

Stochastic Modelling and Computational Sciences

EXAMINING CONSUMER'S JOURNEYS VIA INFORMATIONAL TOUCHPOINTS: DIFFERENCES FOR THE TIME, PRODUCT GROUP AND GENDER

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ABSTRACT

Aim and Objective: *This study aims to investigate the variation in consumer journeys and the use of media/information touchpoints by male and female consumers across different product groups.*

Background: *Media planners seek to optimize touchpoints for effective consumer engagement. However, empirical research on channel planning across genders and products is limited. This study addresses this gap by analyzing touchpoint usage patterns in consumer journeys.*

Methods: *A self-response panel survey collected data from consumers on their use of media/information channels in the six months leading to a purchase. The analysis included mixed negative binomial regression and logistic regression to model touchpoint usage.*

Results: *Consumers use more touchpoints closer to purchase, with a peak in the 3-5 days and 1 week prior. Women generally use more touchpoints than men, especially near the purchase decision. High-involvement products see more touchpoint usage in the middle stages, while low-involvement products peak just before purchase.*

Conclusion: *Understanding the dynamic nature of consumer journeys and touchpoint usage helps media planners optimize strategies for different consumer segments and products.*

Keywords: *Consumer journey, media touchpoints, gender differences, high involvement products, low involvement products, media planning.*

INTRODUCTION

Media and other informational touchpoints that participate in the consumer journey on their path to purchase are of major interest to media planners and marketers: the ability to optimize touchpoints for frequency and synergy would save budgets and lead to more effective results. However, empirical research that would support channel planning across products and consumer groups, such as genders, is not substantial in academia. Although there is probably no expectation that any research would provide precise and stable over-time paths to purchase, general distributions and tendencies of touchpoints for different products over time, used by males and females and supported by additional insights would contribute to the knowledge of planners.

Before making the decision to purchase, consumers experience a certain path of interactions between themselves and product/brand-related touchpoints, known as the consumer journey or path to purchase (Srinivasan et al., 2016). Pre-purchase journeys differ in length, involvement, attention, and reliance on different channels depending on the product group. The task of a media planner is to resonate with the typical information usage patterns and direct the media, as long as control, towards the segment that is in a particular decision-making stage before purchasing effectively. For that reason, the planner needs to be backed up with empirical evidence of what information channels, or touchpoints, different consumer segments typically use for different product groups throughout the length of their journey.

In marketing communication, media channels and other informational touchpoints play in synergy (Li & Kannan, 2014). Very few media channels have the privilege to be directed towards consumers at the peak of the purchase decision and to be a single and key stimulus for the final purchase. Effective alignment of a number of media touchpoints over the entire consumer journey prior to the decision for the variety of consumer segments becomes

Stochastic Modelling and Computational Sciences

a sophisticated task. It is commonly acknowledged that consumers are subject to hierarchical advertising effects from attention to interest, desire, consideration, and the like prior to action (Barry, 2002). Early stages, with little attention and interest, could be classified as passive, whereas later stages before the purchase are active. The task of the advertiser is to move the consumer from the passive to the active stage and later to purchase (Belch & Belch, 2014). However, the activation of consumers' needs is not only the result of exposure to marketing communication. Personal relevance of the product or message, situational circumstances, and current needs determine attention toward marketing communication, and efforts to process the message are related to it (Celsi & Olson, 1988; Pratkanis & Greenwald, 1993). Thus, many factors play together, and the marketer appears in a chicken and egg situation when need and consideration go in line with advertising (and paying attention to it), synergizing with one another. Knowing which media or other informational touchpoints are spotted and considered more actively at particular stages of the consumer journey and using the channels that really play a role closer to purchase decision would support media planners' decision-making.

Media planners often face segmentation by gender. Even if product purchase and usage are not gender specific, media targeted towards genders could be evoked. Demographic (gender) data of media users is nearly the easiest to determine and forecast; therefore, empirical evidence about media/information touchpoints' usage among genders contributes to more effective media planning.

The aim of this research is to track how consumer journeys vary over time and how male and female consumers use media/information touchpoints (channels) throughout their journey prior to purchases for different product groups.

The self-response panel survey was used to collect the data: Consumers were asked to indicate the media/information channels they were using, planned to use, or had exposure to for different time slots, counting six months and more than six months backward to the purchase of the particular product.

MATERIALS AND METHODS

1. LITERATURE REVIEW

1.1. Consumer Journeys - The Mix Of Informational Touchpoints

The concept of consumer journey is widely used to explain and manage brand/product touchpoints consumers are exposed to throughout decision-making and purchase, sometimes followed by experiences during consumption and repetitive purchases. The notion that the overall consumer experience is a derivative of granulated experiences with separate touchpoints and their connections (Rawson et al., 2013) gained a lot of practical recognition. To manage consumer journeys, touchpoints are plotted in detail across consumer decision-making and consumption stages and analyzed alongside with relationship to consumer decision-making stages and thoughts, feelings, or actions (Richardson, 2010). Since it is possible to determine the frequency of particular touchpoints across different consumers and to estimate the impact of different exposures on purchase or overall experience, the attention of marketers is directed towards identifying, weighing, and managing (as long as possible) every consumer/brand touchpoint, followed by corresponding effort and investment distribution across touchpoints (Edelman & Singer, 2015).

Lemon, K. N., & Verhoef, P. C. (2016) classify touchpoints into brand-owned, partner-owned, customer-owned, and social/external/independent. Whereas brand-owned (advertising, webpage, merchandising, package, customer service systems, and the like) and partner-owned (e.g. distributor stores, affiliate website) are controllable and manageable, customer-owned (variety of consumption contexts and experiences during pre-purchase, purchase, and consumption) and social/external/independent (information provided by peers, opinion leaders, other consumers) are difficult to control and manage.

Media and information-related touchpoints demand a substantial marketing investment. They are effective need activation triggers and sources of information in the pre-purchase stages and are able to affect a consumer who is not yet in the active consideration stage (has not come to the store or company's website). Different channels of

Stochastic Modelling and Computational Sciences

media can address consumers who are indifferent to purchase-ready stages: mass media addresses target consumers for attention and interest, and more individually directed media, like dynamic ads, push consumers who already demonstrated interests further through the funnel. Although there is a certain level of blind shooting in planning mass media exposures, still, with current media accountability, certain channels allow comparatively good coverage of demographically or interest-wise segmented audiences.

Although there is a general agreement, that consumers' journey tracking is a complex issue, certain patterns should be distinguishable. Studies on consumer journeys are based on the acknowledgment that different stages or phases exist: in the broad sense, pre-purchase, purchase, and post-purchase phases are distinguished (Lemon & Verhoef, 2016), which could be broken into more detailed stages of purchase idea, brand consideration, brands' comparison, purchase, evaluation after purchase (Voorveld et al., 2016). The stages or phases happen during different time categories before purchase and are characteristic of different involvement and information usage. Just before the purchase, consumers could be classified as being in an active consideration stage. Since attention towards product-related issues is more directed, and higher personal relevance is likely, it could be assumed that consumers more actively search for information or pay more attention to it (Celsi & Olson, 1988; Pratkanis & Greenwald, 1993) in comparison to the passive stage. Prior to purchase, moments could be expected to have the most active consideration or the most active informational push that affected the purchase. Therefore, we propose that the amounts of touchpoints is different within different categories, and the total amount peaks toward the end of the consumer journey.

H1: Consumers use different amounts of touchpoints within different time categories.

H2: Consumers will use substantially more touchpoints closer to the decision of purchase.

Following the classification of partner, social, brand, and consumer-owned (Lemon & Verhoef, 2016) touchpoints, we hypothesize that amount of non-brand-owned touchpoints rises towards the end of the consumer journey since consumers are looking for more additional (sometimes - more objective and credible) sources to make a purchase decision. Since traditional advertising has a genetic feature of praising rhetoric that consumers usually recognize, as long as they recognize the information is paid (Kirkpatrick, 2007), consumers trust other sources more. It was reported that non-traditional media, like guerilla marketing, evoke higher consumer perceived value in comparison to traditional advertising (although results are brand dependent) (Dahlen et al., 2009), user-generated content receives high credibility among consumers (Fan et al., 2018).

H3: More non-brand owned touchpoints are used towards the purchase of the product.

Broadcasted media (or considered promotional) are internally paced delivery media, and audiences have very little control over the speed and timing of informational transfer (Dijkstra et al., 2005). This lack of control tends to put these promotional touchpoints at the beginning (4-6 months prior to purchase, 6 and more months prior to purchase) or middle (from 1 week to up to 1 month prior to purchase) of the consumer journey and since informational channels (like search, website and etc) have higher control of then they can be used, they are often used within last time categories prior purchase (end of consumer journey - purchase day, 1-2 days before purchase), thus hypothesis:

H4: Number of promotional touchpoints is higher in the middle of the consumer journey compared to the end and beginning of the consumer journey

1.2. Gender Differences in Information Collection and Processing

The discussion of whether males and females demonstrate differences or similarities in their behavior is extensive (Shibley, 2005; Meyers-Levy & Loken, 2015). Although there are arguments that gender differences are mainly attributable to physiological capabilities and behaviorally, there are far fewer differences than similarities (Shibley, 2005), also that notable differences are caused by gender identity and role attitude, not sex itself (Fisher, Arnold, 1994), several schools advocate for substantial differences in gender behavior. These are explored further in relation to reactions toward marketing communication or consumer behavior.

Stochastic Modelling and Computational Sciences

One substantial group of gender differences theories could be classified as biological, noting that gender differences are related not only to the reproductive system and the higher physical capabilities of the average male in comparison to the average female but also to brain and hormone activity (Hines, 2010).

A complementary explanation of gender differences is that evolutionary females elaborated more nurturing and caring behavior and were more likely to perform gathering jobs, whereas males were hunting, thus leading to different patterns of aggression, risk-taking, capacities of information collection, processing, and categorization, that historically would be necessary to produce different tasks (Meyers-Levy & Loken, 2015). In a similar manner, better abilities to complete certain tasks are explained through Social structural theory that claims that women were assigned different roles in comparison to men in the majority of world patriarchal structures (Eagly, Wood, 1999). However, it is difficult to delineate outcomes that became masculine or feminine due to social roles vs. the ones more often performed due to physical features (speed, strength, height).

According to the selectivity hypothesis (Meyers-Levy & Sternthal, 1991; Darley & Smith, 1995), which is derivative from evolutionary and biological theory, women, while processing information, look for more comprehensive and complete information sources, whereas men are much more selective, and rely on their (subjective) choices. Therefore, women collect more sources of information (or more pieces of information from one source), more rapidly, are more attentive to fragments or details even if some pieces of information have little relation with an issue, demonstrate a better recall (Heisz et al., 2013; Meyers-Levy & Loken, 2015). Males, on the contrary, select and store the most salient pieces of information, and use them more extensively as an internal source for decision-making instead of supporting the decision with additional data. This effect is explained via the higher information processing threshold males are assumed to have (Meyers-Levy & Loken, 2015), meaning the data has to be more noisy, more vivid, and more relevant to be noticed, processed, and stored for males if compared to females.

It is worth noticing that some gender differences, although documented empirically, so far have weak theoretical foundations (Meyers-Levy & Loken, 2015) or circulate around the above-mentioned theories of deeply rooted biological/social behavior. The examples are risk-related behavior, reaction to information sources, and object or context-related cues. Women react equally well to subjective and objective claims when product risks are low and give preference to objective claims when risk is increasing. However, men do not demonstrate this pattern (Darley & Smith, 1995). Females, in comparison to males, rely more on personal information to reduce risks (Garbarino & Strahilevitz, 2004), read more consumer reviews, or seek assistance before purchase, compared to males, especially for experience goods (Park et al., 2009), and demonstrate more directionally expressed reactions towards positive and negative online reviews (Bae & Lee, 2011). Evidence is provided that females react more extensively to a variety of cues, such as detecting meanings in the background music (Meyers-Levy & Zhu, 2010), and demonstrate better results when visual-spatial tasks are involved (Noseworthy et al., 2011).

Different types of media are constructed in a different manner due to the nature of the channel: printed media allows only two-dimensional portrayal; online can add sound to that; online and TV enables demonstrating video with sound; radio has only sound; personal references are based on information, etc. Paid vs. earned information channels, as well as brand-controlled vs. uncontrolled information channels, are believed to have different levels of objectivity by consumers: paid media has an inborn feature of puffery and excessive rhetoric of praising an item that is offered (Kirkpatrick, 2007), whereas earned or uncontrolled information is consumer generated or spreads due to media or peers recognition, therefore is trusted (Fans et al., 2018; Sengupta et al., 2014). Higher volumes of WOM lead to greater credibility (Yang et al., 2012). Thus, it could be assumed that consumers also are looking for more WOM to get credible information.

Since women collect and rely on more types and sources of information and process the variety of cues more extensively, that leads to the assumption that they should use more information touch points throughout the consumer journey in comparison to men. Moreover, towards the end of the path to purchase, when personal

Stochastic Modelling and Computational Sciences

relevance, as well as risks peak, the number of women's used touchpoints should peak more sharply. The following hypotheses are raised:

H5. Women will use more touchpoints throughout consumer journey in general if compared to men.

H6. Women ratio of used touchpoints will be significantly higher than men in closer to purchase time categories

1.3. Consumer Journey Differences for Different Product Groups

Products are different for consumers in the aspect of involvement, meaning how important the product is to their life or at the moment of purchase decision (Zaichkowsky, 1994). Although involvement in the product category is a personal domain, on the basis of typical consumer behavior, products can be classified across high and low-involvement dimensions into meaningful groups and are referred to as high or low-involvement products (Vaughn, 1986). Whenever the product belongs to an involvement group, more effort will be put into collecting and processing information about it (Petty et al., 1983; Voorveld et al., 2012), including an increasing number of sources consumers use before the decision (Beatty & Smith, 1987). Since for high-involvement products, the lengthier and more consistent considerations are likely, it could be expected that higher amounts of used informational touchpoints will be used a bit earlier before the purchase decision (middle of consumer journey) if compared to low-involvement products. On the contrary, for low-involvement products, the number of touchpoints should peak towards the very end of the consumer journey since little pre-early research and time are necessary before the decision-making. Thus:

H7: Consumers use more touchpoints when buying high-involvement products in the middle of the consumer journey when compared to low-involvement products.

1.4. The Difference in Touchpoint Usage Between Purchasers and Non-Purchasers of a Product

A number of current purchase decisions are continuations or derivatives of previous purchase decisions. Whenever the product was purchased before, and especially if the choice resulted in satisfaction, the consumer journey is likely to take the form of a loop, leading to repetitive decisions (Court et al., 2009). Since the consumer is familiar with the product and perceives less risk (Mitchell & Greatorex, 1993), he/she can substantially improve information search and usage efficiency by using the same touchpoints/ channels (Gensler et al., 2012), by lowering the number of the touchpoints used during the next path to purchase (Dholakia and etc. 2010). The effect of the lower number of touchpoints used for familiar products could also be related to survival bias (Wald, 1980), a behavioral feature of humans to recall and evaluate those events (cues, tasks) that led to more successful results. Whenever certain touchpoints are recalled as leading towards the purchase, others are ignored (forgotten), even if they objectively participated in previous consumer journeys. However, looking into the future, non-purchasers are dealing with unfamiliar (thus, likely, riskier) products and list more reasonable sources they would consult prior to purchase. Thus, the hypothesis is formulated:

H8: Consumers who have purchased the product before will report less touchpoints used in their consumer journeys than those who have not purchased the product.

2. RESEARCH METHODOLOGY

2.1. Research Design

Prior to conducting a consumer survey about the touchpoints, they use over time for different products, seven experts from top media agencies in Lithuania and the Lithuanian Marketing Association were asked to identify, review, and approve the list of potential touchpoints, products, and time categories prior to purchase that would compose the framework for tracking consumer journeys. The initial list of informational touchpoints was adapted from Voorveld et al. (2016) and, after reviewing for synonyms, finalized to 29 (the full list of selected informational touchpoints is provided in Appendix A). They were classified into informational (10) and promotional (19) and additionally classified by ownership: brand-owned (17), consumer-owned (2), partner-owned (2), and social-owned (8).

Stochastic Modelling and Computational Sciences

Product selection was based on the top advertised product groups in Lithuania (Kantar TNS, 2017) and validated by the same expert panel as common products representing different product and service categories in high and low involvement. In total, 13 product groups were tracked, 9 of which were classified as high-involvement products and 4 as low-involvement products (a full list of selected product group classifications is provided in Appendix A).

It was assumed that consumer journey prior to purchase could be reasonably tracked backwards up to around six months. The time categories were counted backward and proposed and approved by the same expert panel. 9-time categories prior to purchase deliberately were not equalized across the journey. Rather, they represent the typical way of consumer thinking when counting backward, with the longest periods towards the beginning of the assumed journey, since as memory decays, precise identifications of events in detailed time become complicated. Namely, the time slots included: day of purchase (*0d*), 1-2 days before the purchase (1-2d), 3-5 days before the purchase (*3-5d*), week before purchase (*1w*), 2-3 weeks before the purchase (2-3w), month before purchase (1m), 2-3 months before the purchase (2-3m), 4-6 months before the purchase (4-6m), more than 6 months before the purchase (*6m+*). Although there is no possibility to determine in advance how long the journey for a particular product category lasts, we assumed that if the journey lasts shorter than six months, that would be tracked by a low or nil number of touchpoints in earlier time slots. There were “empty” intervals between the time categories prior purchase, however, such perceptual thresholds when people jump from daily to weekly to monthly estimates are reasonable to assume.

Further, internet panel was used for consumer survey. Fieldwork took place in Lithuania during May 2017 and was conducted by Norstat, one of the top online research agencies. The panel was controlled to achieve the sample that represents Lithuanian population for crucial socio demographics for people of 18 years and older. A total of 503 respondents (53.7 percent female, Mage = 45.08, SDage = 15.35) completed the online questionnaire.

2.2. Research Instrument

Further, to avoid a lengthy process and fatigue, random rotation was used, exposing respondents only to 10 products out of 15. For each product, they had to identify whether they had purchased the product within the last 6 months. Depending on an answer, the question was about actual behavior (what touchpoints consumers actually have used) or the assumed behavior (“Imagine that you would be going to purchase the product”). Further, for each product, all touch points were presented on the time slot matrix form, where respondents had to select in which time categories specific touchpoints were or would be used. This design allowed to build array of consumer journeys based on time, product group and exact usage of touchpoints. All analyses are performed on the consumer journey level.

RESULTS

1. Outlier elimination and data restructuring

Several characteristic outliers were spotted and eliminated on these principles: journeys with less than 3-time intervals were removed (most of the cases - not filling out the questionnaire properly), and 3 failed respondents were removed (marked all questions with the same answer, even with contradicting questions). Statistical elimination, in this case, was not possible due to data being zero-inflated and count data. The final database consisted of answers from 418 remaining respondents.

2. Consumer Journeys Matrixes (GTT and GTA) and Method of Analysis

After treating for outliers, consumer matrixes were built to represent individual journeys for consumer and product. In total 43 875 journeys were built and GTT matrixes were drawn (*GTT: IDxPRODUCT GROUPxTIME CATEGORYxTOUCHPOINT*). Also, for different time slots, we counted the absolute number of touchpoints, and arrived to 12,188 matrixes (*GTA: IDxPRODUCT GROUPxTIME CATEGORYxTOUCHPOINT AMOUNT*).

Every product group in GTT type matrixes categorized by involvement level (High, freq: 0,763, high, freq=0,736, n(GTT)=43.875). For informational touchpoints - two types of categories created: informational type (promo,

Stochastic Modelling and Computational Sciences

freq: 0.742, information : freq = 0.258) and by touchpoint ownership (brand owned, freq = 0.181, consumer owned, freq=0.0542; partner owned, freq=0.545; social owned, freq=0.219).

Further, total touchpoints' counts within specific time categories or share/ratios of specific touchpoints types within time categories were analyzed. Since count data is discrete, non-normal, and over-dispersed, we model these consumer journeys (Hoef & Boveng, 2007) with negative binomial regression (data following negative binomial distribution). Since every count is correlated among the respondents, the design of the generalized linear mixed-effects model (GLMM) for the negative binomial family is applied, controlling the correlation between the same respondents' answers (Sung et, 2018). This approach, when transformed, gives significant ratio differences between reference groups. For ratio/shares data, three different processes are happening - ratios between (0,1) follow Beta regression (Kieschnick et, 2003), and two logistic regressions (Smithson & Verkuilen, 2006), which define 1, 0 ratios (0 - meaning none of the specific category of touchpoints used, 1 - all of the touchpoints used is from this category).

3. Hypotheses Testing

First, the general distribution of touchpoints across all time slots was tracked. In general, touchpoints are not frequent for the particular product in particular time slot. A mixed (to control for correlation within same respondent journeys) negative binomial regression model was conducted for count outcomes (GTA matrixes used) to account for the high overdispersion present in the data. Medians for different time slots report 0-2 touch points used, however, high standard deviation and higher means explain differences for products. Having in mind that consumers could select from list of 29 touchpoints, the results demonstrate comparatively low numbers of touchpoints used, with the most intensive periods being 3-5 days and 1 week prior to purchase.

Amount of different touchpoints varies among different time categories (Mdn(0d)=1, SD(0d)=3.89, M(0d)=2.26; Mdn(1-2d)=1, SD(1-2d)=4.60 M(1-2d)=3.29; Mdn(3-5d)=2, SD(3-5d)=4.35 M(3-5d)=3.82 Mdn(1w)=2, SD(1w)=4.02 M(1w)=3.64; Mdn(2-3w)=2, SD(2-3w)=3.59 M(2-3w)=2.86; Mdn(1m)=1, SD(1m)=3.66 M(1m)=2.43; Mdn(2-3m)=0, SD(2-3m)=2.65 M(2-3m)=1.36; Mdn(4-6m)=0, SD(4-6m)=2.04 M(4-6m)=0.865; Mdn(6m+)=0, SD(6m+)=2.32 M(6m+)=0.818). Time category is significant predictor for the amount of the **touchpoints** $\chi^2(df = 8) = 2345.88, p < 2.2e-16$. H1 is confirmed: number of touchpoints are significantly different within time intervals.

Further, day of purchase taken as a reference point "0d", and log transform-regression coefficients to get ratios between different time categories prior to purchase: Categories "1-2d": ratio - 1.4938510, "3-5d": ratio - 1.7531799, "1w": 1.6591300, "2-3w": 1.2542237 compared to "1m": 1.0324100, "2-3m": 0.5474519, "4-6m": 0.3428399, "6m+": 0.3253787. The ratio results closer to purchase are much higher than 1, and represent the same trend: the most intensive periods of touchpoints usage are 3-5 days and 1 week prior to purchase, 1-2 days prior are a bit less intensive. Early periods are passive. H2 is confirmed: Consumers use more touch points closer to purchase.

A comparison of brand and nonbrand owned (social and consumer-owned) touch points usage across the journey was made. Social and consumer-owned touchpoints versus total ratio was modeled with combination of Beta-regression (time category was significant F (df = 8) = 15.522, p<0.0001) and logistic binomial regression for **ratio=1 (time: $\chi^2(df = 8) = 273.04, p < 2.2e-16$) and ratio=0 (time: $\chi^2(df = 8) = 395.85, p < 2.2e-16$)**. Results indicate significant differences with time categories "0d" and "1-2d" (ratio: 0d: 0.5117618; 1-2d: 0.4558810; 1w:0.4283706; 2-3w:0.4219757; 1m:0.4147924, 2-3m:0.4405991 ; 4-6m:0.440872; 6m+:0.4234110), thus more non-brand owned touchpoints are used towards the purchase of the product. H3 is confirmed (see table 1).

Promotional versus total touchpoint ratio was modeled with combination of Beta-regression (time category was **significant $\chi^2(df = 8) = 17.039, p < 0.0001$) and logistic binomial regression for ratio=1 (time: $\chi^2(df = 8) = 397.07, p < 2.2e-16$) and ratio=0 (time: $\chi^2(df = 8) = 277.45, p < 2.2e-16$)**. Results indicate significant differences with time categories from "3-5d" to "1m" (ratio: 0d: 0.5009583; 1-2d: 0.5587726; 1w:0.5881212; 2-3w:0.5824757; 1m:0.5788975, 2-3m:0.5584630 ; 4-6m: 0.5639413; 6m+:0.5543273), thus more non-brand owned touchpoints

Stochastic Modelling and Computational Sciences

are used towards the purchase of the product. H4 is confirmed (see table 1): Number of promotional touchpoints is higher in the middle of the consumer journey compared to the end and start of the consumer journey.

Odds of promotional and non-brand touchpoints to reach 100% (ratio=1) or 0% (ratio=0), was modeled with logistic regressions and supports models defined above (see table1).

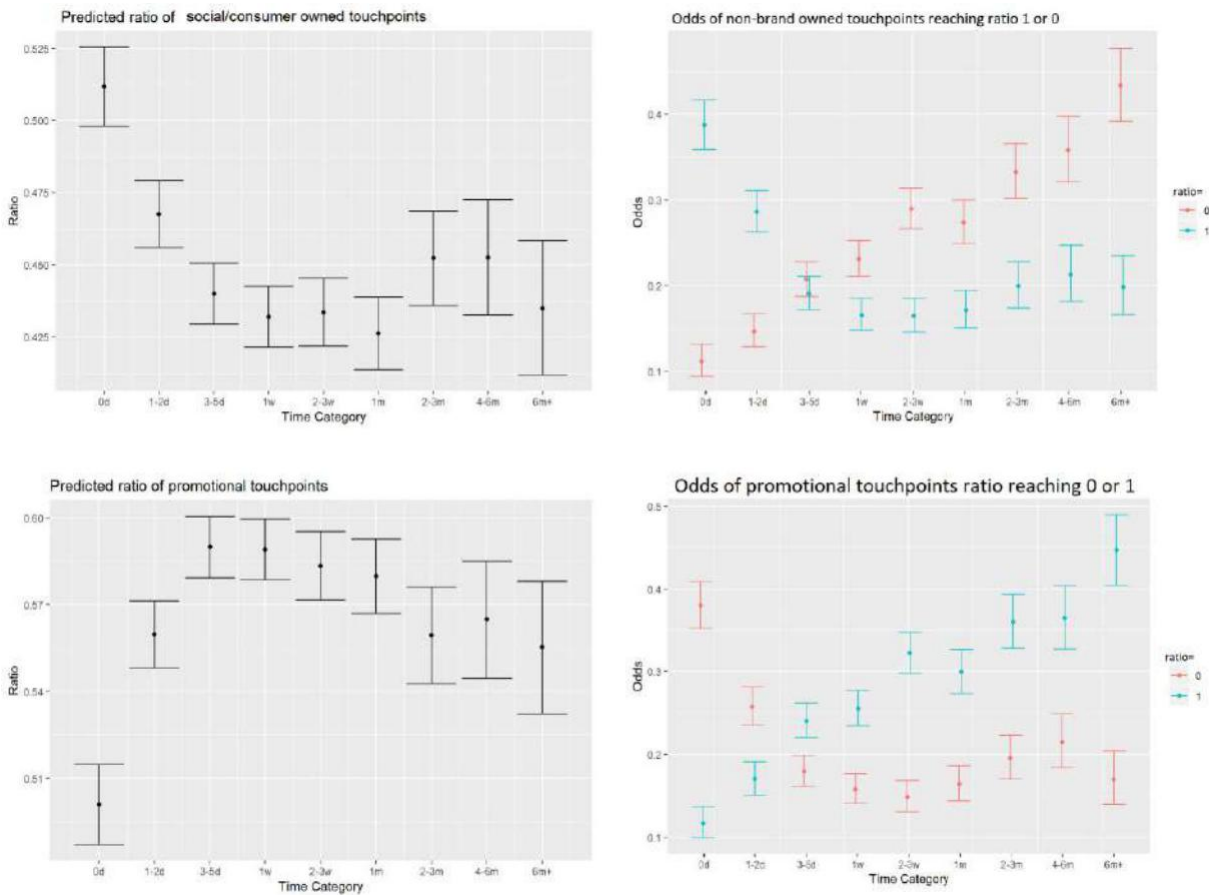


Table 1: Predicted share of promotional touch points within different time categories and share of social and consumer owned touchpoints.

Next, journeys were classified by gender and tested if gender have significant effect on total number of touchpoints used for consumer journey. Mixed negative binomial regression showed significant effects of gender ($\chi^2(df = 1) = 9.7994, p = 0.001746$) and interaction of genderxtime ($\chi^2(df = 8) = 53.1913, p = 9.903e-09$). We choose women as our reference category and model predicts that men to women total amount of touchpoint ratio is 0.7668770 ([0.6164144, 0.9540665] p=0.01), thus men use 76,69% touchpoints of total used by women - thus women will use 30,3% more touch points than men. H5 is confirmed.

Further, we take day of purchase as a reference point "0d" combined with "women" as reference category for ratio estimation and log transform-regression coefficients to get ratios between genderxtime ratios: time category's "1-2d": ratio - 1.1650048 ([0.9151426, 1.4830872] p=0.01), "3-5d": ratio - 1.4326402, "1w": 1.6701473, "2-3w": 1.5851589 compared to "1m": 1.3720853, "2-3m": 1.8010186, "4-6m": 1.4162804, "6m+": 1.3771997. . However, since overall touchpoint amount ratio for men is less than women (0.7668770 ([0.6164144, 0.9540665] p=0.01), men uses more less touchpoints in day of purchase ("0d") and 1-2 days prior

Stochastic Modelling and Computational Sciences

purchase (combined ratios: 0.7668770×1 day of purchase, $0.7668770 \times 1.1650048$) < 1 1-2 days prior purchase), only day of purchase has significant difference. H6 rejected.

Only in the day of the purchase women ratio of used touchpoints is significantly higher than men. (See predicted values for time slots and gender in Table 2).

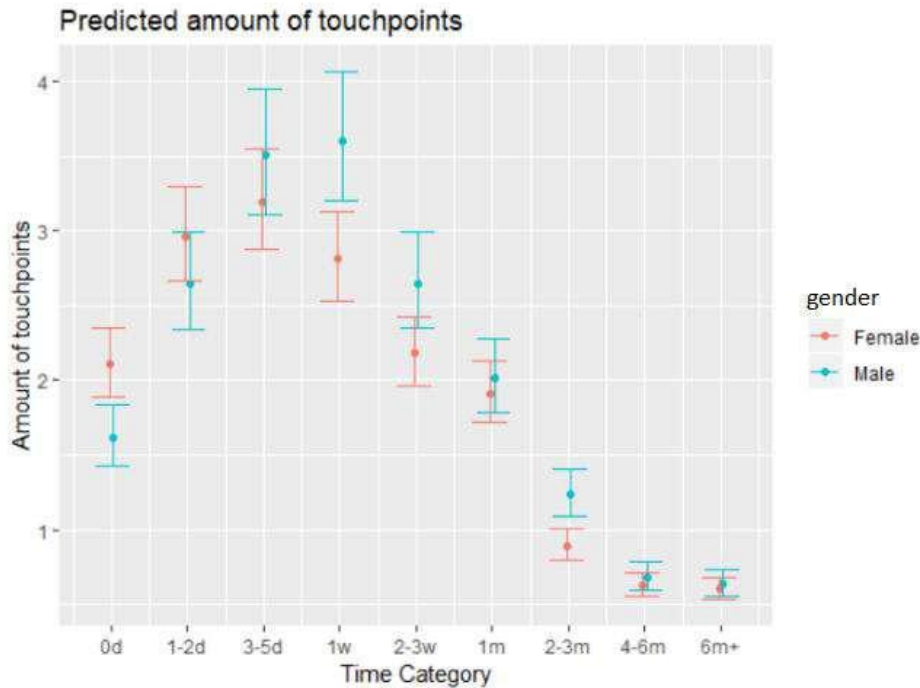


Table 2: Predicted amount of total touchpoints used by gender and time category/time slots.

Modeled consumer journeys were classified by product groups (n=13; food, dyi, mobile phones, internet, mobile services and etc. Mixed negative binomial regression on amount of touchpoints depending on the time category **and product group, showed that product groups are significant** ($\chi^2(df = 12) = 113.08, p < 2.2e-16$) in estimating overall amount of touchpoints. Interaction of **time and product group was also significant** ($\chi^2(df = 96) = 857.52, p < 2e-16$), proving that consumer journeys differ by product groups.

Products groups were classified as high and low involvement. It should be noted that group sizes were unbalanced, however, the applied methods account for uneven groups sizes. Product group type (high/low involvement) **was not significant in predicting amount of touchpoints** ($\chi^2(df = 1) = 2.9215, p=0.087408$), but interaction of time and product group type (high/low involvement) **was significant** ($\chi^2(df = 8) = 48.7069, p=7.235e-08$). Purchase day (“0d”), “high involvement” was chosen as a reference points. High-involvement and time ratios showed that from “3-5d” to “2-3m” categories ratio is less than one (“1-2d” ratio:1.0690533; “3-5d” ratio:0.8136021; “1w” ratio:0.6040558; “2-3w” ratio:0.5357009

“1m” ratio:0.7719614; “2-3m” ratio:0.8830060; “4-6m” ratio:1.0717774; “6m+” ratio: 0.8362189), thus H7 confirmed: consumers use more touchpoint when buying high-involvement products in the middle of the consumer journey , when compared to low involvement products.

For high involvement products, consumers in fact use more touchpoint in the middle of the path to purchase, however, for low involvement products, the amount of touchpoints peak towards the end of journey (see predicted values for time slots and product group type (high/low involvement) in Table 3).

Stochastic Modelling and Computational Sciences

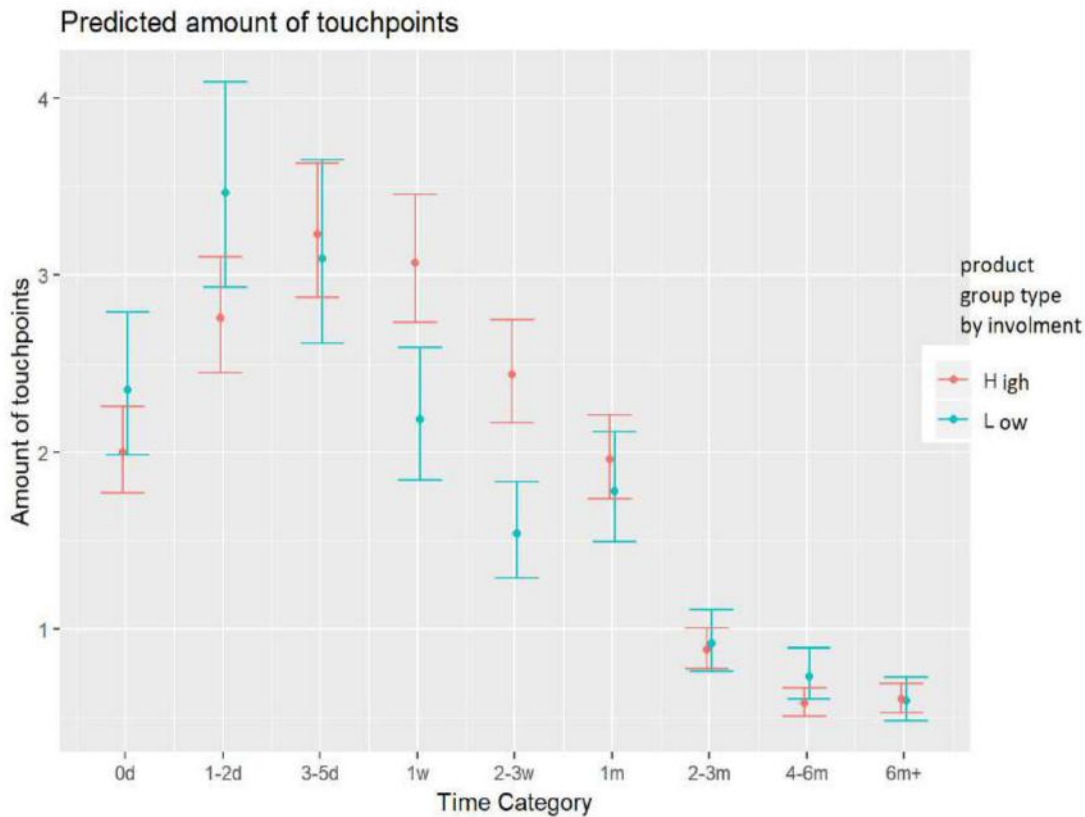


Table3: Predicted amount of total touchpoints used by product group involvement and time category.

In order to compare, whether purchasers vs. non purchasers report different number of touchpoints they use across journey, a mixed negative binomial regression (with controlling for correlation within journeys from the same consumer) on amount of informational touchpoints and (purchase/non-purchase) identified that people **significantly** ($\chi^2(df = 1) = 23.83, p = 1.052e-06$) tend to report less (ratio(purchased vs no-purchased): 0.8392723 [0.7651545 0.9205695] $p=0.01$) touchpoints if they purchased goods than intention based reported journeys. Thus, H8 is confirmed.

CONCLUSIONS AND DISCUSSION

The theory of consumer journey up till now offers more exploratory descriptions of processes behind it rather than theoretically well-grounded frameworks and tools (Lemon, K. N., & Verhoef, P. C., 2016). Nevertheless, the plethora of descriptive insights form a logical and conceptual totality, and when supported with empirical evidence, marketers can gain manageable tools for media planning and allocation. The different number of touchpoints within consumer journey in time categories demonstrate, that every time category in consumer journey should be addressed different as well as a certain pattern shift from brand owned and social owned channels. As predicted, consumer journeys differ over time with reaching peaks in number of used touchpoints in before the purchase for low involvement products, and a bit earlier (middle time slots) for high involvement products. This confirms that purchases funnels have to be analysed in integral manner and different attribution methods for different touchpoints should be implemented in order to understand real effects to decision for purchase.

This study proves that more social and consumer touchpoints are used towards the end of consumer journey. The findings do not eliminate promotional (brand owned) touchpoints: rather, they are used more frequently in the beginning and middle of the purchase journey, and, likely, push consumer from passive to more active phases.

Stochastic Modelling and Computational Sciences

Although the goal of research was not to estimate the effects of particular media, still, it is obvious that brand owned media has delayed effect. Thus, marketers should be patient with advertising results: they are likely to convert into purchase only after some time lag and interaction with non-brand owned stimuli. The complicated issue for marketers is identification, and, if possible, intervention into social or consumer owned touchpoints.

Males use more touchpoints in the middle periods of the journey, whereas women peak at the end of journey. To a certain extent, this is in line with selectivity hypothesis (Meyers Levy and Sternthal, 1991): men might be selecting touchpoints that they find meaningful comparatively early, and rely on them while making decision, whereas women, being more ignorant towards touchpoints in the middle of the journey, when approaching the final decision, collect more information from different sources to validate it. However, in general, gender is not a strong differentiator among touchpoints' usage.

Product category (high vs. low) is much stronger determinant of how much touchpoints will be used across the journey in general, and for particular stages. As expected, high involvement products demand for more informational touchpoints. Low involvement products are purchased using lower numbers of touchpoints. Interestingly, non purchasers (users) identify that they would use more touch points prior to purchasing products, what confirmatory for loyalty loop theory (Court et al., 2009).

Further research could look into the effect of particular combinations of touchpoints over the journey: does adding, removing, or exchanging particular touchpoints change consumer decisions to purchase? More detailed look could be made into the compositions of touchpoints' sets over the journey, for different products, time slots and genders.

REFERENCES

- Bae, Soonyong, and Taesik Lee. "Gender differences in consumers' perception of online consumer reviews." *Electronic Commerce Research* 11, 2 (2011): 201-214.
- Barry, Thomas E. "In defence of the hierarchy of effects: a rejoinder to Weilbacher." *Journal of Advertising Research* 42, 3 (2002): 44-47.
- Beatty, Sharon E., and Scott M. Smith. "External search effort: An investigation across several product categories." *Journal of consumer research* 14, 1 (1987): 83-95.
- Celsi, Richard L., and Jerry C. Olson. "The role of involvement in attention and comprehension processes." *Journal of consumer research* 15, 2 (1988): 210-224.
- Court, Davidd, Dave Elzinga, Susan Mulder, and Ole Jørgen Vetvik "The consumer decision journey." *McKinsey Quarterly*, (2009).
- Dahlén, Micael, Anton Granlund, and Mikael Grenros. "The consumer-perceived value of non-traditional media: effects of brand reputation, appropriateness and expense." *Journal of Consumer Marketing* 26, 3 (2009): 155-163.
- Darley, William K., and Robert E. Smith. "Gender differences in information processing strategies: An empirical test of the selectivity model in advertising response." *Journal of advertising* 24, 1 (1995): 41-56.
- Davis, Harry L., and Benny P. Rigaux. "Perception of marital roles in decision processes." *Journal of consumer Research* 1, 1 (1974): 51-62.
- Eagly, Alice H., and Wendy Wood. "The origins of sex differences in human behavior: Evolved dispositions versus social roles." *American psychologist* 54, 6 (1999): 408.
- Edelman, David C., and Marc Singer. "Competing on customer journeys." *Harvard Business Review* 93, 11 (2015): 88-100.

Stochastic Modelling and Computational Sciences

Fan, Alei, Han Shen, Laurie Wu, Anna S. Mattila, and Anil Bilgihan. "Whom do we trust? Cultural differences in consumer responses to online recommendations." *International Journal of Contemporary Hospitality Management* 30, 3 (2018): 1508-1525.

Fischer, Eileen, and Stephen J. Arnold. "Sex, gender identity, gender role attitudes, and consumer behavior." *Psychology & Marketing* 11, 2 (1994): 163-182.

Garbarino, Ellen, and Michal Strahilevitz. "Gender differences in the perceived risk of buying online and the effects of receiving a site recommendation." *Journal of Business Research* 57, 7 (2004): 768-775.

Gensler, Sonja, Peter C. Verhoef, and Martin Böhm. "Understanding consumers' multichannel choices across the different stages of the buying process." *Marketing Letters* 23, 4 (2012): 987-1003.

Heisz, Jennifer J., Molly M. Pottruff, and David I. Shore. "Females scan more than males: A potential mechanism for sex differences in recognition memory." *Psychological science* 24, 7 (2013): 1157-1163.

Hines, Melissa. "Sex-related variation in human behavior and the brain." *Trends in cognitive sciences* 14, 10 (2010): 448-456.

Hyde, Janet Shibley. "The gender similarities -hypothesis." *American psychologist* 60, 6 (2005): 581.

Hoef, Jay M. and Peter L. Boveng. "Quasi Poisson vs. negative binomial regression: how should we model overdispersed count data?." *Ecology* 88 (2007): 2766-2772.

Kantar TNS. "Overview of advertising volumes. Advertising monitoring. January-April 2017", tns.lt (2017). Retrieved from http://www.tns.lt/file/repository/Reklamos%20apimciu%20apzvalga_201701-04.pdf 05 04 2017

Kieschnick, Robert and Bruce D. McCullough. "Regression analysis of variates observed on (0, 1): percentages, proportions and fractions." *Statistical modelling* 3 (2003): 193-213.

Kirkpatrick, Jerry. "In Defense of Advertising Arguments From Reason, Ethical Egoism, and Laissez-Faire Capitalism." (1994). TLJ Books, Claremont. ISBN: 978-0-9787803-1-9.

Lemon, Katherine N., and Peter C. Verhoef. "Understanding customer experience throughout the customer journey." *Journal of Marketing* 80, 6 (2016): 69-96.

Li, Hongshuang, and P. K. Kannan. "Attributing conversions in a multichannel online marketing environment: An empirical model and a field experiment." *Journal of Marketing Research* 51, 1 (2014): 40-56.

Meyers-Levy, Joan, and Brian Sternthal. "Gender differences in the use of message cues and judgments." *Journal of marketing- research* (1991): 84-96.

Meyers Levy, Joan, and Rui Zhu. "Gender differences in the meanings consumers infer from music and other aesthetic stimuli." *Journal of Consumer Psychology* 20, 4 (2010): 495-507.

Mitchell, Vincent-Wayne, and Mike Grotorex. "Risk perception and reduction in the purchase of consumer services." *Service Industries Journal* 13, no. 4 (1993): 179-200.

Noseworthy, Theodore J., June Cotte, and Seung Hwan Lee. "The effects of ad context and gender on the identification of visually incongruent products." *Journal of Consumer Research* 38, 2 (2011): 358-375.

Park, Jooyoung, Yoesun Yoon, and Byungtae Lee. "The effect of gender and product categories on consumer online information search." *ACR North American Advances* (2009).

Petty, Richard E., John T. Cacioppo, and David Schumann. "Central and peripheral routes to advertising effectiveness: The moderating role of involvement." *Journal of consumer research* 10, 2 (1983): 135-146.

Stochastic Modelling and Computational Sciences

Pratkanis, Anthony R., and Anthony G. Greenwald-. "Consumer involvement, message attention, and the persistence of persuasive impact in a message dense environment." *Psychology & Marketing* 10, 4 (1993): 321-332.

Rawson, Alex, Ewan Duncan, and Conor Jones. "The truth about customer experience." *Harvard Business Review* 91, no. 9 (2013): 90-98.

Richardson, Adam. "Using customer journey maps to improve customer experience." *Harvard Business Review* 15, 1 (2010): 2-5.

Sengupta, Sanjit, and Hui-ming Deanna Wang. "Information sources and adoption of vaccine during pandemics." *International Journal of Pharmaceutical and Healthcare Marketing* 8, 4 (2014): 357-370.

Smithson, Michael and Jay Verkuilen. "A better lemon squeezer? Maximum-likelihood regression with beta-distributed dependent variables." *Psychological methods* 11 (2006): 54.

Srinivasan, Shuba, Oliver J. Rutz, and Koen Pauwels. "Paths to and off purchase: quantifying the impact of traditional marketing and online consumer activity." *Journal of the Academy of Marketing Science* 44, 4 (2016): 440-453.

Sung, Youkyung and Keunbaik Lee. "Negative binomial loglinear mixed models with general random effects covariance matrix." *Communications for Statistical Applications and Methods* 25 (2018): 61-70.

Vaughn, Richard. "How advertising works: A planning model revisited." *Journal of advertising research* 26, 1 (1986): 57-66.

Voorveld, Hilde AM, Edith G. Smit, Peter C. Neijens, and AE Fred Bronner. "Consumers' cross-channel use in online and offline purchases: An Analysis of Cross-Media And Cross-Channel Behaviors between Products." *Journal of Advertising Research* 56, 4 (2016): 385-400.

Voorveld, Hilde AM, Peter C. Neijens, and Edith G. Smit. "The interacting role of media sequence and product involvement in cross-media campaigns." *Journal of Marketing Communications* 18, 3 (2012): 203-216.

Wald, A. "A method of estimating plane vulnerability based on damage of survivors, CRC 432, July 1980." *Center for Naval Analyses* (1980).

Yang, Joonhyuk, Wonjoon Kim, Naveen Ambler, and Jaeseung Jeong. "The heterogeneous effect of WOM on product sales: why the effect of WOM valence is mixed?." *European Journal of Marketing* 46, 11/12 (2012): 1523-1538.

Zaichkowsky, Judith Lynne. "The personal involvement inventory: Reduction, revision, and application to advertising." *Journal of advertising* 23, no. 4 (1994): 59-70.

Stochastic Modelling and Computational Sciences

APENDIX A

Product groups and high/low involvement classification

Product group (13)	HIGH/LOW involvement
Food	Low involvement
Dyi	High involvement
mobile phones	High involvement
internet, mobile services	High involvement
Opticians	High involvement
clothes/shoes	Low involvement
Travel	High involvement
Cosmetics	Low involvement
Pharmacy	High involvement
leisure/entertainment	High involvement
Cars	High involvement
financial/insurance good	High involvement
lottery	Low involvement

Touchpoints and informational/promotional and classification by ownership type

Touchpoint (29)	Informational/promotional	Touchpoint ownership
Read online	informational	social owned
Use search engine	informational	social owned
Ad in news portal	promotional	brand owned
Read promo email	promotional	brand owned
Ad in social networks	promotional	brand owned
Discussion on social networks	informational	social owned
Recommendation by expert	informational	social owned
Discussed with family/friend	informational	consumer owned
Tried the product before buying	informational	consumer owned
Ad in print	promotional	brand owned
Printed material of the brand	promotional	brand owned
Ad in ooh	promotional	brand owned
Ad on/in public transport	promotional	brand owned
Direct mail ad/letter	promotional	brand owned
Ad in TV	promotional	brand owned
Ad in radio	promotional	brand owned
Consultant in the shop	informational	brand owned
Merchandising in the shop	promotional	brand owned
Mobile search	informational	social owned
Mobile sites	promotional	brand owned
Info via SMS	promotional	brand owned
Endorsement by celebrity	promotional	social owned
Ad in shopping print	promotional	brand owned
Product website	promotional	partner owned
Article in website	promotional	brand owned
Visited exposition	informational	partner owned
Telemarketing call	promotional	brand owned
Classified websites	promotional	social owned
Price comparison websites	informational	social owned