devices that consumers primarily use: the home PC, handheld phone, smartphone, and tablet, respectively. The other devices are treated as the last variable, serving as the basis.

Finally, when we observe that customer i engaged in showrooming (i.e., $y_i > 0$) with regard to showrooming probability, we then recognize the customer as a definite showroomer, or $\Pr(c_i = 0|y_i > 0) = 1$. However, if we observe that $y_i = 0$, we can say that the customer is a showroomer with probability

$$\Pr(c_i = 0|y_i = 0) = 1/(1 + q_i e^{\lambda_i}) \tag{5}$$

where $q_i = p_i/(1 - p_i)$. For instance, one would identify a customer who has not engaged in showrooming as a potential showroomer if the value of Eq. (5) is greater than .5, and a non-showroomer if otherwise. However, if a marketer wants to minimize a predetermined expected risk—using a loss function that weighs the loss from misclassifying a potential showroomer as a non-showroomer more heavily than the other way around—then he or she should use a greater threshold, and vice versa. It should be noted that the precision of this classification cannot be assessed unless we have information to identify whether a consumer is a potential showroomer or non-showroomer. Finally, the model's likelihood is calculated by

$$l(\beta, \lambda|y_i) = \prod_{y_i=0} p_i + (1 - p_i)e^{-\lambda_i} \prod_{y_i > 0} (1 - p_i)\frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!}. \tag{6}$$

The likelihood function indicates that all parameters in the zero-inflated (λ's) and count model part (β's) are simultaneously estimated by using all consumers' showrooming frequency data.

6 Data

We collected the data through an online survey implemented by a marketing research company, which called for survey participation in exchange for financial compensation. All who responded to the screener were initially asked if they made any clothing purchases in the past year. Only those who made purchases were allowed to proceed to the next questions. Before asking them to answer the next question, we displayed the definition of showrooming to assure ourselves that they understood the showrooming concept. The definition was previously tested in a pilot study by asking a number of students and faculty members for their opinions. We were convinced that all participants had no difficulty in comprehending its meaning. The final sample size was 500, which is arguably large enough to obtain stable estimates.

6.1 Product category

We selected clothing as the product category to empirically test our hypotheses for two reasons. First, clothing has some attributes that can be verified only through direct inspection. In most cases, consumers need to touch or try the product to make sure that it fits their body size, or that it is made of high-quality materials. Second, clothing purchases tend to occur relatively frequently. Therefore, we expected to observe a substantial variation in the dependent variable (showrooming frequency) among respondents.

6.2 Variable measurements

Regarding the dependent variable, we asked respondents how many times they had engaged in showrooming when buying clothing during the past year. We assumed that a one-year window is appropriate for this study, as this is long enough to yield some degree of variability in showrooming frequencies, yet not too long that a fallibility stemming from forgetting did not severely impact the measurement. Nevertheless, respondents' failure to recall might have contaminated the data; in fact, our data reveals many consumers with extraordinary showrooming frequencies (e.g., 100 times), which seems to be an unreliable amount. Therefore, we conducted Smirnov-Grubbs' outlier test to minimize any potential bias, and 13 participants with showrooming frequencies greater than 12 times were omitted from the analysis as a result.[2] Of the remaining 387 participants, 337 were used for the model calibration, and 50 for the cross-validation.

Figure 2 illustrates the showrooming frequency distribution among the participants earmarked for the analysis. On the one hand, it can be observed that most had engaged in showrooming only once during the past year, and approximately 78% of participants had showrooming frequencies between one and three times. On the other hand, only 13% of participants did not exhibit showroom behavior. Therefore, we did not observe an obvious excess in the zero counts. However, it is intuitively reasonable to expect that a portion of participants were non-showroomers, and drawn from a different population from that of the showroomers. We will test this zero-inflation assumption by comparing the ZIP and Poisson models.

Product involvement was measured using a seven-point Likert scale (ranging from 1 = strongly disagree to 7 = strongly agree) for six items, based on several scales used in prior studies [20, 60–62]. The scale measured the extent to which the subjects expressed an interest in the clothing category, how important it was to them, and how they would anticipate or respond to the purchase of an incorrect product. Regarding prior knowledge, we used a relatively simple yet reliable measure as developed by Flynn and Goldsmith [63], which reflects consumers' perceptions of the amount of product category information they have stored to memory. The measurement of the perceived risk in online shopping was conducted

[2] We find that the result is considerably sensitive to the exclusion of the outliers. The results of a likelihood ratio test revealed that the model's accuracy significantly increased after we omitted the outliers from the analysis.

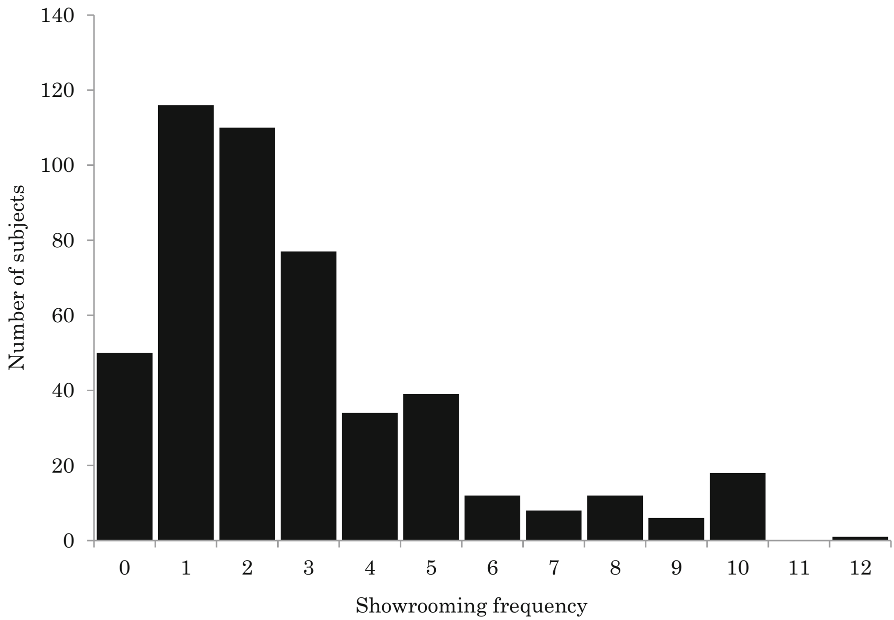

Fig. 2 The distribution of showrooming frequencies

using a scale proposed by Forsythe et al. [56]. However, we used a simplified version of the original scale to reduce the burden on participants that contains items of perceived financial, product, and time/convenience risks. Price consciousness was measured using a subscale of price perception as developed by Lichtenstein et al. [41]. This contains some items concerning the subjects' willingness to search for the best price at a cost of travelling to multiple stores. Table 1 displays the measurements of the independent and dependent variables.

Further, we asked participants how many hours per day they spent browsing the Internet to measure usage experience. Finally, we asked what device they primarily used to access the Internet. Table 2 reveals the correlations among the variables; we observe that some variables are moderately correlated (e.g., involvement and prior knowledge, or age and marital status). However, as the values are less than the conventional threshold (.5), we argue that multicollinearity is not a serious threat in our analysis.

6.3 Dealing with common method bias

We minimize the possible problem of common method bias by conducting a pilot survey of 26 undergraduate and graduate students to check for any possible ambiguity in the questionnaire. We confirmed that all subjects could understand all the questions, and had no difficulty in answering them. Further, we anticipated a high correlation between involvement and prior knowledge, and placed the items of involvement at the beginning of the questionnaire and the prior knowledge items at

Table 1 Variable measurements

Independent and dependent variables	Mean	SD	Source
Showrooming			
The frequency of showrooming when buying clothing in the past year.	3.08	2.83	
Involvement			
I have a great interest in clothing. (IN1)	4.92	1.50	Lastovicka and Gradner [60], Laurent and Kapferer [61], Jain and Srinivasan [62]
It is fun to use this product. (IN2)	5.05	1.37	
I do not think that clothes are attractive products.* (IN3)	2.89	1.42	
I always wonder how my family or friends will react when I purchase new clothes. (IN4)	4.23	1.48	
I would not be disappointed if I made the wrong choice.* (IN5)	3.16	1.35	
I spend as much time as possible making the right decision when buying clothes. (IN6)	4.52	1.35	
Prior knowledge			
I know quite a lot about clothes. (PK1)	3.55	1.50	Flynn and Goldsmith [63]
I know how to judge the quality of an article of clothing. (PK2)	3.36	1.42	
Among my friends, I am an "expert" on clothing. (PK3)	3.06	1.53	
Compared to other people, my knowledge about clothing is poor.* (PK4)	4.47	1.46	
I have no idea about clothing.* (PK5)	3.97	1.53	
Perceived risk			
I cannot trust online companies. (PR1)	3.68	1.34	Forsythe et al. [56]
It is likely that companies could deliver products that differ from what I ordered. (PR2)	3.94	1.35	
I am worried about my privacy being compromised. (PR3)	4.85	1.31	
Placing an order is too complicated. (PR4)	3.51	1.43	
Searching for an appropriate website that sells a product that I want to buy is time-consuming. (PR5)	4.08	1.49	
Pictures of products often take too long to appear. (PR6)	4.02	1.38	
Price consciousness			
I am not willing to make an extra effort to find a lower price.* (PC1)	3.01	1.32	Lichtenstein et al. [41]

Table 1 continued

Independent and dependent variables	Mean	SD	Source
I will grocery shop at more than one store to take advantage of low prices. (PC2)	4.27	1.29	
The money saved by finding lower prices is typically not worth the time and effort.* (PC3)	2.58	1.26	
I would never shop at more than one store to find lower prices.* (PC4)	3.40	1.41	
The time it takes to find low prices is usually worth the effort. (PC5)	4.63	1.37	
Internet usage			
The average time consumers spend surfing the Internet in a day.	2.90	2.26	

* Reversed item

Table 2 Variable correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Showrooming	1.00								
(2) Involvement	**.38**	1.00							
(3) Prior knowledge	**.47**	**.43**	1.00						
(4) Perceived risk	− **.39**	− .02	− .11	1.00					
(5) Price consciousness	**.46**	− **.31**	− **.17**	.02	1.00				
(6) Internet usage	**.34**	− .06	− .08	− .01	.04	1.00			
(7) Female	.03	**.30**	**.26**	.08	**.28**	− .13	1.00		
(8) Age	− **.24**	− .13	− .05	.00	− .09	.10	− .02	1.00	
(9) Married	− .04	.03	.03	− .02	.00	− .06	.10	**.49**	1.00

Bold fonts indicate significant correlations ($p < .01$)

the latter part of the questionnaire. We also reversed the wording of some items to minimize potential acquiescence biases. The main survey explains the research objective for the respondents, and stresses that no right or wrong answer exists. We are convinced that the respondents also noticed that the research company preserved their anonymity; thus, few possible responses resulted from their perceptions of social acceptability. After collecting the data, we conducted Harman's single-factor test and discovered that only 13.54% of the variances are explained by the single factor. Finally, an inclusion of a common latent factor did not lead to a significance difference in the standardized regression weights of the model with and without this factor. Accordingly, we concluded that no serious problem of common method bias exists in our data.

7 Results

7.1 Reliability and validity assessment

We assess our constructs' reliability and validity (i.e., involvement, prior knowledge, perceived risk, and price consciousness) by conducting a confirmatory factor analysis. Table 3 reveals the factor loadings extracted in four factors. We found that all factor loadings were greater than .50; all items' internal consistency and reliability were evaluated using Cronbach's alpha, and Table 4 presents the item-to-total correlation values. Cronbach's alpha values ranged from .80 to .91, suggesting good internal consistency [65]. Further, the value of item-total correlations ranged from .68 to .84, or greater than the recommended value of .60 for field studies [66].

Table 3 Confirmatory factor analysis results

Construct	Item	Factor loadings			
		Factor 1	Factor 2	Factor 3	Factor 4
Involvement	IN1	**.71**	.08	− .11	.15
	IN2	**.72**	.12	.03	.10
	IN3	**.63**	.07	.09	− .19
	IN4	**.54**	.21	.12	.07
	IN5	**.63**	.14	− .15	.24
	IN6	**.60**	.05	.13	− .13
Prior knowledge	PK1	.14	**.72**	.02	.15
	PK2	− .03	**.73**	.14	.06
	PK3	.12	**.70**	.09	− .21
	PK4	.25	**.65**	− .14	.17
	PK5	.07	**.63**	− .21	.01
Perceived risk	PR1	− .18	.02	**.75**	.22
	PR2	.22	.16	**.66**	.27
	PR3	.13	.07	**.73**	− .31
	PR4	.05	.24	**.70**	.14
	PR5	− .04	− .12	**.75**	.03
	PR6	.08	.18	**.69**	− .16
Price consciousness	PC1	− .32	.19	.25	**.73**
	PC2	− .18	.23	.11	**.75**
	PC3	.21	− .09	− .08	**.65**
	PC4	− .23	.01	.07	**.59**
	PC5	.07	− .14	.22	**.54**

Negatively worded items were "reversed-scored." The principal component analysis method was used to extract the loadings, which were then rotated using a varimax rotation with Kaiser normalization

Bold indicates maximum values among factors for the respective items

Table 4 Internal reliability and convergent validity test results

Construct	Item	Internal reliability		Convergent validity			
		Cronbach's α	Item-total correlation	Standardized loading	Standard error	Composite reliability	Variance extracted
Involvement	IN1	.84	.70	.73	.45	.85	.54
	IN2		.74	.74	.43		
	IN3		.71	.65	.50		
	IN4		.72	.62	.45		
	IN5		.73	.67	.42		
	IN6		.69	.65	.47		
Prior knowledge	PK1	.91	.84	.77	.33	.92	.62
	PK2		.81	.81	.35		
	PK3		.82	.76	.38		
	PK4		.77	.72	.46		
	PK5		.79	.71	.45		
Perceived risk	PR1	.80	.74	.80	.34	.82	.53
	PR2		.71	.74	.40		.59
	PR3		.78	.78	.28		
	PR4		.68	.75	.35		
	PR5		.73	.79	.28		
	PR6		.72	.76	.26		
Price consciousness	PC1	.85	.76	.79	.272	.86	
	PC2		.81	.82	.198		
	PC3		.70	.72	.523		
	PC4		.73	.64	.492		
	PC5		.72	.61	.563		

The measurement items' convergent validity was examined using factor loadings, composite reliability, and the variance-extracted measure. As can be observed in Table 4, each item is associated with a factor loading that exceeds the recommended value of .60 [66]. Similarly, all the composite reliabilities were greater than .80, and all variance-extracted measure were greater than .50, indicating the measurement items' convergent validity [66]. Additionally, we tested discriminant validity by comparing the error-adjusted inter-construct correlations with their respective variance extracted measures [67]; see Table 5. The results revealed that all correlations were less than the respective constructs' variance-extracted measures, suggesting discriminant validity between the constructs.

7.2 Model comparison

We then verified the zero-inflation assumption by estimating two competing models: the Poisson and ZIP models. The ZIP model was estimated using the expectation–maximization algorithm. We used the same explanatory variables in the Poisson model as those aforementioned used in the ZIP model. Both models' performances were assessed by comparing the Akaike information criterion (AIC) values and root mean squared error (RMSE) values for the validation data, and by conducting Vuong's non-nested test [64]. The AIC values suggest that the ZIP model outperforms the Poisson model ($AIC_{\mathrm{ZIP}} = 2950$ versus $AIC_{\mathrm{Poisson}} = 3029$). Similarly, the RMSE values also indicate that the former predicts showrooming frequencies in hold-out data better than the latter ($RMSE_{\mathrm{ZIP}} = 14.87$ versus $RMSE_{\mathrm{Poisson}} = 21.26$). Additionally, the Vuong statistic demonstrates the statistical significance of the ZIP model's superiority over the Poisson model ($Vuong_{\mathrm{ZIP/Poisson}} = 2.98$, $p < .01$). Accordingly, we conclude that as the sample contains many non-showroomers, it is appropriate to use the ZIP model. We will discuss this model's estimation results hereafter (see Table 6).

7.3 Hypothesis testing

The ZIP model contains two sets of parameters capturing the effects of some variables on zero-inflation and counts. We use the same explanatory variables in both parts of the model to preserve consistency with the research hypotheses. The model assumption implies that corresponding parameters are expected to have opposite signs, except for the intercepts. Regarding the zero-inflation model, involvement has the anticipated significant effect ($\gamma_1 = -0.86$, $p < .05$), in support of H1a. Thus, we confirm that a consumer with higher involvement has a greater

Table 5 Error-adjusted inter-construct correlations

	(1)	(2)	(3)	(4)
(1) Involvement	(.54)			
(2) Prior knowledge	.48	(.62)		
(3) Perceived risk	− .37	− .04	(.53)	
(4) Price consciousness	.45	− .33	.01	(.59)

Numbers in parenthesis are the extracted variance

Table 6 Parameter estimates

	Poisson	Zero-inflated Poisson	
		Count	Zero-inflation
CONS	1.23 (.13)***	1.31 (.15)***	− 4.23 (2.18)**
INV	.09 (.06)	.04 (.03)	− .86 (.49)**
KNOW	.09 (.03)***	.06 (.03)**	− .20 (.32)
KNOW^2	.02 (.02)	.03 (.02)	.22 (.24)
PRISK	− .07 (.03)***	− .06 (.03)**	.03 (.31)
PCON	.01 (.03)	.07 (.03)***	− 1.19 (.60)**
USAGE	.05 (.03)**	.08 (.03)***	.43 (.29)
FEM	− .02 (.06)	− .01 (.06)	.11 (.68)
AGE	− .08 (.02)***	− .09 (.03)***	− .12 (.30)
MAR	.06 (.07)	.03 (.07)	− .77 (.76)
HOMEPC	.14 (.08)**	.17 (.08)**	1.04 (1.51)
HANDPHONE	.24 (.11)**	.25 (.12)**	− .18 (1.63)
SMARTPHONE	.18 (.07)***	.20 (.07)***	.69 (.79)
TABLET	.17 (.08)**	.15 (.08)**	− .45 (1.29)
AIC	3029	2950	
RMSE	21.26	14.87	
Vuong statistic		2.98	

Standard errors are in parentheses

*** $p < .01$, ** $p < .05$, * $p < .1$

probability of being a showroomer. The estimate of price consciousness is also significant, with the expected negative sign ($\gamma_5 = -1.19$, $p < .05$). This supports H4a, which implies that the probability of showrooming is greater for the consumer who attaches a higher importance to price. However, the effects of prior knowledge, perceived risk, Internet usage, access device usage, and demographic variables appear to be insignificant.

In the count model, we discover that prior knowledge is both positive and significant ($\beta_2 = 0.06$, $p < .05$). However, this is not the case for its squared value, which was expected to have a negative sign ($\beta_3 = 0.03$, $p > .1$). This results in a rejection of H2b, implying that the inverted U-shaped effect of prior knowledge is not observed, as showrooming frequency increases with prior knowledge. The estimate of perceived risk is significant and negative ($\beta_4 = -0.06$, $p < .05$). Thus, H3b is supported, and we confirm that consumers who perceive high risks in online shopping tend to showroom less frequently than those who trust online retailers.

As in the zero-inflation model, price consciousness also appears to have a significant effect in count model ($\beta_5 = 0.07$, $p < .01$), which supports H4b and suggests that price-conscious consumers are more likely to be frequent showroomers than those who are less price-conscious. Further, the estimate for Internet usage is significant, with the anticipated sign ($\beta_6 = 0.08$, $p < .01$). Therefore, H5b is supported, and we conclude that consumers with more Internet experience tend to showroom more frequently than those with less experience.

While demographic variables are not significant in explaining the differences between showroomers and non-showroomers, we discovered that age has a significant, negative effect in the count model ($\beta_8 = -0.09$, $p < .01$), thereby supporting H7b. Thus, we are convinced that younger consumers engage in showrooming more frequently than older consumers. Finally, we discovered that the estimates for focal Internet devices are all significant and positive, implying that consumers who use one of these tend to showroom more frequently than those who use other devices. It is noteworthy that the estimates for handheld and smartphones are greater than those of home PCs ($\beta_{11} = 0.025$ and $\beta_{12} = 0.20$ versus $\beta_{10} = 0.17$). However, this is not the case for tablets, with a slightly lower estimate ($\beta_{13} = 0.15$); thus, we conclude that H9b is only partially supported. Table 7 summarizes the hypothesis testing results.

8 Discussion and implications

The results reveal that the ZIP model outperforms the Poisson model in terms of goodness of fit and prediction ability, indicating that a fraction of participants are indeed non-showroomers. The count data reveals that among those with a zero count, approximately 32% are potential showroomers.[3] This further signifies that the proportion of non-showroomers accounts for only 6.98% of the total sample. The advantage of using a mixture model, such as the ZIP model, is that it allows us to infer whether a consumer is a showroomer. We argue in the proposed framework that this can be at least partially explained by individual characteristics. One key finding is that the level of involvement and price consciousness significantly affects showrooming probability. We find that a consumer with higher involvement has a greater probability of being a showroomer; such a consumer would attach great importance to a product and choose a brand from the category only after deep deliberation. Therefore, he or she would have greater motivation to gather product information at a store before making a purchase to decrease potential risk.

We further find that price consciousness also increases the probability that consumers engage in showrooming. Price-conscious consumers' low willingness to pay creates a greater intention to buy from online vendors that typically offer better prices or other financial benefits. Consequently, these consumers are likely to avoid purchasing at a store, even if they had made a trip to research a product. However, our empirical analysis in the zero-inflation model reveals no significant effects of prior knowledge, perceived risks, Internet usage, access device usage, and demographic variables.

The count model results reveal that prior knowledge impacts showrooming frequency, although differently from what was earlier anticipated. While we assumed the effect to be an inverted U-shape, the estimates indicate this is an increasing function. We posit this results from the fact that the participants have

[3] This can be calculated using Eq. (5).

Table 7 Summary of hypothesis testing results

Hypothesis	Outcome	Determinant	Expected effect	Result
1a	Showrooming probability	Involvement	Positive	Supported
1b	Showrooming frequency	Involvement	Positive	Not supported
2a	Showrooming probability	Prior Knowledge	Inverted U- shape	Not supported
2b	Showrooming frequency	Prior Knowledge	Inverted U-shape	Not supported
3a	Showrooming probability	Perceived risk	Negative	Not supported
3b	Showrooming frequency	Perceived risk	Negative	Supported
4a	Showrooming probability	Price consciousness	Positive	Supported
4b	Showrooming frequency	Price consciousness	Positive	Supported
5a	Showrooming probability	Internet usage	Positive	Not supported
5b	Showrooming frequency	Internet usage	Positive	Supported
6a	Showrooming probability	Gender (female)	Positive	Not supported
6b	Showrooming frequency	Gender (female)	Positive	Not supported
7a	Showrooming probability	Age	Negative	Not supported
7b	Showrooming frequency	Age	Negative	Supported
8a	Showrooming probability	Marital status	Negative	Not supported
8b	Showrooming frequency	Marital status	Negative	Not supported
9a	Showrooming probability	Internet device	Positive effect of mobile device	Not supported
9b	Showrooming frequency	Internet device	Positive effect of mobile device	Partially supported

prior knowledge, ranging from low to moderate levels. Therefore, higher prior knowledge is associated with higher showrooming frequency. We also find that the perceived risks in online shopping can decrease showrooming frequency. This is consistent with prior studies, which suggest that the extent to which consumers perceive uncertainty on the Internet is negatively associated with their intention to buy from online stores [37, 38]. Thus, we conclude that consumers with higher perceived risks in online shopping are less likely to become frequent showroomers.

Another noteworthy finding is that price consciousness appears to have a significant effect on showrooming probability as well as frequency. Therefore, a threshold along the variable continuum seems to separate showroomers and non-showroomers. A larger price consciousness beyond this threshold implies a larger probability of consumers becoming frequent showroomers. Further, Internet usage is also found to influence the extent of showrooming behavior, as showroomers who spend more time using the Internet tend to showroom more frequently. As aforementioned, this may be because the Internet experience is associated with a greater ability to perform tasks when purchasing online, or with the utilization of some tools that can help in buying decisions. Additionally, we discovered that age is the only demographic variable with a significant effect, and this result suggests that showrooming frequency is negatively associated with this variable. Thus, a retailer may anticipate that frequent showroomers are primarily younger customers.

We also find that consumers using mobile devices tend to showroom more frequently than those who use other types of devices. It is noteworthy that handheld phone users are most likely to be frequent showroomers, followed by smartphone users. We interpret this as typical of the Japanese market, in which handheld phone users still comprise a large share of the market despite smartphones' rapid penetration. In fact, many manufacturers still recognize an attractive handheld phone market, and have recently introduced new products with functional features common in smartphones. However, we find tablets have no greater effect than home PCs, which indicates that using such devices is less common than other mobile devices.

This study indicates that individual differences can be used to explain consumer heterogeneity in showrooming behavior. It derives some findings useful in identifying potential showroomers, and is particularly important for retailers who wish to annul the negative effects of showrooming. As retailers typically do not observe showrooming, it is difficult for them to identify customers who would potentially engage in such behavior. It would be more difficult for the same reason to distinguish occasional and frequent showroomers, which creates an issue regarding the manner in which retailers should strategize to combat showrooming. Implementing a strategy that targets all customers, such as price matching, can be too costly and lead to decreased profits. Similarly, targeting random customers with a strategy is unlikely to be effective.

It is possible for a multi-channel retailer selling private-label brands to address showrooming by charging the same price across all channels. In this case, it does not matter whether consumers choose to buy the product online or offline, as the purchases all go to the same seller.[4] However, traditional retailers selling national brands are always threatened by small or medium-sized purely online sellers, which offer products at lower prices to attract consumers to the showroom. It would be arguably more effective if a retailer could discover a strategy to increase potential showroomers' store loyalty. One promising strategy involves increasing switching costs through cross-selling to the segment [5]. Additionally, a retailer may need to

[4] We thank an anonymous reviewer for pointing out this policy.

tailor their strategy when it comes to implementing with different types of customers, such as occasional versus frequent showroomers.

Our empirical results suggest that potential showroomers can be identified if we know some customer characteristics, as high-involvement and price-conscious customers have a higher probability of showrooming. Thus, knowing the levels of the two characteristics would help retailers better direct their strategies to combat showrooming. However, customer involvement information is not readily available in many cases, and a retailer may need to conduct surveys to collect relevant data. If retailers record their customers' purchasing history, price consciousness may be inferred from customers' responses to price changes. Further, this study also demonstrates that prior knowledge, perceived risk, price consciousness, Internet usage, age, and device usage can be used to identify whether a customer is an occasional or frequent showroomer.[5] Thus, given the information in these variables, retailers could customize strategies for different type of showroomers to improve their effectiveness. Demographic variables, such as customers' ages, can be immediately acquired from membership data, as many retailers have adopted loyalty programs. However, retailers should conduct additional surveys to collect information regarding other variables.

Recent developments in digital marketing have created new possibilities for the efficient collection of consumer information [68]. For example, a marketer may utilize online promotional tools, such as online contests or sweepstakes, which require consumers to provide relevant information or answer some profile-related questions to enter these contests or sweepstakes. Further, recent developments in information and telecommunications technology have enabled firms to customize their customer interactions, which can be useful in better targeting customers and preventing their showrooming behavior. For example, a major retailer in Japan has developed a mobile service application that allows the company to know whether a customer is visiting one of their stores. Thus, they can engage a customer visiting their store in real-time if they know the customer is a potential showroomer. This new technology, combined with accurate consumer data, should improve the effectiveness of strategies to decrease the losses from showrooming.

9 Conclusions

This study developed a framework to investigate the determinants of showrooming behavior. We focused on some individual characteristics that potentially affect whether and to what extent a consumer engages in showrooming. Based on literature regarding consumer search and online shopping behaviors, we built several hypotheses concerning the influences of our variables. We further empirically tested these hypotheses using data collected through an Internet survey to derive some important findings: (1) whether a consumer's engagement in

[5] This can be accomplished by using the expected showrooming frequency conditional on customer characteristics, or $E(y_i) = (1 - p_i)\lambda_i$. The small and large values of $E(y_i)$ correspond to occasional and frequent showroomers, respectively.

showrooming can be predicted from his or her levels of involvement and price consciousness; and (2) that the differences between occasional and frequent showroomers can be explained by the levels of prior knowledge, perceived risk, Internet usage, price consciousness, access device usage, and age.

These findings can provide a basis for appropriate customer segmentation and effective targeting to decrease the negative effects of showrooming, and can help retailers identify which customers tend to engage in showrooming. Further, these results allow retailers to identify occasional and frequent showroomers, and allow for the customization of a more feasible combat strategy. However, we also realize that this study has some limitations. First, we examined the framework only within the clothing category. Although we also anticipate similar results in other categories, additional investigation is needed to improve this study's generalizability. Second, the online survey is potentially subject to a selection bias, as participants are generally frequent Internet users. However, we can decrease this bias by, for example, conducting traditional survey methods with random sample designs.

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