Empirical Studies in Consumer Shopping Journey: Two Essays Examining Consumer Information Search And Purchase

by

Meheli Basu

M.S. Electrical and Computer Engineering, University of Iowa, 2015

Submitted to the Graduate Faculty of the

Joseph M. Katz Graduate School of Business in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy

Marketing

University of Pittsburgh

2020

UNIVERSITY OF PITTSBURGH

JOSEPH M. KATZ GRADUATE SCHOOL OF BUSINESS

This dissertation was presented

by

Meheli Basu

It was defended on

February 25, 2020

and approved by

J. Jeffrey Inman, Associate Dean for Research and Faculty
& Albert Wesley Frey Professor of Marketing, Marketing

Vanitha Swaminathan, Thomas Marshall Professor of Marketing, Marketing

Kirk Wakefield, Edwin W. Streetman Professor of Retail Marketing, Baylor University

Hristina Nikolova, Diane Harkins Coughlin and Christopher J. Coughlin Sesquicentennial
Assistant Professor, Boston College

Mina Ameri, Assistant Professor of Business Administration, Marketing

Dissertation Advisor: J. Jeffrey Inman, Associate Dean for Research and Faculty
& Albert Wesley Frey Professor of Marketing, Marketing

Empirical Studies in Consumer Shopping Journey: Two Essays Examining Consumer Information Search And Purchase

Meheli Basu, PhD

University of Pittsburgh, 2020

This dissertation is directed toward understanding shoppers' search and purchase processes in both online and offline domains. The first essay in my dissertation examines shoppers' online omni-channel path to purchase. The second essay analyzes shoppers' search and purchase in an offline grocery store.

In essay 1, I study search and purchase behavior in the digital domain. I examine conversion rates on mobile versus desktop for deadline driven purchases (viz., event tickets) to see how the consumer's choice of device in the digital path to purchase, influences conversion rates. The path from start to finish is mapped by using browsing and transaction data provided by StubHub and by applying econometric modeling, I study the impact of device switching vs single device use and interaction of device choice with time to event to determine purchase outcomes. The results show that the conversion rate for a PC-only web path is significantly higher than a mobile only path. Purchase likelihood significantly decreases with device switching and is higher for PC-to-mobile switching than for the reverse. In studying the interaction between time-to-event from initial search and device used, initial search on a mobile device results in a lower probability of purchase for distant consumption. Experimental results show that search inconvenience associated with mobile use outweighs purchase risk concerns to impede purchase on mobile.

In essay 2, I study shoppers' sensitivity to nutritional promotions and consequent purchase in the offline domain. This research examines how shopper reaction to nutritional information in retailer promotions impact sales. By analyzing frequent shopper data for 40,000 shoppers during a twenty-seven month period, provided by a regional supermarket chain, this research examines whether sensitivity toward price promotions is affected by heightening the salience of nutritional information via featuring nutrition promotions in the grocery chain's weekly circular. The central hypothesis is that product level sales is improved by featuring nutrition promotions. Importantly, this research investigates the spill-over effects of nutrition promotions on sales of other products in the same category and the sales of products in a different category. The moderating effects of shopper characteristics (nutrition consciousness and share-of-wallet) and category characteristics (higher vs lower nutrition category) on the effect of nutrition promotion on sales are further studied. Simply adding nutritional information in the price promotion circulars is found to lead to additional increase in weekly product level and category sales. Interestingly, shoppers with higher nutrition consciousness and lower spending at the retailer store react more positively to nutrition promotions. Results also indicate that nutritional information display improves sales more, when featured in lower nutrition categories.

THIS DISSERTATION IS DEDICATED TO MY FAMILY

Table of Contents

List of Tables

List of Figures

ACKNOWLEDGMENTS

I'd like to first thank my advisor and dissertation committee members. I am beyond grateful to my advisor Dr. Jeff Inman for his relentless patience and guidance through the past years. Jeff, thank you for supporting, encouraging and teaching me so much about the exciting field of consumer analytics and marketing research. You are an inspiration and I'm so thankful to have had you as a teacher, mentor, and friend. I could not have asked for anything more and look forward to continuing working together in the future. Thank you, Dr. Kirk Wakefield, for being an amazing co-author. You are a wonderful teacher, mentor, and a friend and I am so grateful for the generosity you have shown me. I look forward to our continued research collaborations and I hope to learn much more from you in the coming years. Thank you Dr. Hristina Nikolova, for your patience and encouragement through our research collaboration. I have learnt so much from you over the course of the last year and hope to imbibe the principles of rigor, tenacity and honesty toward work, from you. Thank you Dr. Vanitha Swaminathan for opening up my mind toward numerous research directions through your seminar, which was the best part of my semester that year. Thank you for your words of encouragement, they have meant the world to me. Thank you Dr. Mina Ameri, for your tremendous help and encouragement, last year. I would also like to thank all faculty members of the marketing faculty at Katz who have helped me grow through the past years and achieve however much I have through these years as a doctoral student in Marketing. Thank you, Dr. Jennifer Shang and Dr. G.G. Hegde for being my first mentors in the first year of my doctoral studies. Thank you Carrie Woods and Dr. Dennis Galletta and all members of the doctoral office for being so friendly and helpful throughout this journey. Your words of reassurance have always calmed me in times of uncertainties. I would also like to thank all doctoral candidates at Katz for being such good friends and helping me make memories in the past years.

On a personal front, I thank my parents for being my first teachers, my first friends and my first mentors in life. You have taught me to dream and given me the wings to live my dreams. I thank my brother for the unconditional love and support and the necessary occasional grounding to help me stay focused. I thank my in-laws for their continued support and for being a second family to me. I thank my roommates and friends for being the calm in my hours of stress and doubt and for the countless conversations on life, PhD and feminism over coffee.

And last but not least, my dear husband, Dr. Aniruddha Dutta, thank you for being my rock, my best friend, my partner, and my inspiration. I could not have done it without you, and I count my blessings every day for having you in my life.

1.0 Introduction

I have always been intrigued by real-world problems and have delved into research areas where I can use quantitative models to generate practical actionable marketing insights. My research is directed toward understanding shoppers' search and purchase processes in both online and offline domains. To that end, my dissertation looks at how shoppers search and discern information in their purchase path. With the evolving nature of technology, advent of big data and their profound impact on business managers, looking at managerial problems with a quantitative marketing lens can improve informed decision-making. Using econometrics, optimization techniques, machine learning and marketing models, both my dissertation essays analyze real world data from companies to understand the path to purchase of consumers. In doing so, my research implies high external validity, by rigorously analyzing about 1M online user sessions on a digital ticket exchange and resale website and about 6M shopper transactions at an offline retail store. My dissertation lies at the intersection of three research domains: digital and mobile marketing, consumer analytics and shopper's purchase journey.

My first dissertation essay titled "The Impact of Device used in Digital Paths on Deadline-Driven Purchase Decisions" studies search and purchase behavior for deadline-driven online purchases. Organizations dedicate resources to improve the mobile-shopping experience but know little of how the use of a mobile device alters shopper behavior compared to desktops. This research examines conversion rates on mobile versus desktop for deadline driven purchases (viz., event tickets) to see how the shopper's choice of device in the digital path to purchase influences conversion rates. Xu et al. (2017) and Haan et al. (2018) compare paths of users who switched between device types but do not compare device switching paths with single device users due to their data constraints. This research does, on the other hand, compare paths and conversion rates for single device use vs device switching. This paper has important theoretical contributions to the online customer journey literature. To my knowledge, this is the first paper that studies device switching behavior in deadline-driven online shopping, in context of a real-world search mapped to actual purchases on one of the world's largest online ticket exchange websites. Deadline plays a very important role when purchasing entertainment tickets as games and other similar event tickets have a fixed time for consumption and as such, the decision to make a purchase is very strictly driven by a deadline.

This research, supported by a Marketing Science Institute grant, maps shopper path from start to finish by using browsing and transaction data provided by StubHub and by applying econometric modeling, I study the impact of device switching vs single device use to determine purchase outcomes. The device switching pattern and subsequent purchase probability is hypothesized to be different for deadline-driven purchases than other type of online purchases. The results show that the conversion rate for a PC-only web path is significantly higher than a path involving only a mobile device. Purchase likelihood significantly decreases with device switching. Contrary to the findings by Haan et al. (2018), this study finds purchase rates are higher for PC-to-mobile switching than for the reverse. Additionally, experiment results show that search cost associated with mobile use outweighs purchase risk concerns to impede the shopper journey toward purchase. However, device switching leads to higher sales volume when a purchase is made, presenting a trade-off to online retailers between conversion rate and sales volume. The most significant managerial implication is to motivate single-screen (same device) user sessions for deadline-driven shopping as sessions completed on the same device are shown to be associated with higher purchase likelihood than those involving device switching.

My second dissertation essay titled, “The Impact of Heightening Simplified Nutritional Information on Shoppers’ Sensitivity to Price Promotions” studies shoppers’ sensitivity to nutrition promotions (defined as the display of a summary nutritional score (NuVal score) next to a product featured in the grocery chain’s weekly circular), and consequent purchase in the offline domain after the NuVal score system has been in effect for some time. Grocery retailers play a key role in the fight against the social epidemic of obesity by offering diverse health and wellness programs at the point of sale. While prior research has contributed significant insights into the success of such programs in promoting healthy choices, their impact on retailers' sales is still not fully understood. This is precisely the objective of this research – to examine how shopper reaction to nutritional information in retailer promotions impact sales. The goal in this study is to examine whether sensitivity toward price promotions is affected by heightening the salience of nutrition information via featuring nutritional promotions in a retailer’s weekly flyers.

By analyzing 6.1M shopper transactions, using frequent shopper data for more than 40,000 shoppers during a twenty seven-month period, provided by a regional grocery chain, this research examines if heightening the salience of nutritional information by featuring nutrition promotions in the grocery chain’s weekly circular improves the sales of products. Importantly, this research investigates the moderating effects of shopper characteristics (nutrition consciousness and share-of-wallet) and product characteristics (high or low nutrition products) on nutrition promotion sensitivities. Applying a hierarchical linear model on sales of products nested within four product categories: meat, seafood, produce and bakery, this is the first nutrition research to show that nutrition promotions have a positive spill-over effect on sales in the category, i.e., they increase product sales in the category promoted. Additionally, nutrition promotions are more effective in lower nutrition categories. Interestingly, nutrition promotions improve sales more for light shoppers, as well as those with high nutrition consciousness. The spill-over effects of cross-category promotions are overall negative.

These results are also supported by implementing a neural network on the imbalanced data set, and the non-parametric sensitivity analysis reveals that interactions of shopper's average monthly spending with both product level and category level nutrition promotions are more significant than the interactions of nutrition consciousness with either product or category level nutrition promotions. This research has important practical implications for grocery retailers. Since, grocery retailers are always putting out product promotions, a simple act of just putting out nutritional information for at least the healthier products in the category brings attention to the entire category and can help improve sales of not only individual products in the category but also the overall sales of all products in the given category. Such a practice presents novel information to the shoppers regarding relative nutritional information of the product as well as perceived nutritional quality of similar products in the category.

Consumer targeting can also be effective when mailing out product promotions selectively. Especially mailing product promotion flyers with nutritional information to shoppers with lower average monthly spending at the retail store can grab attention of such shoppers because of novelty of the information and can help convert more purchases from this class of shoppers. Also, it is important that shoppers with more nutrition consciousness be reached out with NuVal scores featured on product promotions because this group of shoppers seek out nutrition information more actively from others.

2.0 ESSAY 1: THE IMPACT OF DEVICE USED IN DIGITAL PATHS ON DEADLINE-DRIVEN PURCHASE DECISIONS

Organizations design mobile apps and pages optimized for mobile but know little of how the use of a mobile device alters behavior compared to desktops. Marketers dedicate resources to minimize search effort given mobile device limitations and then promote mobile channels with high acquisition costs per install, registration and in-app purchases. The question: Is it worth it to push traffic to mobile? This research examines conversion rates on mobile versus desktop for deadline driven purchases (viz., event tickets) to see how the consumer's choice of device in the digital path to purchase influences conversion rates. We find that the best-case scenario for conversion is a search and purchase completely on PC. Next is mobile only. Device switching spells trouble for conversion rates but corresponds with higher total sales per transaction.

Past research takes the perspective of retailers, but not the consumer. We map the path from start to finish (buy or abandon) using three years of StubHub browsing and transaction data to challenge past assumptions about the effects of device choice and switching on sales and sales volume. Experimentally we demonstrate that search inconvenience (cost) associated with mobile use outweighs purchase risk concerns to impede the customer journey toward purchase.

The answer to the question (Is it worth it to push traffic to mobile?) will force retailers to evaluate the trade-off between higher conversion rates if consumers stick with a mobile device throughout the digital journey versus switching behavior that may accrue higher sales per transaction but lower conversion rates. One solution is to reduce perceived search costs or implement other interventions to keep customers on a single device to complete the purchase.

2.1 Theoretical Background and Hypotheses

2.1.1 Mobile Literature and our Research

Consumers may surf websites making informed purchasing decisions from anywhere at any time, but the experiences along the digital path to purchase may differ by device type. The increasing importance of mobile channels as alternatives to traditional online search on desktop personal computers (PCs) is well documented (Brinker, Lobaugh and Paul 2012; Husson et al. 2014). However, we know little regarding how mobile devices change behavior (Melumad, Inman and Pham 2019) as consumers transition between multiple screens from first search on the way to buy or abandon. Strom, Vendel and Bredican (2014) call for research in online shopping to explicate mobile device behavior throughout the buying process. Multiple mobile channels potentially modify search, purchase and consumption behavior, thus changing the online shopping experience over time (Dennis et al. 2016; Verhoef, Kannan and Inman 2015).

Our research integrates consumer search behavior to quantify the drivers of purchases across device types. We focus on online browsing versus buying and how the choice of device type influences path completion, specifically for a deadline-driven purchase. Our research builds on prior research focused on understanding the difference in user behavior between online and offline channels (e.g., Ansari, Mela and Neslin 2008) and examining the effects of marketing tactics delivered on mobile devices (e.g., Bart, Stephen and Sarvary 2014; Wang, Malthouse and Krishnamurthi 2015). While important, this research provides limited insight into the relative effect of device type (mobile vs. PC) on purchase incidence and sales volume. This is the focus of our research.

We compare and contrast purchase likelihood on mobile vs personal computer. We empirically study device-specific effects in the path to purchase of event tickets by analyzing web-traffic and purchase data from a large ticket exchange website over the course of three years. Given deadlines for ticket purchases, we seek to understand which path-related factors increase purchase likelihood. We begin from the point of the initial search session and follow each turn along the way of the online journey to understand if and how device switching between search and purchase steps impact deadline-driven purchases.

We seek to understand which device-specific paths lead to the highest conversion rates. We examine if a path involving all sessions on a single device type (PC-only or mobile-only) leads to a significantly different conversion rate than a path with device switching. We also assess whether a search session on a PC and subsequent switching to a mobile device has a significantly different purchase likelihood compared to a path with search on a mobile device and subsequent switching to PC. Relatedly, we also examine the effects of the device used for initial (first) search as well as the number of pages viewed on mobile devices on purchase likelihood. In a subsequent experiment, we explore contributors to differential purchase likelihood (if any) in mobile vs. PC paths based on perceived search convenience or purchase risks associated with mobile and which of these two may improve or impede the use of mobile devices for digital shopping.

Second, we examine the role of time-to-event of the initial device choice on conversion rates. Does the device choice for the initial search session for an event interact with the time to consumption (number of days to event date) to significantly influence purchase likelihood? Purchasing event tickets may generalize to the purchase of other experiences such as vacations, advance movie tickets, and restaurant reservations and deadline-driven material goods purchases such as holiday or gift shopping. We also examine how the number of search sessions, average search session duration, and the proportion of time spent on specific search pages affect purchase likelihood. Third, we examine the effect of device type on sales volume. We explore whether sales volume differs significantly across devices and if device switching alters sales volume compared to the use of a single device type.

Contrary to existing literature in the mobile domain focused on retailer strategies in the form of mobile promotions and targeting, our research examines consumer online behavior across device types and extends the literature on online path to purchase and multi-channel switching. Mandel and Johnson (2002) find that specific online page designs can change attribute significance and preferences, thus dynamically influencing purchase decisions as users move from page to page exposed to page-specific stimuli. Bucklin and Sismeiro (2003) show that the paths and the time spent on each online page predicts purchase intentions. Sismeiro and Bucklin (2004) show that browsing experiences predict task completion for all online consumer decisions. We extend this literature to include differential effects based on device selection (mobile vs PC) for search and subsequent online purchases by individual consumers. On the use of multiple channels, Bilgicer et al. (2015) find that multichannel customers spend more than mono-channel customers in the short run but revert to their regular consumption patterns in three years. Prior literature shows that multichannel shopping results in higher customer profitability (Venkatesan, Kumar and Ravishankar 2007) and lower price sensitivity (Chu et al. 2010). We extend the findings on the effect of multichannel consumption to the context of multi-device consumption of online retail websites for deadline-driven purchases.

In summary, we empirically investigate differential paths in the journey due to device-specific contrasts, integrating search behavior of consumers, including device switching, in predicting purchase likelihood. We also examine whether purchasing on mobile devices leads to higher or lower subsequent sales volume. Search and sales data from a large ticket exchange website is analyzed to study the real-time search behavior of consumers, alternating between devices and how these search patterns influence final purchases. With the ubiquity of mobile phone use, developing a quantitative model to explain how device choice affects consumer search and subsequent online purchase behavior will enable online retailers with dual channels (traditional world-wide website as well as mobile browsers and applications) to implement appropriate mobile targeting strategies to engage consumers at the right stage of the purchase funnel.

We first review the literature on online decision making and mobile marketing effects, then rationalize our research propositions. Throughout we refer to conversion rates and purchase likelihood interchangeably. We discuss our model and test our propositions using three years of data from StubHub, controlling for device self-selection. We then present an experiment to examine mediation effects of device-specific perceived convenience versus risk on purchase likelihood. The experiment also serves as a robustness check by assigning participants to a specific device type as a means of controlling for self-selection of device. We close with a discussion of our contributions and implications of the findings for research and marketing practice.

2.1.2 Online Decision Making

Most prior research in online decision making has focused on user behavior in online compared to offline channels or on “mobile marketing” (i.e., marketing tactics delivered via mobile devices). Ansari et al. (2008) find that web purchasing is associated with lower subsequent sales volume than buying from other outlets. Existing literature (Bell, Corsten and Knox 2011; Li and Kannan 2014) has attempted to decode the path to purchase of online users to determine what factors affect the conversion rate from search to purchase on websites. Sismeiro and Bucklin

(2004), Moe and Fader (2004), and Park and Fader (2004), among others aggregate measures of web browsing behavior to estimate online purchase conversions. Montgomery et al. (2003) propose a dynamic multinomial probit model to predict the path factors that increase the likelihood of purchase. Rather than looking at an isolated purchase occasion on a landing page, the path decodes the sequence of pages visited, as the consumer makes decisions to abandon the search or keep looking at each page, leading to the decision to (abandon) purchase.

Recently, researchers have begun to delve into the effects of mobile devices in the online purchase funnel. Existing research has tended to focus on marketing practice, considering the effects of mobile promotions, online advertisements and the adoption of mobile shopping on purchase behavior (e.g., Haghirian, Madlberger and Tanuskova 2005; Hui et al. 2013; Li and Kannan 2014; Wang, Malthouse and Krishnamurthi 2015; Hu, Du and Damangir 2014, Danaher et al. 2015; Hoban and Bucklin 2015; Zubcsek, Katona and Sarvary 2017). Initial evidence suggests positive effects of mobile promotion on in-store spending and mobile shopping order frequency.

Shankar and Balasubramanian (2009) identify four key issues of mobile marketing: drivers of mobile device/service adoption, the influence of mobile marketing on customer decision-making, formulation of a mobile marketing strategy, and mobile marketing in the global context. Luo et al. (2013) and Fong, Fang and Luo (2015) explore consumer response to mobile promotions, concluding that marketers can increase purchases by temporal targeting and geographical targeting. Mobile offers new marketing tactics enabling retailers to provide tailored, time- and location-sensitive advertising and promotions in store as well as personalized marketing offers (Bart, Stephen and Sarvary 2014; Chun*g*, Rust and Wedel 2009).

Burford and Park (2014) argue that smartphone use among adults has steadily increased over the past decade due to the extensive use of mobile applications (apps) requiring a one-time download and instant access. App use offers a more selective view of information than encountered on the expansive world wide web. A 2015 editorial from Google's micro moments observed that 66% of smartphone users use phones to look up something they saw on a television commercial, while 91% of smartphone users turn to their phones for ideas while doing a task. In short, individuals frequently search for commodities, services and coupons on a smartphone more than on a desktop.

An important question in the mobile space is whether mobile devices are just new channels to search or browse or are they viable alternatives for purchase decisions, to some extent replacing desktop personal computers. Ghose and Han (2014) estimate that app demand increases with the in-app purchase option, while it decreases with the in-app advertisements shown while engaged with the app. Mobile channels also directly interfere and interact with other channels (Rapp et al. 2015). Manzano, Mafe and Blas (2009) establish that consumer innovativeness (in switching from personal computer to smartphone), mobile affinity and internet compatibility favorably drive a user to purchase via smartphone. Bellman et al. (2011) suggest that using mobile apps, especially with an informational/user-centered style, has a positive persuasive impact in shifting purchase intensions, increasing interest in the brand and the brand's product category.

2.1.3 Device Specific Path to Purchase

A major advantage of the mobile channel is the flexibility it offers with respect to time and place. Mobile devices with internet connectivity can be used anytime at any place, impacting the customer journey (Verhoef, Kannan and Inman 2015). Personal computers do not provide this degree of flexibility of access. Recent research (Dinner, van Heerde and Neslin 2015; Kim, Wang and Malthouse 2015; Huang, Lu and Ba 2016; Gill, Sridhar and Grewal 2017) has established that the adoption and usage of mobile applications increases overall consumer spending. However, in exploring search differences on mobile phone and personal computers, Ghose, Goldfarb, and Han (2013) conclude that small screen sizes increase the search cost on mobile phones compared to personal computers. Thus, although consumers spend more search time on mobile devices due to greater accessibility, higher search cost discourages in-depth search of information via mobile. Instead, consumers tend to skim basic product information and move to alternate related products or unrelated digital domains. In fact, mobile channels have specific characteristics that make them less suitable for purchase (Haan et al. 2015). Search cost on PCs tends to be lower due to bigger screen sizes enabling consumers to explore more information and specifications of alternative products.

Wang, Malthouse and Krishnamurthi (2015) observe that mobile devices may not be the most optimal channel for promoting products that require greater consideration during the buying process. They also find that shoppers tend to use mobile devices to shop for habitual products already have a history of purchasing. Chang (2010) identifies risk as the major concern for consumers making mobile purchases. Multiple smartphone applications running in the background allow for real-time tracking of user locations, which may lead to an increased risk of hacking of personal accounts and passwords. Zhou’s (2011) summary of key security and privacy concerns underlines the factors impinging upon user adoption of location-based services on smartphones. These might deter consumers from logging credit details for frequent purchases on smartphones. Thus, we propose:

P1: Purchase likelihood is lower when either search or purchase session (last session in the user's online path) is on a mobile device as opposed to a PC.

2.1.4 Effect of Device Switching on Purchase Conversion

Haan et al. (2018) analyze clickstream data from an online retailer that offers various product categories and find that the conversion rate is significantly higher when customers switch from a more mobile (e.g., smartphone) to a less mobile device (e.g., desktop). However, we argue that for a deadline-driven event, purchase likelihood is higher when device switching from a PC to a mobile device (smartphone or tablet) than switching from a mobile device to PC. Due to lower search cost on a PC (Ghose, Goldfarb, and Han 2013), a consumer gathers more in-depth product knowledge in the search session on PC and then moves to subsequent sessions. So, even if switching to a mobile device, the user is already equipped with more product information and can make a better-informed purchase.

Due to higher search cost on mobile, the subsequent sessions on a mobile device begin with inadequate information, leading to higher probability of product abandonment (Wang, Malthouse and Krishnamurthi 2015). This effect should be even more pronounced in purchasing scheduled experiences since users have a finite time period to purchase, with each minute potentially incurring costs as inventory availability and prices change. In sum, lower search costs are incurred when the search begins on a PC, reducing uncertainty and increasing confidence in the information obtained when initiating the customer journey. Hence a path involving switching from a PC to a mobile device is expected to have a higher probability of purchase likelihood than a path involving switching from a mobile device to a PC. Therefore:

P2: Purchase likelihood is higher when there is a switch from a PC to a mobile device than switching from mobile device to a PC.

We examine how device switching in either direction (PC→Mobile; Mobile→PC) may affect conversion rates compared to single device use. Since a user can switch devices multiple times, for model simplicity, for a path that involves more than a single device use, we focus on the direction of device switching in the last user session from the previous session.[1] This approach reasons that since search information is updated for all new user sessions the user has the most updated information in the search session just before the final user session before buying or abandoning. To that end, we focus on four types of device-specific paths to purchase:

- Path 1: All user sessions on PC
- Path 2: Switch from PC to mobile device in the last user session
- Path 3: Switch from mobile device to PC in the last user session
- Path 4: All user sessions on mobile device

Purchase likelihood for path 4 is expected to be lower than path 1 because of higher search cost and the risks associated with mobile transactions, as discussed in proposition 1. Xu et al. (2017) and Haan et al. (2018) compare paths of users who switched between device types but do not compare device switching paths with single device users due to their data constraints. Our research does, on the other hand, compare paths and conversion rates for single device use vs device switching. A path maintained on a single device type through every search session is apt to

[1] The information accumulated in the initial search session is crucial in forming purchase intention. Therefore, in our device-specific path analysis and subsequent purchase likelihood prediction, we also account for device selection in the initial search session.

be more focused and directed compared to a path with device switching, with the latter leading to different searches after the switch due to differences in search cost (Ghose, Goldfarb, and Han 2013). A user beginning a search on mobile may select tickets to consider. Subsequent mobile sessions with similar interface and search cost facilitates exploring details of the same item and eventual purchase if sufficiently confident of the information gained from the prior session(s). Alternatively, a search may launch on mobile and shift to PC. The search cost on PC is lower compared to mobile (particularly when compared to an app) and a user might easily encounter other attractive options (including multiple browser tabs) compared to mobile-only paths. A user in the second scenario may be more prone to abandon the path of the first item search and embark on a new search/purchase path. In a third scenario, the consumer might initially search on a PC and then move to a smartphone, where the higher search costs may hinder progress and increase the likelihood of abandonment. In sum, device switching may lead to differential search costs encountered across sessions leading users to stray from the path to purchase. Thus, paths 1 and 4 are expected to result in higher purchase likelihood than paths 2 and 3. Path 2 is expected to result in a higher purchase likelihood than path 3 for a deadline-driven event, as discussed in proposition 2. Thus, we propose that purchase likelihood reduces as we move in the following order of online path choices:

P3: Purchase likelihood (PL) for path 1 > PL for path 4 > PL for path 2> PL for path 3.

2.1.5 Effect of Time on Conversion Rates

The moderating effect of time on purchase likelihood when search starts on a mobile device (compared to PC) is also of interest. Time is an important search consideration and more so when search, purchase and consumption are constrained with finite time parameters for deadline-driven decisions. Extending decision-making time extends complexity because of the dynamic nature of inventory quality, availability and pricing. Our focus on the purchase of sports tickets bear similarities with theatre, travel, and other admissions purchased to gain an experience on a specific date and time. Research on intertemporal choices (Hoch and Loewenstein 1991; Kirby and Marakovic 1996; Frederick, Loewenstein and Donoghue 2002; Zauberman et al. 2009; Wakefield and Wakefield 2018) demonstrate that consumers devalue future costs and downplay the effort involved in completion of future consumption. Mobile searches are unlikely to be highly detailed given higher search costs and limited displays. Thus, searching for a more distant future consumption on a mobile device is likely to involve less exploration of in-depth information compared to proximal consumption. Hence, we predict:

P4: Purchase likelihood for distant consumption is lower when initial search is logged in from a mobile device as opposed to a PC.

The context of advance purchases of admissions to events and experiences is an interesting avenue to examine digital paths to deadline-driven purchases. We analyze traffic and transaction data from a large ticket exchange website to empirically examine the real-time search behavior of consumers, alternating between devices and how their search paths influence final purchases. We also conduct an experiment to compare and contrast search convenience and purchase risk on mobile (vs PC) that may improve or impede favoring one device type over the other for digital shopping.

2.2 Online Purchase Conversion

2.2.1 Description of Data

We examine three years of user sessions on StubHub, a dominant online ticket exchange portal, for search and purchase of a Power 5 university's sports tickets. Tickets are listed for football, men's basketball and women's basketball for home games. The device type in the meta data for each session includes PC, smartphone and tablet. We categorize smartphone and tablet into mobile device types and contrast purchase likelihood on these devices with that on PC. Detailed search data is examined to understand consumer search behavior and how the path to (non)purchase differs between devices. We also assess the differential effects of device selection and other path characteristics on the conversion rates. Each path is identified by matching consumer IDs from the search and traffic data. Housed in separate databases, the transactions and search traffic data were provided by StubHub for all consumer logins from Jan 2015 to May 2017. We were able to match search traffic with transactions for all path related variables for roughly 75% of consumer transactions on the website.

2.2.2 Model Free Evidence

Our data has a total of 10,747 users who visited StubHub website pages listing for the university's sports tickets from Jan 2015 to May 2017. Of these, 9.8% of users searched for men's basketball tickets, 83.7% searched for football tickets and 6.5% searched for women's basketball tickets. Since our analysis is based on data provided by StubHub, the scope includes users logged into StubHub accounts with recognized IDs. We examine transaction variables to build a statistical model for predicting online sales volume per transaction in the next section. The primary variables of interest are device used, session length, time of session logins, as well as game characteristics. The variables are described in detail in Appendix A. StubHub provided detailed pages as a user moved through the search. A page view refers to the user's hit on that particular page. The data contains timestamps enabling us to arrange pages in the order accessed. Later analysis looks at average session time and average dwell time on each page in a session.

The pages are classified into six types and a pictorial representation of all six pages as they appear on StubHub is outlined in Figure 1.

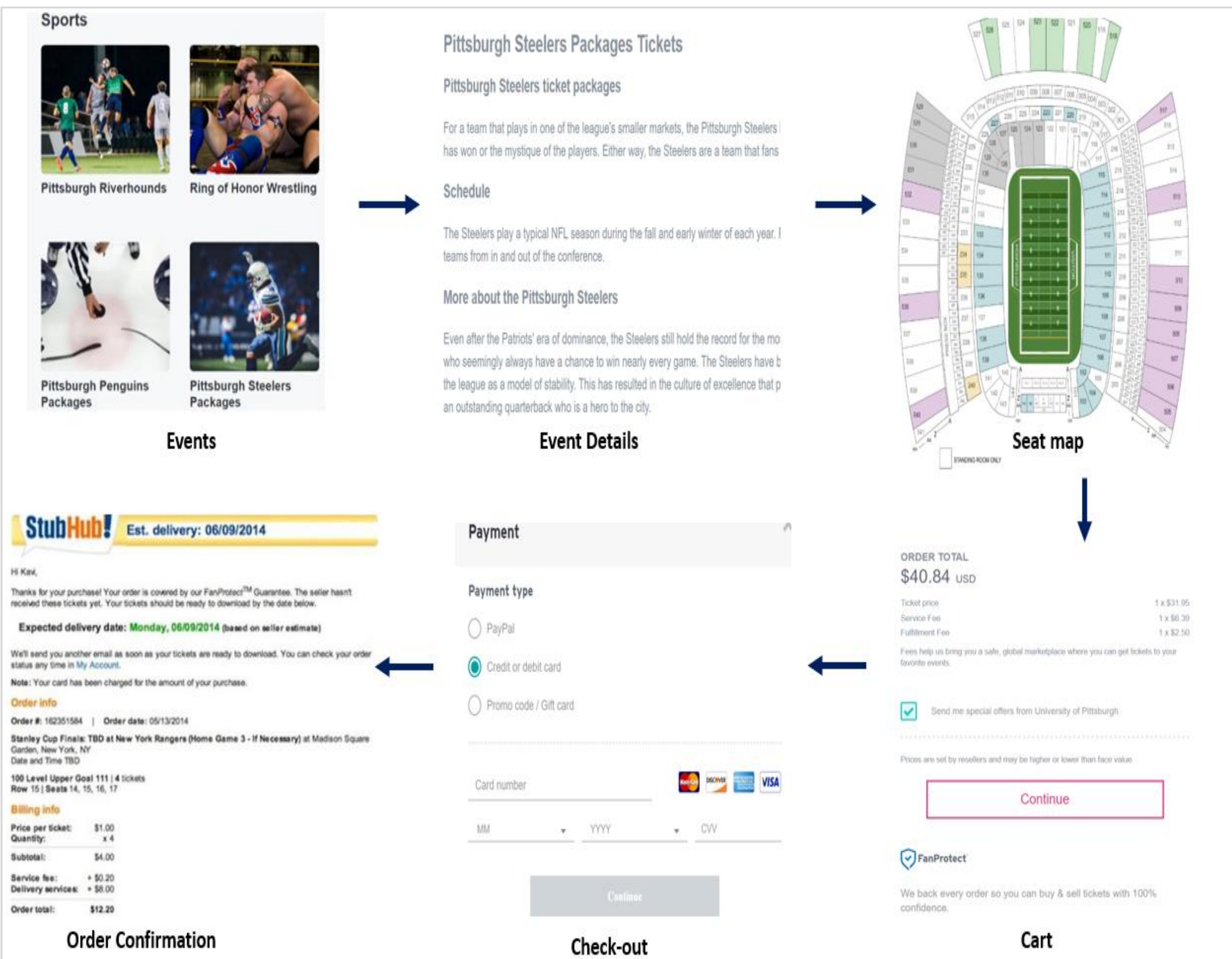


Figure 1: User Online Path on StubHub

The event page (contains all listings of events consistent with keyword search, such as events in a city or sports events), event details page (with detailed information about a specific event upon click-through), seat-map page (seat chart and corresponding ticket prices for specific tier seats), cart page (shows items added to cart), check-out page (where the user selects a preferred payment method) and order confirmation page (thank you page with order confirmation details). Detailed classifications are provided in Appendix A. The frequency of pages visited by users across all purchase and non-purchase web paths are summarized in Table 1.

Table 1: Percentage Frequency Of StubHub Pages Across All Web Paths

Traffic type	Event	Event details	Seat-map	Cart	Checkout	Order
Purchase	24.63	34.95	19.52	2.36	10.20	8.34
Non-purchase	49.53	32.08	17.73	.12	.54	NA

We analyze user movement on these pages throughout search and purchase sessions. We construct and study the path based on the pages visited in the user sessions for each game and assign a unique identifier corresponding to a concatenation of user ID and a specific game. For example, a unique identification is created for user ID 10894995 searching for a football game held on October 1, 2016. Using this process, we end up with 22,391 unique identifiers (user ID + game) and hence 22,391 user paths. The company did not divulge demographic information because of privacy concerns. We segment our analysis of search and purchase sessions of 22,391 online paths according to device used to log-in for search and purchase sessions. There are 5082 unique paths ending in purchase, as compared to 17,309 that do not convert into purchases. Overall search session logins (sessions without order confirmation pages) by device type are as follows: Smartphone sessions (67.6%), PC sessions (20.8%), and tablet sessions (11.6%). Online device selection for the initial search session leading to purchases are: PC (56.2%), smartphone (36.5%), and tablet (7.3%). Appendix B contains the Markov transition matrices for switching probabilities between different web pages on StubHub for paths that converted into a purchase and for paths which did not convert into a purchase.

In the purchase sessions, users spent the most time on the event details page. In non-purchase sessions, users spent the most time on the event page with a smaller percentage of users moving on to the event details pages. The seat-map page is the third most frequented page searched after the event and event details pages. Of the 22,391 online paths taken by 10,747 users visiting StubHub between Jan 2015 to May 2017, 5531 paths were completed entirely on a PC, 8195 paths were completed entirely on a smartphone, 3874 paths had device switching from PC to mobile in the last user session, while 4791 paths had device switching from mobile to PC. Table 2 contains descriptive statistics on path characteristics: number of user sessions, average length of session, days to event data from search, and number of average pages on a PC and a mobile device.

Table 2: Descriptive Statistics For Event-Specific User Path Parameters

Path parameter	Mean	Median	Std. Dev
Number of user sessions	5.29	4.00	5.88
Average session length (min)	34.50	31.72	1.40
Days to event from initial search	77.37	7.00	59.57
Days to event from last session	35.13	29.00	47.52
PC logged in pages	7.29	7.00	22.52
Smartphone logged in pages	34.40	26.00	67.01
Tablet logged in pages	9.36	8.00	25.32

2.2.3 Purchase Likelihood Model Development

We predict purchase likelihood from user behavior parameters throughout the search and subsequent purchase sessions (or non-purchase last session). Of specific interest are device selection for initial search session, use of single vs multiple device types (device switching) while looking for a specific event ticket, and other path behaviors including the number of sessions, average time spent per session, and number of days to event from session login. Since, the primary objective is to understand PC vs mobile online behavior, sessions on a smartphone and on tablet were categorized as mobile sessions. We also analyze the effect of the interaction between time-to-event and initial search device choice.

2.2.3.1 Stage 1: Device Selection Model

To control for self-selection of device (PC or mobile) during a session in the online journey, we incorporate an additional model layer in which a user's choice of device for an online session is examined in relationship to three time-related variables: whether the user session is a weekend session, the number of days to the event and the year of online retail site access (2015, 2016 or 2017). We examine (a) the likelihood that users may follow paths differently on a weekday vs weekend, (b) whether sessions far in advance of the event are different from late ones (measured in terms of number of days to event) and (c) whether device use in web sessions in 2016 and 2017 differed significantly from device use in 2015 given the penetration of smartphones in the marketplace over this time period.

A correction factor is calculated from this additional stage of a multinomial logit model of device selection for an online session. We use a 2-stage "conditional expectations correction" model for endogeneity based on the approach adopted by Dubin and McFadden (1984) to control for endogeneity of the consumer choice between household appliance portfolios. This 2-stage model approach to account for endogeneity (arising out of self-selection of device for session login in our case) has also been used by Vroegrijk, Campo and Gijsbrechts (2013) to control for endogeneity in consumer shopping patterns. In stage-I, we compute the probability of selecting a preferred device for login during an online session. By doing so, we control for the device choice during sessions in the user's online path to purchase. The device selection model is specified as follows:

$$P\left(device_{ij} = s\right) = \frac{e^{\left(\beta_{0ij}+\beta_{1ij}WS_{ij}\ +\ \beta_{2ij}DTE_{ij}+\beta_{3ij}\ 2016_{ij}+\beta_{4ij}\ 2017_{ij}\ \right)}}{\sum_{k=1}^{2} e^{\left(\beta_{0k,ij}+\beta_{1k,ij}WE_{ij}+\beta_{2k,ij}DTE_{ij}+\beta_{3k,ij}\ 2016_{ij}+\beta_{4k,ij}\ 2017_{ij}\right)}} \qquad [1]$$

The device choice equation [1] is specified as a binomial logit model, where the dependent variable, *P(device$_{ij}$ = s)* is the probability that in the session for the j^{th} event ticket, user *i* selects a device *s* between two possible device choices: a PC (reference device) and a mobile device. The variable *WS* indicates weekend logins as opposed to weekday logins. *DTE* is used to describe the number of days left from a user session time to the event time. Device choice for online access is also predicted by year, with 2015 as the baseline.

2.2.3.2 Stage 2: Purchase Likelihood Model

In stage II, we compute the probability of user *i* making a purchase at the end of the online path for event j. The purchase likelihood model [2] takes the following form:

$$logit\left(P_{purchase_{ij}}\right) = \beta_{0ij} + \beta_{1ij}first_{mobile_{ij}} +\ \beta_{2ij}page_{PC_{ij}} + \beta_{3ij}page_{mobile_{ij}} + \beta_{4ij}\sum_{k=1}^{2}\hat{p}_{devsearch_{k,ij}} \cdot \hat{p}_{devlast_{kij}} + \beta_{5ij}sessions_{ij} + \beta_{6ij}time_{ij} +\ \beta_{7ij}t_{1ij} + \beta_{8ij}t_{2ij} + \beta_{9ij}t_{1ij} \cdot \hat{P}_{firsmobile_{ij}} + \beta_{10ij}event_{ij} + \beta_{11ij}details_{ij} + \beta_{12ij}map_{ij} + \beta_{cij}game_{ij} + \beta_{13ij}CF_{dev_{ij}} + \epsilon_{ij} \qquad [2]$$

The purchase likelihood model is specified as a binomial logit model where the dependent variable, likelihood of purchase at the end of user *i*'s path for event *j* is computed as a function of the following predictor variables:

$first_{mobileij}$	mobile device is chosen device over PC for initial search
$page_{PCij}$	number of pages logged in from a PC[2]
$page_{mobileij}$	number of pages logged in from a mobile device
$sessions_{ij}$	average number of web sessions in the path
$time_i$	average number of minutes spent per session
t_{1ij} and t_{2ij}	days to event from initial search and last search respectively
$event_{ij}$, $details_{ij}$ map_{ij}	number of searches pages belonging to each type of page
$\sum_{k=1}^{2} \hat{p}_{devsearch_{kij}} * \hat{p}_{devlast_{kij}}$	interaction of the device used for search (2nd last user session before final session) and device of last session
$t_{1ij} * \hat{P}_{firstmobile_{ij}}$	the interaction of the number of days remaining to the event from initial search and the use of mobile device
$game_{ij}$	linear combination of game characteristics (given in [3])
CF_{devij}	correction factor for self-selection among device types for login (given in [4])

An interaction term is computed based on the probabilities of the device used in an initial search and in the last session. The predicted probabilities are obtained from the device selection equation [1] that studies parameters affecting device selection for initial search. We estimate the

[2] We also considered average user pages per session as a predictor variable. However, it was highly correlated with average session time, so we retained average session time in the final model.

interaction of the predicted probability of endogenous variable (mobile vs PC login), borrowed from the interaction principle used for endogenous interaction terms in 2-stage least squares regression. Since each device can take two values (k =1 for PC and k=2 for mobile), this interaction variable will lead to four different paths:

a) $PC_{search} * PC_{last}$: path with all sessions completely on PC,

b) $PC_{search} * mobile_{last}$: path switched from PC to the last session on a mobile device, c) $mobile_{search} * PC_{last}$: path switched from mobile to the last session on PC, and

d) $mobile_{search} * mobile_{last}$: consumer with all sessions on mobile.

Purchase likelihoods on the last three paths are compared to the purchase likelihood for the path entirely on a PC. For calculating the interaction of the number of days remaining to the event from initial search and the use of mobile device, the variable t_1 (number of days to event from initial search) is mean-centered and interacted with $\hat{P}_{firstmobile_{ij}}$, which is the predicted probability of selecting a mobile device, smartphone or tablet over PC for initial search. As before, we interact number of days to event with the predicted probability of device choice as estimated in the device selection equation [1]. The linear combination $game_{ij}$ includes the following variables constituting different characteristics of *game j* for which a ticket is purchased by user *i*:

$$\beta_{cij} game_{ij} = \beta_{c1ij} big_{\mathrm{ij}} + \beta_{c2ij} con_{\mathrm{ij}} + \sum_{k=2}^{3} \beta_{c3kij}\, g_{kij} \qquad [3]$$

where,

big_{ij}: a 1/0 variable indicating whether the game played is with a perennially Top 25 ranked conference member

con_{ij}: a 1/0 variable indicating whether game played is with a 2nd tier conference (unranked) member

g_{kij}: game type variable, indicating whether the user *i* purchased game *j* is a basketball *(b)*, football (*f*) or women's basketball(*w*) game, with basketball(*b*) as the reference game type.

The correction factor, CF_{devij} is incorporated for self-selection among devices arising out of devices used for an online session. CF_{devij} is calculated from the following equation [3] as given by Dubin and McFadden (1984):

$$CF_{dev_{ij}} = \frac{\hat{P}_{mobile_{ij}} * ln(\widehat{P}_{mobile_{ji}})}{1 - \hat{P}_{PC_{ij}}} \qquad [4]$$

where, $\hat{P}_{mobile_{ij}}$ and $\hat{P}_{PC_{ij}}$ are the predicted probabilities of choosing a mobile device or a PC to login during a given session. Both $\hat{P}_{mobile_{ij}}$ and $\hat{P}_{PC_{ij}}$ are calculated from the device selection model. By including the correction factor for self-selection among device choices for each session, we control for endogeneity arising due to inclusion of self-selected device choice for the initial search and subsequent device switching during multiple sessions. Since PC is the reference category, the correction factor controls for using mobile as compared to PC in a session. The following section presents the empirical identification and the results of the device selection and purchase likelihood models.

2.2.4 Empirical Identification and Results

Since we control for variables such as weekend search, hours to the event and year by including the correction factor from stage 1, this model setting reduces concerns of endogeneity issues in self-selected device choice and thereby offers a reliable estimation of purchase likelihood. Our empirical identification relies on the conditions of the specification; namely, the number of web sessions in each path, the average session length, and the number of days remaining to the event as random and exogenous variables. User session length and the number of web sessions are not likely pre-determined when the user starts searching for tickets. Rather, these evolve as the user goes through the search process and is subjected to availability on the ticket seller (StubHub) and/or competitor websites (SeatGeek, Vivid Seats, etc.). We add to prior attempts (Bell, Corsten and Knox 2011; Li and Kannan 2014) to understand how path characteristics affect the conversion rate from search to online purchase.

The time when the user begins the search is dependent on the information available to each user about a specific event. This information is unknown and exogenous to the sellers' information unless the seller (StubHub) targets the consumer at specific time points. StubHub did not have any such applicable promotion during the time the data was recorded and hence we consider this time variable (number of days to event) exogenous in our model. Given the main results in stage two, we control for event-related parameters such as game type and game popularity (conference game or big conference games) to determine how conversion rates vary with differential device logins during search and purchase.

2.2.4.1 Model Stage 1 Results

Table 3 contains the results of our device selection model. This model looks at time related factors impacting the selection of a device type during a user session. We predict the probability of choosing a mobile device (vs PC) for each session depending on whether the session occurred on a weekday or weekend, the number of days left to event date and the year of access.

Table 3: Unstandardized Parameter Estimates For Search Device (Mobile Vs PC) Selection Model

Parameter	Parameter description	Coefficient
WS	*weekend session*	.604***
DTE	*days to event*	.0004*
2016	online session in 2016	.170***
2017	online session in 2017	.274***
Const	constant term	-.739***

Reference category: PC; significance level: * p< 0.05, ** p< 0.01, *** p <0.001, BIC = 862.88

Compared to PC, the likelihood of a session login from a mobile device is 1.8 times higher on a weekend. As days to the event increases, the likelihood of a session login on a mobile device increases as compared to PC. The likelihood of mobile session logins increases in 2016 by 0.17 times and in 2017 by 0.27 times as compared to PC in 2015.

2.2.4.2 Model Stage 2 Results

Table 4 contains results of the second stage of our econometric model to predict purchase likelihood. Compared to PC, initial search on a mobile device lowers the likelihood of making a purchase by 62%, implying that consumers carry forward higher purchase intentions when initial search is on a PC rather than a mobile device. Confirming P3, the likelihood of purchase decreases as we move from (a) PC-only, (b) to mobile-only, (c) from PC to mobile, and (d) lastly, mobile to PC. Notably, in case of multiple device use, searching on PC and then switching to mobile yields a higher purchase likelihood than the reverse (mobile to PC). Compared to PC-only paths, using mobile-only reduces the purchase likelihood by 66%, supporting P1. Purchase likelihood is lower when either initial search or the last user session is on a mobile device.

Table 4: Unstandardized User Path Parameter Estimates For Purchase Likelihood

		Main effects model (1)	**Interactions model (2)**
Parameter	**Parameter description**	**Coefficient**	**Coefficient**
sessions	average number of sessions	-.025***	-.019***
t1	days to event from initial search	.457***	.137***
t2	days to event from last session	.053***	.046***
time	average session length (min)	.0002***	.0004*
$first_{mobile}$	initial search from mobile	-1.366***	-.976***
$page_{PC}$	pages logged on PC	.0041***	.0040***
$page_{mobile}$	pages logged on mobile	-.070***	-.0074
event	number of event pages	-.285	-.128
details	number of event details pages	.214***	.214***
map	number of map pages	.433***	.131***
$t1 \times first_{mobile}$	days to event X initial search on mobile		-.403***
$PC_{search} \times mobile_{last}$	switch from PC to mobile		-1.352***
$mobile_{search} \times PC_{last}$	switch from mobile to PC		-1.802***
$mobile_{search} \times mobile_{last}$	all sessions on mobile		-1.099***
big	game with top team	-1.621***	-1.618***
con	game with 2nd tier team	.110***	.097***
f	football game ticket	.423***	.362***
w	women's basketball game	.0000	00000
CF_{device}	correction factor for self-selection of device type	-9.8496	-8.554***
const	constant term	.0001(0.000)	.0003 (0.000)

Ref category: PC; significance level: * p< 0.05, ** p< 0.01, *** p <0.001, BIC(1) = 23582, BIC(2) = 12452

Device switching from PC to a mobile device decreases likelihood of purchase by 74%, while device switching from a mobile device to PC reduces purchase likelihood by 83% as compared to using only PC on the consumer journey. This provides support for P2 that purchase likelihood is higher for a path switching from PC to a mobile device than when there is a switch from a mobile device to a PC. Each additional page searched on a PC increases the log-odds of purchase by around 0.4 times (for an additional 10 pages searched on PC, purchase likelihood of the item increases by 40%), while each additional page on a mobile device reduces the log-odds of purchase by around 0.7 times (for an additional 10 pages searched on a mobile device, purchase likelihood of the item falls by 70%). We later discuss the marketing implications of these findings which may run counter to the market push toward all things mobile. User path characteristics also significantly influence conversion rates. With each unit increase in the number of sessions, the log-odds of making a purchase falls by 0.019, indicating strong purchase intent leads to fewer sessions. With each unit (minute) increase in average session time, the log-odds of making a purchase increases by 0.0004, implying that more purchase-oriented (versus search-oriented) paths involve longer average user sessions. Thus, more purchase-oriented paths involve fewer online sessions with higher average session (dwell) time. Seemingly miniscule on a per person basis, the magnitude of effects on the billions of dollars of transactions from ticket resellers makes this a meaningful significant effect.

Purchase likelihood increases by 0.137 times with each unit increase in the number of days from initial search session to the event date. The greater the number of days between the last search and the event date increases purchase likelihood by 0.046 per unit change (each additional day). The higher the proportion of event details pages visited during sessions significantly increases purchase likelihood. Each additional visit to the event detail page and seat map page increases the log-odds of purchase by 0.21 times and 0.13 times respectively.[3]

We now turn to proposition P4 – the interaction between time-to-event from initial search and device used. Initial search on a mobile device results in a lower probability of purchase for distant consumption. If initial search is on a mobile device (compared to PC), the log odds of purchase reduces significantly by 0.403 for each additional day in advance of the event date. Confirming P4, this increase in time before consumption when initiated via mobile devices produces a multiplicative “double whammy” effect, decreasing purchase likelihood. The worst-case scenario (for StubHub) is when consumers search for tickets far in advance via mobile. Such initial searches suggest fewer well-planned purchases are browsed on mobile devices far in advance of the event.

Finally, we have also controlled for game characteristics. The search for conference games results in significantly higher purchase likelihood than non-conference games, but games against top-ranked opponents did not. The search for football games resulted in significantly higher purchase likelihood than basketball games, while there is no significant difference in purchase likelihood for women’s basketball games. To be expected, product quality influences conversion rates.

---

[3] We also considered the quadratic relationships between number of event details page as well as seat-map page visits and purchase likelihood but found no significant effects.

2.3 Effect of Device Selection on Sales Volume

We now address our third research question to determine how device choice impacts dollar sales volume per transaction. We examine if device choice for purchases and the use of multiple devices have a bearing on dollar sales volume for 5082 completed purchases.

2.3.1 Description of Data

StubHub provided detailed sales record of 22,391 transactions from 2015 to mid-2017. Overall purchase sessions (i.e., those containing order confirmation pages) by device type are as follows: PC =74.5%, smartphone: 18.8%, and tablet: 6.7%. Table 5 contains descriptive statistics for the transaction variables.

Table 5: Descriptive Statistics of Sales Variables

	Mean	Median	Std. Dev
Days to event from purchase	24.53	14.33	36.04
Total $ sales	252.73	221.45	121.84
Average Ticket Price ($)	100.58	75.69	91.656

Of the 5082 purchases, nearly 9% of tickets were purchased for premium (high priced) seating zones, 24% were upper-level price range tickets and the rest were low priced (mid-level) seating zone tickets. About 77% of tickets purchased involved the use of a single device, while 23% of tickets purchased involved the use of multiple device types in the path to purchase.

2.3.2 Sales Volume Estimation Model Development

We predict dollar sales volume in an online transaction of game tickets of the focal university from device used and path parameters. Following Ataman, Heerde and Mela (2010), due to lack of information on past online search history, we specify an additional equation for predicting purchase volume from device used for purchase. We controlled for ticket characteristics including average ticket price of the event ticket purchased, whether the game is a weekend game, if it is a conference game, type of sport (football, mean or women's basketball) and seat zone selected. We also examine the interaction between device switching and the choice of device for purchase. We test how the use of multiple devices influences sales volume for a transaction on PC compared to a transaction on a mobile device. The sales volume model [5] takes the following form:

$$\begin{aligned} Sales_{ij} &= \beta_0 + \beta_{1ij} purchase_{\ mobileij} + \beta_{2ij} sessions_{ij} + \beta_{3ij} p_{ij} + \beta_{4ij} \log\left(DTE_{ij}\right) \\ &+ \beta_{5ij} first_{mobile_{ij}} + \beta_{6ij} switch_{ij} + \beta_{7ij} purchase_{\ mobileij} \\ &* switch_{ij} + \beta_{8ij} purchase_{\ mobileij} * \log\left(DTE_{ij}\right) + \beta_{9ij} CF_{dev_{ij}} + \beta_{cij} ticket_{ij} \\ &+ \epsilon_{ij} \end{aligned} \qquad [5]$$

Here, $purchase_{\ mobileij}$ is a 0/1 variable indicating use of a mobile device for purchase; $session_{ij}$ is the number of web sessions in user *i*'s path for event *j*; p_{ij} is the average number of pages in each session; DTE_{ij} is the number of days remaining to the event from the purchase date. We designate $first_{mobile_{ij}}$ as a 1/0 variable indicating use of a mobile device for initial search; $switch_{ij}$ is the use of both PC and mobile to search during different sessions (the user *i*'s path to purchase for event j's ticket). Other variables include:

$purchasemobile_{ij} * switch_{ij}$: 1/0 variable indicating whether a purchase session on a mobile device was switched from a search session on PC;

$purchase_{\ mobileij} * \log\left(daystoevent_{ij}\right)$: interaction of the 1/0 variable indicating a mobile purchase with days to event from purchase date;

CF_{devij} is calculated from [4] to control for endogeneity (self-selection) of device used for online session;

$ticket_{ij}$ denotes a control for ticket characteristics, calculated from [6] to remove the confounding effect of specific ticket characteristics on the relationship between device selection and total sales.

$$\beta_{cij}\, ticket_{ij} = \beta_{c1ij}\log\left(ATP_{ij}\right) + \sum_{k=2}^{3} \beta_{c2ijk}\, SS_{ijk} + \sum_{k=2}^{3} \beta_{c3ijk}\, g_{ijk} + \beta_{c4ij}Con_{ij} + \beta_{c5ij}WE_{ij} \qquad [6]$$

$ticket_{ij}$ is a linear combination of variables constituting different characteristics of event *j* ticket purchased by user *i*,

ATP_{ij}: variable indicating average ticket price of transaction,

SS_{ijk}: selection variable for seat section among mid-level (mid), upper-level (upper) and premium (prem) zone seats (with mid-level section as the reference group),

g_{ijk}: game type variable, indicating whether the user *i* purchased game *j* is a basketball (b), football (f) or women's basketball (w) game, with basketball as the reference game type,

Con_{ij}: 1/0 variable indicating whether the game played is a conference game, and

WE_{ij}: 1/0 variable indicating whether the game is played on a weekend.

2.3.3 Results

Table 6 reports results of purchase device selection and ticket (event) related parameters in estimating sales volume. Average sales volume (total $ sales) falls by $41 when a purchase is made from a mobile device as compared to PC. Compared to the use of single device in the customer journey, the use of multiple devices increases sales volume by $27.

Table 6: Unstandardized Parameter Estimates For Sales Volume Model

Parameter	Parameter description	Coefficient
sessions	average session length	-.009
log (DTE)	days to event	7.603**
p	average number of pages per session	.912*
$first_{mobile}$	initial search on mobile	-9.036***
$Purchase_{mobile}$	purchase on mobile	-40.728***
switch	switch	26.955**
$purchase_{mobile}$ × *switch*	search on PC and purchase on mobile	3.971**
$purchase_{mobile}$ × *log (DTE)*	purchase on mobile X days to event	.227***
CF_{dev}	Correction factor for self-selection of device	3.240***
logATP	average ticket price	510.194***
WE	weekend event	92.093***
prem	premium seat	133.133***
upper	upper level seat	63.354***
f	football game ticket	89.604***
w	women's basketball game	-60.332*
Const	constant term	135.638***

significance level: * $p< 0.05$, ** $p< 0.01$, *** $p<0.001$, $R^2 = 0.604$

The interaction of device switching and mobile as the purchase device results in an increase of average sales volume by nearly $4. Thus, search on PC and then switching to mobile yields a higher sales volume than other paths, such as the mobile-only path. Recall that our analysis of purchase likelihood revealed that the use of PC-only has the highest purchase likelihood and that use of a single device in the user path yields higher conversion rates than a path involving device switching across sessions. However, these results reveal that device switching yields higher overall sales volume. Our analysis of average ticket prices (all transactions in the database) indicate that 70% of transactions occur within 15 days prior to the event, accompanied by declining average ticket prices as the date to the event approaches.

Interaction of log (days to event) with purchase on mobile increases sales volume on a mobile device by $0.23. More advance purchases yield higher sales volumes on a mobile device. With each unit (page) increase in the average number of pages per session, sales volume increases by around $1. Greater movement between pages in each session suggests buyer interest and thereby contributes to higher estimated sales volume. Sales volume increases significantly with each additional day remaining to event, translating to an increase in sales volume by $7.60. Average ticket price (ATP), as expected, corresponds with dollar sales volume. A weekend event increases average sales volume by $92 over a week-day event. Similarly, a conference game increases average sales volume by $91 compared to a non-conference game. Premium and medium zone seats garner significantly higher sales volume than upper level seats: Premium seat totals were $133 more and medium zone seats totaled $63 more on average. Compared to a men's basketball game, a football game generates $89 more per transaction, while a women's basketball game generates $60 less per transaction than a men's basketball game. The same patterns would hold for cruise ships or resorts for their best accommodations.

In summary, our analysis of sales volume yields four key insights. First, the initial search for a ticket on a mobile device reduces sales volume compared to initial search on PC. Second, average sales volume is higher when the purchase is made on PC as compared to a mobile device. Third, the use of multiple devices increases sales volume compared to the use of a single device in the entire path. Finally, switching from search on PC to mobile leads to higher sales volume compared to use of mobile-only.

2.4 Mediation Analysis Experiment

While we have controlled for selection in the StubHub analysis, we also conducted an experiment via Amazon Mechanical Turk to thoroughly control for device self-selection via random assignment to device type conditions. From our econometric analysis of StubHub data, we find that use of a single device type leads to significantly increased purchase likelihood of a deadline-driven purchase than when using multiple device types. In this experiment, we contrast purchase likelihood when users are assigned to a single device for search and purchase: either PC or smartphone. This experiment also examines mediation effects of device-specific perceived convenience and/or risk on purchase likelihood for participants assigned to PC-only and mobile-only search and purchase tasks. Our objective is to understand what contributes to differential purchase likelihood for a user assigned to a mobile device (vs PC), particularly whether consumers experience differential search cost on mobile devices or higher purchase risk. Thus, this experiment acts as a robustness check against self-selection of device type effects on purchase likelihood, as well as studies the mediation effect of convenience vs risk on the relationship between device used for search and purchase likelihood.

2.4.1 Procedure

Participants (N = 200) participated through Amazon Mechanical Turk in a between-subjects (PC vs Mobile) study. Participants were asked to visit www.ticketmaster.com, a ticket sales and distribution company. Participants were asked to imagine they were visiting New York City next month and instructed to search and make a hypothetical purchase decision on a ticket for an event in the city. Participants were randomly assigned to search and make a purchase decision either from a PC or a smartphone. Meta data confirmed that 167 participants used the assigned device and were subsequently used in our analysis. The mean search time for participants was approximately 3.5 minutes.

After searching, participants were then asked to rate ease of search and confidence. Ease of search was measured with the question "the search was easy for me" on a 10-point Likert scale (not true at all to very true). Search confidence was measured with, "I was confident in searching on this website" on a 10-point Likert scale (not true at all to very true). They were then asked to make a hypothetical purchase decision on the same assigned device for one of the event tickets of interest. Participants were asked to rate (1-10) how likely they were to make a purchase (not at all likely to very likely). Similarly, participants rated (1-10; not true at all to very true) the risk of purchase ("the purchase was risky for me") and confidence in buying ("I was confident in buying tickets from this website."). Appendix C contains the complete list of questions asked in this experiment. For an attention check, participants were asked to recollect which website they were asked to search and on what device they were asked to use to purchase tickets; 89% passed the attention check manipulations, rendering 178 usable responses for analysis.

2.4.2 Results

Ease of search (PC: M = 8.42 vs. smartphone: M= 6.09, $t = 6.39$, $p < .001$) and search confidence (PC: M = 7.42 vs. smartphone: M = 4.71, $t = 6.51$, $p < 0.001$) were significantly higher on PC than on smartphone. Conversely, purchase risk reported on PC (M = 4.63) was not significantly different ($t= 1.16$, $p = 0.2459$) than on smartphones (M = 4.39). Purchase confidence for those assigned to PCs (M = 7.42) was, however significantly higher ($t = 8.473$, $p < .001$) than those assigned to smartphones (M = 4.71). Table 7 contains correlations between the constructs of interest.

Table 7: Correlations between Perceived Search and Purchase Feelings

	Search confidence	**Search Ease**	**Purchase risk**	**Purchase confidence**	**Purchase likelihood**
Search confidence	1	.737**	.097	.677**	.512**
Search Ease	.737**	1	-.295*	.578**	.488**
Purchase risk	.097	-.295*	1	.002	.003
Purchase confidence	.677**	.578**	.002	1	.604**
Purchase likelihood	.512**	.488**	.003	.604**	1

****Correlation significant at 0.01 level 1**

We assess whether the assignment of device choice (PC = 1, Smartphone = 0) for search and consequent purchase decision influences the likelihood of ticket purchase and examine possible mediators of this relationship. Since search ease is strongly correlated with search confidence and purchase confidence for single device users, we create a measure of perceived convenience by averaging the participant's ease of search, confidence associated with search, and confidence associated with purchase (Cronbach's alpha = 0.85). We test if perceived convenience mediates the relationship between device type and purchase likelihood. Alternatively, we also test if perceived risk mediates the relationship between device type and purchase likelihood.

A mediation analysis (Hayes and Preacher 2014) shows that perceived convenience mediates purchase likelihood of ticket. Device type, (the independent variable) is a significant predictor of purchase likelihood (the dependent variable; $\beta = 3.440$, $p < .001$) and perceived convenience (the mediator; $\beta = 2.369$, $p < .001$). Convenience is a significant predictor of purchase likelihood ($\beta = 2.083$, $p < .001$). However, when we include both convenience and device choice in the model for purchase likelihood, only convenience remains significant ($\beta = 2.013$, $p < .01$), thus providing support for the mediating role of perceived convenience associated with use of PC over smartphone. However, there was no significant mediation role of perceived risk associated with use of PC over smartphone for purchase. Hence, we observe that participants assigned to PC over smartphone indicated higher likelihood of purchase and convenience, rather than risk, is the significant mediator of this relationship for deadline-driven purchases. These results replicate our earlier analysis of StubHub data and also partly explains higher conversion rates when users switch from PC to mobile rather than the reverse. Overall, search ease and confidence outweigh risk concerns associated with deadline-driven purchase decisions.

2.5 General Discussion

The distinction between mobile and personal computer use on consumer behavior opens the doors to a new research arena. Organizations design apps optimized for the online purchase experience on mobile but know little about the alternative user behavior on a mobile device compared to PC. The question our research tries to answer is if it is worth it to push online traffic to mobile. This research examines conversion rates on mobile versus desktop for deadline driven purchases (viz., event tickets) to see how the consumer's choice of device in the digital path influences conversion rates. Whereas prior literature primarily focused on the retail side of mobile (e.g., studying effectiveness of mobile applications, targeted ads on the mobile channels), our research focused on the consumer decision-making side of the mobile channel.

Our work yields four key implications regarding: (1) the impact of device-specific paths, (2) the impact of time to consumption on digital conversion rates, (3) the impact of device used for purchase on overall purchase volume and (4) the impact of search cost (convenience) vs purchase risk on the likelihood of purchases on mobile vs PC. We elaborate on these findings and key contributions, followed by contributions to practice and then directions for future research.

2.5.1 Key Contributions

2.5.1.1 Device-specific paths

Our primary purpose was to assess the influence of device-specific paths on PC and/or mobile devices on the purchase likelihood of deadline-driven purchases. Analysis of 22,391 digital paths of 10,747 users who visited the StubHub website pages listing of a large university's sporting events from Jan 2015 to May 2017 yields three main insights regarding these paths. First, initial search on a mobile device significantly lowers the likelihood of making a purchase as compared to initial search on a PC. Specifically, first search on a mobile device lowers the likelihood of making a purchase by 62% as compared to first search on a PC. Thus, we conclude that consumers carry forward higher purchase intentions when they first search on a PC rather than first logging in to search on a mobile device. Second, of the four possible path combinations, the PC-only path produced the highest purchase likelihood, followed by mobile-only, PC-to-mobile, and lastly mobile-to-PC. As compared to a PC only path, purchase likelihood falls by about 66% for a mobile only path. It falls by about 74% for a path switching from PC to mobile in the final user session and by about 83% for a path switching from mobile to PC, in comparison to a PC only path. Third, the usage of multiple devices during the online shopping journey significantly harms conversion rates for deadline-driven purchases, as evident by significant reduction in purchase likelihood in paths switching from PC to mobile or the reverse in comparison to PC only and mobile only paths.

As a supplement to our StubHub analysis and experiment, we conducted a short survey among the same university's sports fans in August 2018 to understand how consumer demographics impact device choice to search and purchase game tickets online. Of the 1048 participants, all indicated owning both desktop (PC) and a mobile device (smartphone or tablet). Consumers were asked to indicate their most often chosen device when buying tickets for different home games of the university. A majority (54%) reported using a PC for both search and purchase, 31% prefer searching and purchasing on a mobile device, 9% users preferred to search on a PC and buy via mobile, and roughly 6% of users preferred to search on a mobile device and purchase on a PC. These reported preferences reinforce our finding that the most preferred paths are for PC-only, over mobile-only, or device-switching from either PC-to-mobile and lastly mobile-to-PC. The most frequently cited open-ended responses from those using a PC (versus a smartphone) for online web browsing affirm the lower search cost of PC vs. mobile in terms of effort: ease of use, convenience, familiarity, large size of screen, and the ability to see maps more clearly. These factors appear to impede deadline-driven search costs on mobile devices more than purchase risk, which was not explicitly mentioned by any of the respondents.

2.5.1.2 Impact of time to consumption

Our analysis reveals that user path characteristics influence the likelihood concluding the journey with a purchase. This yields two related highlights with key managerial implications. First, the greater the number of days between initial search and the event date, the greater the conversion rate. Prompting users to search further in advance is more likely to produce purchases than promoting last-minute searches. Second, as days to the event increase, initial search on a mobile device, compared to a PC, reduces the likelihood of purchase. Identifying users by device type and date to event during the search process may allow differential incentives to promote conversion.

2.5.1.3 Purchase Volume

We estimated sales volume on StubHub in the same period, based on path specific parameters as well as device selection. Three key findings emerge. First, average sales volume falls by $41 when purchased on a mobile device, compared to purchases on PC. Coupled with the deleterious effect of mobile vs PC on purchase likelihood, mobile use represents bad news on both fronts. Firms can seek effective interventions at key touchpoints on the online journey to counteract these effects. Second, although the use of multiple devices lowers conversion rates, our analysis reveals using multiple devices increases sales volume by approximately $27 vis-à-vis a single device purchase path. Third, using multiple devices increases average sales volume by $4 when concluding on a mobile device. That is, although purchase likelihood decreases, a PC-to-mobile path (compared to mobile-only) leads to the $4 increase in sales volume per sale.

The tradeoff between conversion rates and sales volume leaves sellers in a conundrum. Taken together, our findings suggest the need for sellers to promote searching and purchasing further in advance (e.g., offer incentives for buying in advance), beginning searches on PCs (e.g., catching people on PC sessions and incentivizing conversion), and finding ways to reduce search costs on mobile (e.g., redesign mobile sites and apps).

2.5.1.4 Search convenience vs purchase risk

In a follow-up experiment, we find that search convenience, compared to purchase risk, mediates the impact of device type on purchase decision. In the search phase, consumers browsing on a PC form a stronger purchase intention in the initial search session than when browsing on mobile. Fewer well-planned purchases are browsed on mobile devices. Consequently, average sales volume is higher when purchases are made on a PC compared to mobile. Use of multiple devices decreases purchase likelihood, however, increases the sales volume when purchases are made.

2.5.2 Managerial Implications

Web retailers can distinguish between marketing strategies targeted at consumers on PC vs mobile in real time. Online sellers can target users based on browsing behavior, serving different messages and offers to different users based on dwell time, pages searched, cursor movement and other meta data. Push notifications and on-screen messages triggered by browser activities (viz., cursor moving toward the back button) or page events may intercede to reduce exits. Hotwire.com conducts over 120 experiments a year based on “conversion veins” optimizing conversion rates and overall customer experiences (Rusonis 2015). Our work suggests event sellers can better optimize conversion rates based on device-in-use and considering other path-specific characteristics.

Our first recommendation centers on when and how marketers promote mobile channels to increase conversion rates. The best conversion rate is for PC-only followed by mobile-only. Sellers like StubHub, Hotwire, Priceline, airlines, hotels and other booking agencies for travel or leisure would do well to prompt or promote users whose first search is on PC or mobile to remain online to complete the purchase. These sellers can track user web-traffic patterns to identify device-switchers and then incentivize accordingly to complete the purchase with push notices or retargeting ads while they are still on the same device. The challenge is creating effective messages with appropriate timing to enhance the shopping experience without increasing cognitive dissonance or regret for beginning the search in the first place. Future research aimed at appropriate nudges or message frames are needed to improve present retargeting methods.

Our second recommendation is for sellers to intervene in the search or purchase stage to reduce (perceived) inconvenience on mobile. If the user is not on a PC, mobile-only and PC-to-mobile have better conversion rates than mobile-to-PC. This places the onus on the seller to motivate completing the purchase on mobile. Sellers may offer special rewards to app-users or to those who follow them on social media. Sellers can target users using pixel and event tracking to identify recent searches to deliver dynamic product ads via Instagram or Facebook for users to complete the purchase on the same device within a specified time period. While utilitarian interface design can enhance ease of use and convenience (Ozturk et al. 2016), rewards, offers and messages can convey information that increases perceived ease of use. Social acceptance messages, including FOMO (fear of missing out), may directly influence or overcome inconvenience issues (viz., Hodkinson 2019). Indirectly, marketers can influence ease of use by enhancing feelings of trust (Zhou and Lu 2011). Easily accessible (positive) customer reviews and other social cues may enhance trust and thereby perceived convenience.

Third, mobile purchases are less likely to occur far in advance of the event date, indicating that mobile usage is prone to be last minute impulse purchases. Online sellers may have trained buyers to wait until late. Similar to other secondary ticket market reports, our data shows 70% of all ticket purchases were within 15 days of the event. A Google-search for “last minute deals” turns up 826,000,000 hits while “early bird deals” generate about one-tenth the hits. In the same way that Walmart and others offer early-bird deals ahead of Black Friday, sellers of deadline-driven purchases can increase conversion rates by rewarding planning ahead. Importantly, these offers can be made one-to-one rather than one-to-many by identifying and rewarding chronically late buyers to change behavior. For example, if a routinely late mobile buyer searches for an event weeks in advance, the seller can intervene with a reward or reinforcement message for the early search and hopefully generate early conversion. Push notices or email campaigns targeting these same late buyers may motivate early searches, resulting in higher conversion rates.

Finally, our study shows buyers are willing to pay more for big games. As is common, sellers promote big events via the seller’s app or email campaigns. However, our data suggests sellers may do well to begin these promotions further in advance to attract those willing to plan ahead (and spend more) and to alter behavior among those prone to wait. Shu and Gneezy (2010) find people often delay enjoyable experiences. However, procrastination can be reduced when the window of opportunity is constrained. They suggest shorter rather than longer deadlines to overcome tendencies to construe ample time in the future to complete purchases. Instead of offering deals for advance purchases for “this month only,” make offers with shorter deadlines of days or even hours. Again, these times can be tested one-to-one for those who bought “big events” in the past or for first-time buyers in up-sell situations.

2.5.3 Future Research

Our finding that switching from search on a PC to purchase on a mobile device leads to greater conversion than switching from search on a mobile device to purchase on a PC is the reverse of the results reported by Haan et al. (2018). While future research is needed to identify the drivers of this reversal, we note our context differs. They examine tangible goods in ready supply rather than intangible experiences with diminishing supply and inherent deadlines. It would be interesting to see if purchases during the Christmas season in the Haan et al. data exhibit a similar pattern to the one we find. Finally, ours is more recent (2015-2017 vs. 2011-2012) in the U.S., compared to Europe. Such differences in time and place may interest marketers and researchers.

Research and development should explore ways to increase (perceived) search convenience on mobile applications or browsers to increase conversion rates. In the mediation analysis experiment, device choice is mediated by convenience rather than risk. Since inconvenience consists of both search cost and confidence, managers may take a two-step approach. Modifications to interface design on apps and other mobile channels can increase the ease of search (viz., Zhao and Balague 2015). Search confidence can be boosted by using reinforcement learning to track real time searches and availability on the mobile app and sharing that information with users.

Finally, our research is an important step in examining the role of device type in the online shopper journey. Our empirical approach suggests the need for improved conceptual models of online consumer decision making processes incorporating device choices in deadline driven purchases. Given penetration and habits in different markets, mobile devices may instill an "explore" mindset and PCs may instill an "execute" mindset.

3.0 Essay 2: The IMPACT OF HEIGHTENING SIMPLIFIED NUTRITIONAL INFORMATION ON SHOPPERS' SENSITIVITY TO PRICE PROMOTIONS

Grocery retailers offer a range of wellness initiatives to fight the obesity endemic. While prior research has contributed significant insights into the success of such programs in promoting healthy choices, their impact on retailers' sales is still not fully understood. This research examines shopper reaction to nutritional information in retailer promotions and how that impact sales. The goal in this study is to examine whether sensitivity toward price promotions is affected by heightening the salience of nutrition information via featuring nutritional promotions in a retailer's weekly flyers. We build a hierarchical linear model to analyze the effect of product level nutrition promotions on sales of products, spill-over effects of category-level weekly nutrition promotions on sales of other products in the category and the cross-category spill-over effects of category-level weekly nutrition promotions on sales of products in a different category. Using panel data across four product categories for about 40,000 shoppers of a grocery chain's frequent shopper program, over a 27month period, we demonstrate that adding nutritional information in price promotion flyers significantly improves net sales per product level transaction. There is a positive spill-over effect of nutrition promotions on products in the same category, whereas, a negative spill-over effect of nutrition promotions on products in the same category. The results also reveal that the positive spill-over effect at category level nutrition promotions is stronger for lower nutrition categories, whereas the negative spill-over effect from promotions in other categories is not moderated by category healthiness. Further, the positive spill-over effect of both product level and category level nutrition promotions on product sales is stronger for shoppers with higher nutrition consciousness and lower monthly spending at the grocery retailer. The negative spill-over effect of cross-category nutrition promotions on product sales is weaker for shoppers with higher nutrition consciousness.

3.1 Theoretical Background and Hypotheses Development

Grocery retailers offer diverse health and wellness programs at the point of sale in the fight against the obesity endemic. Food retailers are evaluated by consumers on the basis of how well they support their goal of eating healthy (Food Marketing Institute 2018). While prior research has contributed significant insights into the success of such programs in promoting healthy choices among consumers (e.g., Nikolova and Inman 2015; Newman et al. 2018), their impact on retailers' sales is still not fully understood. This is precisely the objective of our research – to examine how consumer reaction to nutritional information in retailer promotions impact sales.

While retailers provide shoppers with simplified nutritional information in a variety of forms (e.g., color coding, nutrition scores), we focus on the use of NuVal scores, a comprehensive nutrition scoring system, ranging from 1 to 100 with higher scores signifying healthier products. Prior research has examined how the introduction of the NuVal scoring system impacts shoppers' purchases (Nikolova and Inman 2015). In contrast, our research examines consumer responses after the nutrition scoring system has been in place for a while and its novelty has worn off. Specifically, we look at the impact of featuring the NuVal scores of products in the weekly promotion flyers on retailer sales. Earlier research has suggested that consumers have difficulty comprehending the nutritional information on product packages (Nielsen, 2012) and therefore this deters the consumer from using useful information from the nutritional facts on product packages, in their purchase decision making process. We propose and test the central hypothesis that including NuVal score in the price promotion circular improves sales of products as well as net category level sales of the retailer. This hypothesis is based on the finding that an objective nutritional score alleviates the difficulty in comprehending information from nutrition labels on packages and enables consumers to make more informed purchase decisions by weighing in the nutritional information easily conveyed by the NuVal score (Nikolova and Inman 2015). In addition to examining the impact of NuVal promotion on the sales of the product promoted, we also study the spill-over effect on sales from other products being promoted in the same category as well the spill-over effect on sales from products being promoted in a different category. In doing so, we assess the effect of a price promotion or a nutrition promotion, for example, apples (NuVal score of 96) in the weekly flyer on the sales for all products in the produce category (for example, oranges) as well as on the sales for all products in a different produce category (for example, salmon fillets).

We also examine how the afore-mentioned NuVal promotion effects vary across low vs high nutrition product categories and across shoppers with high vs low average nutrition consciousness and with varying monthly spending at the given grocery retailer. These shopper characteristics are evaluated by analyzing shopper baskets in past trips and examining average NuVal scores of the shopping basket and the average monthly spending of the shopper at the specific grocery retailer. Since products (food items to examine impact of nutrition promotions on sales) are nested within categories, and we are investigating the category level and cross-category level effects of NuVal promotion on product sales, with further moderating effects of individual shopper characteristics, we construct a hierarchical linear model to account for product category level and shopper level predictor variables. Further, we also check if the effects of NuVal promotion variables on product level sales are replicated at the category level sales.

We use frequent shopper purchase data of 40,000 shoppers across a twenty-seven month period combined with manually coded promotional data from the grocery chain's weekly flyers to measure consumer response. That is, we assess the effect on sales resulting from the display of nutritional promotions in addition to price promotions in the weekly circular. Price promotions are defined as the display of discounted prices featured in the weekly circular. We define nutritional promotions as the display of a summary nutritional score (i.e., NuVal score) next to a product featured in the grocery chain weekly circular. Figure 2 depicts two examples of products on nutrition promotion in the retailer promotion circular.

Figure 2: Nutrition Promotion (NuVal Score promoted on weekly circular)

We examine if sensitivity toward price promotions is affected by heightening the salience of nutritional information via featuring nutritional promotions in the weekly flyers. As a robustness check, a feed forward neural network architecture is also designed for more accurate prediction of substantial category level factors for predicting change in product level sales (Asadi et al., 2019). As the linear statistical modelling approach sometimes simplifies the complexity learning from big data, employing the neural network analytical approach makes it possible to achieve more precise predictions in comparison to the typical regression techniques (Chan and Chong, 2012).

Utilizing such a two-stage method provides additional holistic comprehension above and beyond that provided by a linear and compensatory statistical predictive analytical approach (Zabukovsek, et al., 2018). Further robustness checks, studying impact of nutrition promotion on quantity of product purchased as well as the moderating effect of difference in the promoted NuVal score from the mean category NuVal score on the impact of nutrition promotion on product sales, have been employed to examine stability and robustness of effects. A category level sales analysis is also conducted to test if the effects of nutrition promotion on the product level sales are replicated at the category level net sales, i.e., we test whether nutrition promotion on one or more products in a given category has a positive spill-over effect on the weekly net sales of all products in the category.

3.1.1 Effect of Nutrition Promotion on Product Sales

The effect of price promotions on product sales has been studied extensively in the literature and researchers have generally found that there is a positive association between price promotions and sales of utilitarian products (Blattberg & Neslin 1990; Raju, 1992; Chandon, Wansink, Laurent, 2000). Differentiating our research from the price promotion literature, our goal is to study how nutrition promotions, i.e., featuring a comprehensive nutrition score (in the form of NuVal score) on weekly retailer promotion flyers, impacts sales of products.

The NLEA act of 1990, that mandated food manufacturers to disclose the nutritional content of food products on their packaging implementation, has sparked numerous academic research publications (Keller et al. 1997; Mathios 2000; Moorman 1996; Variyam and Cawley 2006). However, the consensus in the academic research community is that the NLEA was only partially successful in improving consumers' food decisions and diets (e.g., Balasubramanian and Cole 2002; Moorman 1996). The difficulty of reading and discerning nutritional labels in packaging, as is evident by the fact that 59% of consumers have trouble comprehending the information on the Nutrition Facts panel (Nielsen 2012), may be a deterrent factor in the effectiveness of these labels. This leads consumers to ignore the comprehensive Nutrition Facts panel (Balasubramanian and Cole 2002; Roe, Levy, and Derby 1999), and instead depend on their past use information or rely on outside word-of-mouth, to make purchase decisions. This is where a simple nutritional score, for example, NuVal scores, ranging from 1 to 100 with higher scores signifying healthier products, should make it easier for shoppers to comprehend the overall healthiness of the product.

In studying simplified nutrition information extensively (e.g., Andrews, Netemeyer, and Burton 1998; Garretson and Burton 2000; Levy and Fein, 1998), researchers have found favorable effects on consumers' food choices (Berning and Sprott 2011; Kozup, Creyer, and Burton 2003). Hence, putting nutritional information in form of a nutrition score, like the NuVal score, on price promotion flyers should work in two ways:

a. alleviate difficulty of discerning nutritional information from packaging labels;
b. improve effectiveness of price promotions to induce higher sales.

Hence, we hypothesize a positive impact of nutrition promotions on sales of the product promoted.

H1: There is a positive effect of nutrition promotions on sales of the promoted product.

3.1.2 Spill-over category nutrition promotion effects

Although the impact of promotions can be measured in terms of sales at the item level (SKU), brand level and category level, the category level sales is the most significant level of analysis for retailers (Ailawadi et al. 2009).The effect of price promotions on sales of products in the given category has been well-studied in the literature. In one of the first studies, Walters and MacKenzie (1988) do not find any evidence that sales of promoted items stimulate sales of unpromoted items. But even though in specific product categories, price promotions have been shown to cause short term gain but long term decline in category sales volume for the retailer (Dawes 2004), category level nutrition promotions are proposed to have a significant positive impact on sales of products in the given category, many researchers have found positive impact of price promotions on overall category sales because they increase shoppers' attention to the category even though they might decrease attention and search in other categories (Walters, 1991; Tam and Ho 2006; Fong et al. 2016). To that end, it is presumed that due to the close complementarity of food items in terms of nutrition value in any given product category, promoting products on nutrition promotion should bring attention to the entire category and have a positive impact on the sales of products in the given category. It is further assumed that retailers will have the innate tendency to selectively promote nutrition value of products that are as healthy or healthier than most products in any given category in order to have a positive "halo effect" on the nutrition perception of the entire category. This is also supported in the preliminary analysis of 11,152 products promoted by a regional grocery retailer chain in the US in 111 weeks from Jan 2013 to March 2015. Thus, by selectively promoting products with high nutrition value, the retailer can positively impact the perceived healthiness of the entire category and increase shoppers' attention to the given category as well as higher overall favorable evaluation.

Importantly, because featuring NuVal score on price promotions are expected to increase shopper sensitivity to product promotions (Nikolova and Inman, 2015), we predict that featuring nutrition promotions in the category in addition to the price promotions will lead to an additional increase in overall sales in the category. Thus, we propose the following hypothesis:

H2: Nutrition promotion on a product in a given category has a positive spill-over effect on sales of all other products in the same category.

Cross-category effects of promotions have also been shown to be particularly important in retail management (Hruschka, Lukanowicz, and Buchta, 1999; Ailawadi and Harlam, 2004). Wedel & Zhang, 2004 price theorize that promotional effects are asymmetrical across categories. Kumar and Leone, 1988 establish that the increase in category level sales due to promotions could be at the expense of other product categories. On the other hand, Ailawadi *et al.* (2006, 2007) find a positive "halo" effect of promotion on sales of other specific categories like beauty and general merchandise products in the store. But largely in the literature, promotion of products in one category have been most often found to significantly reduce sales in a different category (Walters 1991; Leeflang and Selva 2012). Nutrition promotion on any product in a specific food category brings attention to that category at the cost of other categories, i.e., shifts consumer preference and attention from other categories. Elevated interest in a product category due to novelty of information featured on promotions of products that are of relatively high nutrition value is hypothesized to result in improvement in sales of a products in the given category at the cost of products in other non-featured categories. We hypothesize the following:

H3: Nutrition promotion on a product in a given category has a negative spill-over effect on sales of products in a different category.

3.1.3 Moderating Effect of Shopper Characteristics

We further hypothesize that the effect of price promotions on sales will be stronger for shoppers with higher retailer's share-of-wallet (higher grocery expenditures at the store) because heavy users exhibit greater deal-proneness (Hackleman and Duker 1980). The effect of nutrition promotions on sales, however, is predicted to be weaker for shoppers with higher share-of-wallet, because the featured nutritional information will be less novel for heavy users. As such, more regular shoppers with higher share of wallet, are less likely to gain substantial additional nutritional information from the NuVal score on the promotion, to incorporate in their purchase decision. Hence, these shoppers will not experience a change in sensitivity toward products on price promotions with the addition of NuVal score featured on them. Thus, we hypothesize the following:

H1a: The effect predicted in H1 is stronger for shoppers with lower average monthly spending. Nutrition promotions will be more novel for light shoppers.

Similar to purchase of specific products, light shoppers, who are not regular buyers of specific product categories, are expected to increasingly purchase products in categories with featured nutrition promotions because of novelty of information. This effect should be weaker for more regular shoppers since they have well-formed shopping patterns. As such, the effect in H1a should cumulatively lead to increases sales of a product in a category with featured nutrition promotions. Thus, we have the following formal hypothesis:

H2a: The effect predicted in H2 is stronger for shoppers with lower average monthly spending.

Similarly, even the negative spill-over from nutrition promotions to the sales of products in a different category should be stronger for light shoppers because the shopper will be more attentive to the category on nutrition promotion due to novelty of information. Also, nutrition promotion is proposed to induce switching to promoted category more in less regular shoppers in consistence with the impact of promotions inducing brand switching in new customers (Raghubir, Inman and Grande, 2004). Thus, we have the following formal hypothesis:

H3a: The effect predicted in H3 is stronger for shoppers with lower average monthly spending.

We further predict that the effect of nutrition promotions on sales will be stronger for shoppers with higher nutrition consciousness, since such shoppers react more positively to the provision of nutrition information at the point-of-sale (Andrews, Burton and Kees, 2011). Shoppers with high nutrition consciousness seek out products which are healthier and therefore tend to search for nutrition information, when making a product purchase decision. Such shoppers are expected to put significant weight to the health incentives offered by nutritional value of food, above and beyond the monetary incentives offered by price promotions. Hence, featuring NuVal score on product promotions should have a stronger impact on shoppers with higher nutrition consciousness by dispelling quality concerns on promoted products, and hence drive more sales of products in categories which have higher number of price promotions with NuVal values. Thus, we propose the following:

H1b: The effect predicted in H1 is stronger for shoppers with higher nutrition consciousness.

Healthy shopping is viewed as difficult and effort is required to make the healthy choice (O'Brien et al 2013). Thus, nutrition promotion results in lesser search cost for seeking out high nutrition food categories for nutrition conscious customers. Also, nutrition promotion on top of price promotion may act as an incentive for healthy consumers to reaffirm their food choice by choosing rewards, viz price and nutrition promotions, that are congruent with the promoted nutritious consumption effort (Kivetz 2005). Thus, the positive impact of price promotions on all products in the given category should be higher for shoppers with higher nutrition consciousness. Formally,

H2b: The effect predicted in H2 is stronger for shoppers with higher nutrition consciousness.

A healthier shopper will pay close attention to the nutrition value of products (Andrews, Burton and Kees, 2011) and as such through prior shopping heuristics, should have stronger preferences for product purchase in healthier categories. Thus, a nutrition promotion in a given category should be less effective in pulling away attention from a different product category. Hence, we propose that although nutrition promotions on higher perceived nutrition categories is proposed to have a higher impact on purchase of products in the category by the healthier shopper, if the promotion is in a lower nutrition category, it is proposed that there will not be a profound impact on category switching by healthy consumers. Though the positive spill-over effect from a product to others in the category should be strong, the negative spill over to other categories should be lower. Thus, negative spill over from nutrition promotion in a different category should be weaker for shoppers with higher nutrition consciousness as such shoppers have more well-formed product nutrition intuitions developed from systemic seeking of nutrition value of all products.

H3b: The effect predicted in H3 is weaker for shoppers with higher nutrition consciousness.

3.1.4 Moderating Effect of Product Category Characteristics

Pricing promotions on products by retailers are set on following certain category and brand level promotion strategies (Dhar & Hoch, 1997; Hoch, Dreze and Purk, 1994; Levy & Weitz, 1998). Similarly, as primary analysis in our research supports, retailers are proposed to self-select among products when selecting which products to promote on nutrition promotions. Intuitively, retailers are expected to promote products that are of relatively higher nutrition value than the average nutrition of the given category. It is expected that nutrition promotions should have a greater positive impact on products belonging to categories with lower perceived nutrition as such promotions promote novel information in such food categories and thus attention to the lower nutrition products as well as to lower nutrition product categories. Also, low nutrition categories will have lower share of sales among high nutrition conscious shoppers. Featuring nutrition promotions in lower category products signals the consumers to re-evaluate the healthiness of the entire category. Thus, we propose the following effects for product level and category level nutrition promotions:

H1c: The effect predicted in H1 is stronger for lower nutrition products.

H2c: The effect predicted in H2 is stronger for products in lower nutrition categories.

On the other hand, if a product is perceived to be of lower nutrition (i.e., belongs to a lower nutrition category), then nutrition promotions in other categories will further strengthen the relative perception of lower nutrition of the given product. This will further take away attention from the lower nutrition product.

H3c: The effect predicted in H3 is stronger for products in lower nutrition categories.

3.2 Impact of Nutrition Promotions on Product Level Sales

In this section, we empirically analyze the impact of weekly product level and category level nutrition promotions on transaction level product sales. We test H1-H3, regarding the impact of nutrition promotion, in the form of featuring NuVal score on promotion flyer, on product level sales in a transaction, and the spill-over effect on sales from other products being promoted in the same category as from products being promoted in a different category. Thus, we test the impact of product level NuVal promotion, category-level NuVal promotion as well as cross-category NuVal promotion on aggregate sales of individual products per transaction. Additionally, we also examine the moderating effects of shopper characteristics, i.e., average monthly spending and nutrition consciousness of shopper as well as average category nutrition on the impact of product-level as well as category and cross-category NuVal promotion on product sales. We examine frequent shopper data from a grocery chain with a two-stage HLM model. In understanding impact of price promotions, researchers in the past have used a number of different empirical approaches. Manchanda, Ansari, Gupta, 1999 utilize a multinomial probit model for cross-category utilities across multiple categories. Song and Chintagunta, 2006 use a log-log regression model for understanding cross-category price promotion effects with aggregate store-level data. Walters and Mckenzie,1988 employ a structural equation modeling approach to understand effect of price promotions on non-promoted products and overall store sales. van Heerde, Leeflang, Wittink Marketing Science, 2004 employ regression analysis for studying cross brand and cross-period effects of store-level promotions.

Since in our analysis, products (food items to examine impact of nutrition promotions on sales) are nested within categories, and we are investigating the category level and cross-category level effects of NuVal promotion on product sales, with further moderating effects of individual shopper and category characteristics, we construct a hierarchical linear model (HLM) to account for product category level and shopper level predictor variables. Pooling sales data across product categories may result in aggregation biases (Blattberg and George 1991) due to difference in the nature of how consumers shop in these categories. Employing HLM model helps in accounting for heterogeneity across different product categories.

3.2.1 Data Description

A regional super-market chain provided us with weekly promotion flyers as well as frequent shopper purchase data over a period of 27 months from Jan 2013 to March 2015. The weekly promotion flyers, over the given time period, provides detailed information on promotion of products in the given week, including category of product on promotion and whether nutritional information, in the form of NuVal score, was displayed in the promotion. We analyze product promotions in 4 categories: meat, produce, seafood and bakery, since we are interested in studying the impact of nutritional information in food products promotions, on their sales. This enables us to get promotion variables from a sample of 11,152 product promotions, using which we examine if the focal product or any other product, both in the focal product's category and in a different category, is featured in the promotion flyer with a NuVal score. This helps us the examine whether promoting the focal product or any other product in the same or different category impacts the sales of the focal product per transaction. The frequent shopper purchase data contains detailed shopper purchase information over 27 months, including type and quantity of products purchased per shopping trip, money spent per shopping trip, dates of purchase, NuVal value of products purchased. Excluding outlier transactions from the frequent shopper purchase data, we examine 6.1M transactions of 41,000 shoppers over a period of 27 months.

The merged and final constructed data set consists of the following variables: the date and hence week in which a purchase is made, the shopper who made the purchase, the total number of units purchased, the total dollar amount per product that the shopper paid, whether a product was on price promotion at the time on purchase, whether NuVal score was present on the promotion piece if product was on price promotion, whether the product category (we consider four product categories: meat, produce, bakery and seafood) had price promotion in a given week, whether the product category had price promotion with NuVal score in a given week. We denote the binary variable category NuVal promotion as one, if any product other than the focal product in a given category has a NuVal promotion that week, and zero otherwise. Similarly, we denote the binary variable cross- category NuVal promotion as one, if any product in a category different from the focal product, has a NuVal promotion that week, and zero otherwise.

After removing purchase records with outliers, we have about 6.1M product transactions of about 40,000 shoppers over 111 weeks with systematic recorded data over a span of 27 months from Jan 2013 to March 2015. We also have a sample of the weekly grocery promotion flyers. After carefully examining them, we counted number of "meat" category product promotions, as an example, averaged over five weeks. The maximum number of "meat" category product promotions appearing in a weekly grocery flyer in the five weeks is 48 (including those in the butcher section, frozen section and some other sections). Averaging out across all categories over all weeks, the number of weekly price promotions in a given category ranges from 0 to 69, and the average is 17. Out of these price promotions, the number of weekly promotions with NuVal score in a given category ranges from 0 to 32, and the average is 9. The average category nutrition is calculated by averaging across the NuVal values of all products in a given category that was sold in the 27 months period. Table-8 contains the summary statistics of important predictor variables in our analysis.

Table 8: Descriptive Statistics of some Weekly Category level Promotion Variables

Weekly Category Level Promotion Variables	**Min**	**Mean**	**Max**
total number of weekly category price promotions	0	16.641	69
total number of weekly nutrition promotions	0	9.282	32
NuVal score of produce category	72	91.7	100
NuVal score of seafood category	47	65.5	93
NuVal score of meat category	13	22.8	37
NuVal score of bakery category	7	19.8	31

The mean NuVal score of products in produce, seafood, meat and bakery in the given data is 91.7, 65.5, 22.8 and 19.8, respectively. Since, produce and seafood have higher average NuVal score, we characterize them as high nutrition categories, while meat and bakery with lower average NuVal score are characterized as low nutrition categories. Accordingly, the moderator variable, category mean nutrition is instrumentalized as a binary variable, namely high nutrition category, which is assigned value one if the focal product belongs to the produce or seafood category, and a value zero if the focal product belongs to the meat or bakery category. We also observe that the average mean NuVal score of products on nutrition promotion are 96.5 for produce category, 100 for seafood category, 29.8 for meat category and 49.2 for bakery category. This implies that the mean NuVal scores of products on nutrition promotion in any given category is higher than the mean NuVal score of the category. This indicates that there is an overall bias on the retailer's side in promoting high nutrition products in any given category. But since this intuitive bias is consistent across all categories being analyzed, this does not result in a category specific bias in our analysis.

3.2.2 Econometric Model Development

Since all products of interest in the analyzing effect of nutrition promotion on sales, belongs to one of the four food categories, namely produce, seafood, meat and bakery, we implement a Hierarchical Linear Model (HLM) specification for testing all the hypotheses. The outcome variable, *sales* denotes the transaction amount per product transaction and in analyzing the sales, we do control for per unit price of product. The predictor variable, *price promotion* is a binary 0/1 variable indicating whether a given product is on price promotion, whereas the variable, *nutrition promotion* is a binary 0/1 variable indicating whether a given product is on nutrition promotion, i.e., whether the product's NuVal score is being promoted on the promotion flyer. *Category price promotion* is a binary 0/1 variable indicating whether any other product in the category of the focal product is on price promotion, whereas the variable, category *nutrition promotion* is a binary 0/1 variable indicating whether any other product in the category of the focal product is on nutrition promotion. *Cross category price promotion* is a binary 0/1 variable indicating whether any product in a category different from that of the focal product is on price promotion, whereas the variable, category *nutrition promotion* is a binary 0/1 variable indicating whether any product in a category different from that of the focal product is on nutrition promotion.

As mentioned earlier, the moderator variable, *high nutrition category*, is assigned value one if the focal product belongs to the produce or seafood category, and a value zero if the focal product belongs to the meat or bakery category. The shopper characteristics are calculated as follows. The moderator variable, *monthly spending* is calculated as the average dollars spent by a shopper per transaction by averaging over each purchase expenditure. This implies the average share of wallet for the grocery retailer per customer. The second shopper level moderator variable, *nutrition consciousness* is obtained by averaging over the NuVal values of products purchased per basket for every shopper transaction at the grocery retailer. The multivariate mixed model specification for the studying the main effects and interaction effects, for examining all hypotheses, is as given in [7]:

$$\begin{aligned}
&sales_{ijk} \\
&= \beta_0 + \beta_{1ijk} price\ promotion_{\mathrm{i}} + \beta_{2ijk} nutrition\ promotion_{\mathrm{i}} + \beta_{3ijk} category price\ promotion_{\mathrm{j}} \\
&+ \beta_{4ijk} category\ nutrition\ promotion_{\mathrm{j}} + \beta_{5ijk} cross\ category price\ promotion_{\mathrm{j}} \\
&+ \beta_{6ijk} cross\ category\ nutrition\ promotion_{\mathrm{j}} \\
&+ \beta_{7ijk} high\ nutrition\ category_{\mathrm{j}} + \beta_{8ijk} monthly\ spending_k \\
&+ \beta_{9ijk} nutrition\ consciousness_k \\
&+ \beta_{10ijk} nutrition\ promotion_i \text{ x } high\ nutrition\ category_{\mathrm{j}} \\
&+ \beta_{11ijk} category\ nutrition\ promotion_j \text{ x } high\ nutrition\ category_{\mathrm{j}} \\
&+ \beta_{12ijk} cross\ category\ nutrition\ promotion_j \text{ x } high\ nutrition\ category_{\mathrm{j}} \\
&+ \beta_{13ijk} nutrition\ promotion_i \text{ x } monthly\ spending_k \\
&+ \beta_{14ijk} category\ nutrition\ promotion_j \text{ x } monthly\ spending_k \\
&+ \beta_{15ijk} cross\ category\ nutrition\ promotion_j \text{ x } monthly\ spending_k \\
&+ \beta_{16ijk} nutrition\ promotion_i \text{ x } nutrition\ consciousness_k \\
&+ \beta_{17ijk} category\ nutrition\ promotion_j \text{ x } nutrition\ consciousness_k \\
&+ \beta_{18ijk} cross\ category\ nutrition\ promotion_j \text{ x } nutrition\ consciousness_k + \beta_{19pijk} week \\
&+ \sum_{j=1}^{3} \beta_{20pijk}\, category_j + \beta_{21ijk} price\ per\ unit_i + \text{€}_{ijk} \qquad [7]
\end{aligned}$$

where,

$sales_{ijk}$: net $ purchase of product *i* by shopper *k* in category *j*

$price\ promotion_{\mathrm{i}}$: 1/0 variable: 1 if product *i* is on price promotion; 0: otherwise

$nutrition\ promotion_{\mathrm{i}}$: 1/0 variable: 1 if product i is on nutrition promotion; 0: otherwise

$category price\ promotion_{\mathrm{j}}$: 1/0 variable: 1 if any product other than focal product i is on price promotion in the focal product category *j*; 0: otherwise

$category nutrition\ promotion_{\mathrm{j}}$: 1/0 variable: 1 if any product other than focal product i is on nutrition promotion in the focal product category *j*; 0: otherwise

$cross\ category price\ promotion_{\mathrm{j}}$: 1/0 variable: 1 if any product category other than the focal product category *j* has one or more products on price promotion; 0: otherwise

$cross\ category nutrition\ promotion_{\mathrm{j}}$: 1/0 variable: 1 if any product category other than the focal product category j has one or more products on nutrition promotion; 0: otherwise

$high\ nutrition\ category_{\mathrm{j}}$*:* 1/0 variable: 1 if product belongs to produce or seafood category; 0: if product belongs to meat or bakery category

$monthly\ spending_k$: shopper *k*'s average spending at retailer

$nutrition\ consciousness_k$: nutrition consciousness of shopper k

$category_j$: 1/0 variable indicating whether product belongs to category j (meat or produce or seafood as compared to base category of bakery)

$price\ per\ unit_i$: per unit price of product i

$week_i$: sequential number of weeks of product *i* transaction

Since, we analyze products purchased by individual shoppers per transaction, which are nested within specific product categories and we are interested to not only examine effects of product nutrition promotions, but also the spill-over effects of category level and cross-category level nutrition promotions on product sales in each shopper transaction, we estimate our multivariate mixed model in the form of a 2-level HLM model specification. When adding predictor variables in the 2-level HLM model with interactions, we chose to grand mean center them (i.e., we subtract the overall mean of that variable from each product level transaction score). Regarding the method of estimation, we use Maximum Likelihood estimation as it is better suited to our unbalanced data, which has more zero promotions than non-zero promotions, as is expected from such grocery data sets where there will be more products not on weekly promotion, as opposed to those that are on promotion, the effect of which we aim to predict on sales, reflected in frequent shopper transaction records. To verify the main effects of transaction level product variables, namely *price promotion* and *nutrition promotion*, along with transaction level shopper characteristic variables, *monthly spending* and *nutrition consciousness*, category level effects, namely category *price promotion*, *nutrition promotion, cross category price promotion* and *cross category nutrition promotion*, and the interaction effects of variables at the nested levels, on the transaction level net sales of a given product, we estimate the HLM model specification of [7] as a system of equations, where the product and shopper level variables are at the transaction level and each product is nested within a specific category, and hence category level variables are estimated at level-2 of the HLM model, along with interaction terms.

3.2.3 Results

Table 9 contains results of the HLM estimation with MLE of the mixed model specification in [7]. The detailed effects of product-level, category-level and cross-category level spill-over effects of nutrition promotion on sales of products per transaction, as well as moderating effects of shopper characteristics are discussed below.

Table 9: HLM Model for analyzing hypotheses for product level sales

Parameter	Estimates	Hyp supported
Fixed Effects		
Intercept (∂00)	5.183***	
price promotion (∂10)	2.402***	
nutrition promotion (∂20)	2.915***	*H1 supported*
category price promotion (∂01)	-3.061***	
category nutrition promotion (∂02)	2.673***	*H2 supported*
cross category price promotion (∂03)	-.359**	
cross category nutrition promo (∂04)	-1.738*	*H3 supported*
high nutrition category (∂05)	.256***	
shopper nutrition consciousness (∂30)	.028**	
shopper monthly spending (∂40)	.132**	
price per unit (∂50)	1.031***	
produce (∂05)	.856***	
seafood (∂06)	.919***	
meat (∂07)	.577*	
week (∂60)	.007*	
Interaction terms		
nutrition promotion × shopper monthly spending	-7.142***	*H1a supported*
category nutrition promotion × shopper monthly spending	-5.520***	*H2a supported*
cross category nutrition promotion × shopper monthly spending	.000	*H3a not supported*
nutrition promotion × shopper nutrition consciousness	2.212***	*H1b supported*
category nutrition promotion × shopper nutrition consciousness	1.051***	*H2b supported*
cross category nutrition promotion × shopper nutrition consciousness	.006*	*H3b supported*
nutrition promotion × high nutrition category	-2.558***	*H1c supported*
category nutrition promo × high nutrition category	-1.791***	*H2c supported*
cross category nutrition promo × high nutrition category	0.000	*H3c not supported*
Variance Components		
Residual (eij)	6.657	
Intercept (u0j)	14.645	

shopper nutrition consciousness (u1j)	0.001	
shopper monthly spending (u2j)	0.001	

bakery is used as the reference category; significance level: * $p < .05$, ** $p < .01$, *** $p < .001$

3.2.3.1 Main effects of Nutrition Promotions on Sales

There is a positive impact of price promotion on sales of a product (b= 2.402, p<.0001), while featuring NuVal score on the product promotion, further improves product sales (b= 2.915, p<.0001). Hence, this finding supports proposed H1 that there is a positive effect of nutrition promotions on sales of a product. When other products in the same category as the focal product are promoted in the price promotion flyers, there is a negative spill-over effect on sales of the focal product (b = -3.061, p< 0.001). This makes sense intuitively due to complementarity of certain product types in the same product category and when another product is on price promotion, purchase volume of the promoted product should improve at the cost of reduced sales of the focal product to derive maximum price utility. On the other hand, when other products in the same category are featured with their NuVal score on the price promotion flyers, there is a positive spill-over effect on sales of the focal product (b = 2.673, p< 0.001), supporting proposed hypothesis H2 that there is a positive spill-over effect of nutrition promotions in a given category on sales of other products in the category. Having products featured with nutrition scores on price promotion flyers, draws attention to not only the product itself, but the entire product category and improves sales of all products in the given category. When any product in a product category different from the focal product category is promoted in a given week, the impact on the sales of the focal category is negative, both in the case of price promotions in a different category (b = -0.359, p< 0.01) and nutrition promotions in a different category (b = -1.738, p< 0.05). This supports H3 that there is a negative cross category spill-over effect of nutrition promotions on sales of products in a different product category. Thus, these results support the main effects of nutrition promotion on sales as proposed in H1-H3: positive effect of nutrition promotion on individual products, positive spill-over effect of nutrition promotion on any product in a given category, and negative spill-over effect of nutrition promotion on any product in a different category, on the sales of the focal product.

3.2.3.2 Main effects of Shopper and Product Category Characteristics on Sales

Average monthly spending of a shopper at the grocery retailer store is calculated as each shopper's average monthly total basket purchases at the store. We find that for shoppers with higher average monthly spending, per transaction sales are higher ($b = .132$, $p < .01$). Nutrition consciousness of shopper is calculated as the average quantity-weighted NuVal score of each shopper's purchases across the 27-month period. We find that for highly nutrition conscious shopper, per transaction sales are higher ($b = .028$, $p < .01$). Thus, we find that shoppers with higher average monthly spending and those with higher nutrition consciousness spend more dollars per product transaction. Examining impact of average nutrition of a product category on sales of product, we find that the overall spending per product transaction is higher for products belonging to the higher nutrition categories of produce and seafood than for products belonging to the lower nutrition categories of meat and bakery ($b = 0.256$, $p < .001$).

3.2.3.3 Moderating effects of Shopper and Product Category Characteristics on Impact of Nutrition Promotions on Sales

First, let us examine the moderating effect of shopper characteristic, average monthly spending on the impact of nutrition promotion on sales. The effect of nutrition promotion on sales of product is weaker for shoppers with higher average monthly spending than those with lower average monthly spending ($b = -7.142$, $p < 0.001$). This supports our proposed hypothesis H1a that the positive impact of a product featured with nutrition score in a promotion flyer, on its per transaction sales volume, is stronger for shoppers with lower average monthly spending likely due to novelty of information that lighter shoppers derive from the featured NuVal score on the promotion flyers. The spill-over effect of nutrition promotion on any other product in the same product category as that of the focal product, on sales of the focal product, is similarly weaker for shoppers with higher average monthly spending than those with lower average monthly spending ($b = -5.520$, $p < 0.001$). This supports our proposed hypothesis H2a that the positive spill-over effect of one or more nutrition promotions in a given category on per transaction sales volume of other products in the same category, is stronger for lighter shoppers with lower average monthly spending than for those who typically spend more at the retailer store. However, when examining the moderating effect of shopper's monthly average spending on the spill-over cross category nutrition promotions effects on sales of a focal product in a different category, we observe no significant moderating effect. Thus, H3a does not hold and the negative cross category spill-over impact of nutrition promotion is not significantly different for shoppers with higher vs lower average monthly spending at the grocery retailer store. Thus, in analyzing moderating effects of shopper characteristics, average monthly spending on nutrition promotion impact on product sales, hypotheses H1a examining product level nutrition promotions and H2a examining category level nutrition promotions are supported, while H3a examining cross-category level nutrition promotions is not supported.

Second, let us examine the moderating effect of shopper characteristic, nutrition consciousness on the impact of nutrition promotion on sales. The effect of nutrition promotion on sales of product is stronger for shoppers with higher nutrition consciousness than those with lower nutrition consciousness ($b = -2.212$, $p < 0.001$). This supports our proposed hypothesis H1b that the positive impact of a product featured with nutrition score in a promotion flyer, on its per transaction sales volume, is stronger for healthier shoppers due to the inclination of such shoppers to seek nutrition information of products. The spill-over effect of nutrition promotion on any other product in the same product category as that of the focal product, on sales of the focal product, is similarly stronger for shoppers with higher nutrition consciousness than those with lower nutrition consciousness ($b= 1.051$, $p<0.001$). This supports our proposed hypothesis H2b that the positive spill-over effect of one or more nutrition promotions in a given category on per transaction sales volume of other products in the same category, is stronger for healthier shoppers with higher nutrition consciousness than for those who typically have lower nutrition consciousness. When examining the moderating effect of shopper's nutrition consciousness on the spill-over cross category nutrition promotions effects on sales of a focal product in a different category, we observe that the spill-over interaction effect coefficient is positive ($b= 0.006$, $p<0.05$). Thus, this supports the effect predicted in H3b that the negative spill-over effect of cross-category nutrition promotion on sale of a product in a different category is weaker for shoppers with higher nutrition consciousness. Thus, in analyzing moderating effects of shopper characteristics, nutrition consciousness on nutrition promotion impact on product sales, all hypotheses H1b examining product level nutrition promotions, H2b examining category level nutrition promotions are supported, and H3b examining cross-category level nutrition promotions are supported.

Finally, let us examine the moderating effect of product category characteristic, nutrition level characterized through the binary 1/0 variable higher nutrition category (1: product belongs to produce or seafood category; 0: product belongs to meat or bakery category) on the impact of nutrition promotion on sales. The effect of nutrition promotion on sales of product is weaker for products belonging to the higher nutritious categories of produce or seafood than those with belonging to the higher nutritious categories of meat or bakery (b= -2.558, p<0.001). This supports our proposed hypothesis H1c that the positive impact of a product featured with nutrition score in a promotion flyer, on its per transaction sales volume, is stronger for categories with lower perceived nutrition due to re-evaluation of the category nutrition from novelty of featured nutrition score. Similarly, the spill-over effect of nutrition promotion on any other product in the same product category as that of the focal product, on sales of the focal product, is weaker for higher nutritious categories of produce or seafood than for lower nutritious categories of meat or bakery (b= -1.791, p<0.001), thus supports our proposed hypothesis H2c and resulting in positive re-evaluation of an otherwise perceived lower nutrition category and resulting in stronger positive spill-over effects. However, when examining the moderating effect of category nutrition on the spill-over cross category nutrition promotions effects on sales of a focal product in a different category, we observe no significant moderating effect. Thus, H3c does not hold and the negative cross category spill-over impact of nutrition promotion is not significantly different for categories with lower vs those with higher perceived nutrition. Thus, in analyzing moderating effects of category nutrition on nutrition promotion impact on product sales, hypotheses H1c examining product level nutrition promotions and H2c examining category level nutrition promotions are supported, while H3c examining cross-category level nutrition promotions is not supported.

In our analysis, we also initially included the type of price promotion, such as price-cut or buy-one-get-one offers and their interaction effects to control for the variation in price promotion type and how that impacts the effect of featured nutrition score, but those terms yielded VIFs*> 10, and hence finally dropped them and only retained the binary variable price promotion, indicating whether or not a product is featured on the promotion flyer. To make VIFs comparable across dimensions, VIF is calculated as: $GVIF^{\frac{1}{2df}}$, where GVIF is generalized VIF and Df is the number of coefficients in the subset (Fox and Monette, JASA, 1992). In effect, this reduces the GVIF to a linear measure.

3.2.4 Robustness Checks

We perform two robustness checks to measure stability of the hypotheses tested in the HLM model specification of the effects of product, category and cross-category nutrition promotion effects on product sales and the moderating characteristics of shopper characteristics, i.e., average monthly spending and nutrition consciousness, and product category characteristics, i.e., high vs low nutrition category. In the first robustness test, we substitute the dependent variable $ sales volume per product transaction with the quantity (i.e., number of units) purchased per product transaction. The expectation is the main and moderation effects should be consistent as in the HLM specification of the mixed model [7], since quantity of product purchased is proportional to the $ sales volume per product transaction. We also control for per unit product price. The mixed model for HLM estimation is as follows [8]:

$$
\begin{aligned}
&units_{ijk} \\
&= \beta_0 + \beta_{1ijk} price\ promotion_{\mathrm{i}} + \beta_{2ijk} nutrition\ promotion_{\mathrm{i}} + \beta_{3ijk} category price\ promotion_j \\
&+ \beta_{4ijk} category\ nutrition\ promotion_{\mathrm{j}} + \beta_{5ijk} cross\ category price\ promotion_{\mathrm{j}} \\
&+ \beta_{6ijk} cross\ category\ nutrition\ promotion_{\mathrm{j}} \\
&+ \beta_{7ijk} high\ nutrition\ category_{\mathrm{j}} + \beta_{8ijk} monthly\ spending_k \\
&+ \beta_{9ijk} nutrition\ consciousness_k \\
&+ \beta_{10ijk} nutrition\ promotion_i \text{ x } high\ nutrition\ category_{\mathrm{j}} \\
&+ \beta_{11ijk} category\ nutrition\ promotion_j \text{ x } high\ nutrition\ category_{\mathrm{j}} \\
&+ \beta_{12ijk} cross\ category\ nutrition\ promotion_j \text{ x } high\ nutrition\ category_{\mathrm{j}} \\
&+ \beta_{13ijk} nutrition\ promotion_i \text{ x } monthly\ spending_k \\
&+ \beta_{14ijk} category\ nutrition\ promotion_j \text{ x } monthly\ spending_k \\
&+ \beta_{15ijk} cross\ category\ nutrition\ promotion_j \text{ x } monthly\ spending_k \\
&+ \beta_{16ijk} nutrition\ promotion_i \text{ x } nutrition\ consciousness_k \\
&+ \beta_{17ijk} category\ nutrition\ promotion_j \text{ x } nutrition\ consciousness_k \\
&+ \beta_{18ijk} cross\ category\ nutrition\ promotion_j \text{ x } nutrition\ consciousness_k + \beta_{19pijk} week \\
&+ \sum_{j=1}^{3} \beta_{20pijk}\ category_j + \quad \beta_{21ijk} price\ per\ unit_i \qquad [8]
\end{aligned}
$$

where,

$units_{ijk}$: number of units of product *i* purchased by shopper *k* in category *j*.

All independent variables are as defined in model [7] equation. The results of this robustness test are presented in Table-10.

Table 10: Robustness Check 1: HLM results with d.v.: quantity purchased

Parameter	Estimates
Fixed Effects	
Intercept (∂00)	1.221***
price promotion (∂10)	1.021***
nutrition promotion (∂20)	2.671***
category price promotion (∂01)	-.007**
category nutrition promotion (∂02)	.067**
cross category price promotion (∂03)	-.003*
cross category nutrition promo (∂04)	-.062*
high nutrition category (∂05)	.015**
shopper nutrition consciousness (∂30)	.003*
shopper monthly spending (∂40)	.001*
price per unit (∂50)	1.702***
produce (∂05)	.771*
seafood (∂06)	.319*
meat (∂07)	.014
week (∂60)	.001
Interaction terms	
nutrition promotion × shopper monthly spending	-.004**
category nutrition promotion × shopper monthly spending	-.002**
nutrition promotion × shopper nutrition consciousness	.003**
category nutrition promotion × shopper nutrition consciousness	.001**
cross category nutrition promotion × shopper nutrition consciousness	.002*
nutrition promotion × high nutrition category	-.007*
category nutrition promo × high nutrition category	-.001*

bakery is used as the reference category; significance level: * $p < .05$, ** $p < .01$, *** $p < .001$

We observe the same overall effects in the HLM model specification when the dependent variable is quantity of products purchase per transaction instead of $ sales volume per product transaction. We find support for H1-H3, H1a, H2a, H1b, H2b, H3b, H1c H2c studying the main effects of nutrition promotion at the product, category and cross-category level as well as the moderating effects of average monthly spending and nutrition consciousness of the shopper as well as category nutrition. Additionally, we control for price of unit product ($b = 1.702$, $p < 0.001$), sequential number of week over the given time period and category type as produce ($b=.771$, $p<0.05$), seafood ($b=.319$, $p<0.05$) and meat product sales ($b=.014$, $p>0.05$) as compared to the reference category, bakery and these effects are consistent as well.

In the second robustness test, we add two interaction effects variables to test the moderating effect of the difference in promoted nutrition score and the mean category nutrition. This analysis helps us understand whether promoting higher nutrition products in a category on nutrition promotions has a stronger positive effect on sales of products in the category. Specifically, at the product level nutrition promotion, we interact the binary 1/0 variable, *nutrition promotion* (is the product on nutrition promotion) with the difference in promoted NuVal score and the mean NuVal score of products in the given category. At the category level nutrition promotion, we interact the binary variable, *category nutrition promotion* (is any other product in the focal product's category on nutrition promotion) with the difference in mean promoted category NuVal score and the mean NuVal score of products in the given category. We apply an HLM model specification of the following mixed model [9]:

$$
\begin{aligned}
&sales_{ijk} \\
&= \beta_0 + \beta_{1ijk} price\ promotion_{\mathrm{i}} + \beta_{2ijk} nutrition\ promotion_{\mathrm{i}} + \beta_{3ijk} category price\ promotion_{\mathrm{j}} \\
&+ \beta_{4ijk} category\ nutrition\ promotion_{\mathrm{j}} + \beta_{5ijk} cross\ category price\ promotion_{\mathrm{j}} \\
&+ \beta_{6ijk} cross\ category\ nutrition\ promotion_{\mathrm{j}} \\
&+ \beta_{7ijk} high\ nutrition\ category_{\mathrm{j}} + \beta_{8ijk} monthly\ spending_k \\
&+ \beta_{9ijk} nutrition\ consciousness_k \\
&+ \beta_{10ijk} nutrition\ promotion_i \text{ x } high\ nutrition\ category_{\mathrm{j}} \\
&+ \beta_{11ijk} category\ nutrition\ promotion_j \text{ x } high\ nutrition\ category_{\mathrm{j}} \\
&+ \beta_{12ijk} cross\ category\ nutrition\ promotion_j \text{ x } high\ nutrition\ category_{\mathrm{j}} \\
&+ \beta_{13ijk} nutrition\ promotion_i \text{ x } monthly\ spending_k \\
&+ \beta_{14ijk} category\ nutrition\ promotion_j \text{ x } monthly\ spending_k \\
&+ \beta_{15ijk} cross\ category\ nutrition\ promotion_j \text{ x } monthly\ spending_k \\
&+ \beta_{16ijk} nutrition\ promotion_i \text{ x } nutrition\ consciousness_k \\
&+ \beta_{17ijk} category\ nutrition\ promotion_j \text{ x } nutrition\ consciousness_k \\
&+ \beta_{18ijk} cross\ category\ nutrition\ promotion_j \text{ x } nutrition\ consciousness_k \\
&+ \beta_{13ijk} nutrition\ promotion_i \text{ x } (NuVal\ score_i - mean\ category\ NuVal\ score_j) \\
&+ \beta_{14ijk} category\ nutrition\ promotion_j \text{ x } (mean\ promoted\ category\ NuVal\ score_i \\
&- mean\ category\ NuVal\ score_j) + \beta_{21pijk} week + \sum_{j=1}^{3} \beta_{22pijk}\, category_j \\
&+ \beta_{21ijk} price\ per\ unit_i \qquad [9]
\end{aligned}
$$

where,

$sales_{ijk}$: net \$ purchase of product *i* by shopper *k* in category *j*

$NuVal\ score_i - mean\ category\ NuVal\ score_j$: (promoted product nutrition score – mean category nutrition score)

$mean\ promoted\ category\ NuVal\ score_i - mean\ category\ NuVal\ score_j$: (mean promoted category nutrition score – mean category nutrition score)

All other independent variables are as defined in model [7] equation. The results of this robustness test are presented in Table-11.

Table 11: Robustness Check 2: HLM results with moderation effect of promoted product healthiness on sales

Parameter	Estimates
Fixed Effects	
Intercept (∂00)	5.204***
price promotion (∂10)	.098***
nutrition promotion (∂20)	.014***
category price promotion (∂01)	-.064**
category nutrition promotion (∂02)	.023**
cross category price promotion (∂03)	-.002*
cross category nutrition promo (∂04)	-.001*
high nutrition category (∂05)	6.202***
shopper nutrition consciousness (∂30)	.003**
shopper monthly spending (∂40)	.008**
price per unit (∂50)	1.117***
produce (∂05)	8.903***
seafood (∂06)	2.172*
meat (∂07)	.007*
week (∂60)	.001
Interaction terms	
nutrition promotion × shopper monthly spending	-.012**
category nutrition promotion × shopper monthly spending	-.001**
nutrition promotion × shopper nutrition consciousness	.028**
category nutrition promotion × shopper nutrition consciousness	.002**
cross category nutrition promotion × shopper nutrition consciousness	.001*
nutrition promotion × high nutrition category	-.462***
category nutrition promo × high nutrition category	-.001*
nutrition promotion × (promoted nutrition – mean category promotion)	1.097***
category nutrition promo × (mean promoted category nutrition – mean category promotion)	.002*

bakery is used as the reference category; significance level: * p < .05, ** p < .01, *** p < .001

We observe positive coefficients for both additional interaction terms. If a product is on nutrition promotion, the positive effect of nutrition promotion on its sales increases with increasing difference of the promoted nutrition score from the mean category nutrition score ($b=1.097$, $p < 0.001$). This means that the sales of products promoted on nutrition promotion are higher for higher nutrition products within any given category. Similarly, if a category has one or more products on nutrition promotion, the positive spill-over effect on sales of non-promoted products in the same category increases with increasing difference of the mean nutrition score of products promoted in the category from the mean category nutrition score ($b=.002$, $p < 0.05$). This means that the spill-over effect of having nutrition promotion on one or more products in a given category on sales of non-promoted products in the same category is higher if the more nutritious products in any given category are promoted. Thus, it is imperative that when retailers are self-selecting among products for featuring on the promotion flyer with nutrition information, they should choose to feature higher nutrition products for highest positive spill-over effect to the sales of all products in a given category. Additionally, for all other effects, we find support for all hypotheses in studying the main effects of nutrition promotion at the product, category and cross-category level as well as the moderating effects of average monthly spending and nutrition consciousness of the shopper as well as category nutrition.

3.2.5 Non-parametric Sensitivity Analysis

In this section, we fit an artificial neural network to our data for non-parametric sensitivity analysis of predicting substantial category level factors for predicting change in product level sales. Linear statistical modeling approach sometimes simplifies the complexity learning from imbalanced big data (in our data we have more products that are not on nutrition promotion vs those that are on nutrition promotion), employing neural network achieves more precise predictions (Chan and Chong 2012). Thus, a 2-stage method provides additional holistic comprehension above that provided by a linear and compensatory predictive approach (Zabukovsek et al. 2018). The goal is to conduct a sensitivity analysis for critical factors tested in our hypotheses in order to rank effects tested significant in our HLM analysis. The dependent variable is net sales per transaction level product sales. The predictor variables of interest are those that tested to be significant in the HLM analysis of mixed model [7]. The goal of the neural network (NN) is to mathematically train the system to learn feature (predictor variable) importance, evaluated from the weights derived from each node in the NN architecture. The NN analytical approach makes it possible to achieve more precise predictions by considering non-linearities in comparison to the typical regression techniques.

3.2.5.1 Neural Network Model Architecture

In our model, we have designed a neural network with four layers: the input layer, hidden layer 1, hidden layer 2, and output layer. There are 13 factors (as in model 2) in the input layer. Hidden layer 1 has 7 nodes, hidden layer 2 has 4 nodes and the output layer has 1 node. The number of nodes (neurons) in each layer has been chosen as the mean of the neurons in the input and output layers (Heaton, 2008). It is a feed forward neural network, where connections between the nodes do not form a cycle. Such a feed-forward neural network with at least three layers of nodes is called a multi-layer perceptron (MLP). Thus, we have designed a four-layer MLP. Figure 3 is an example depiction of a four-layer MLP visualization.

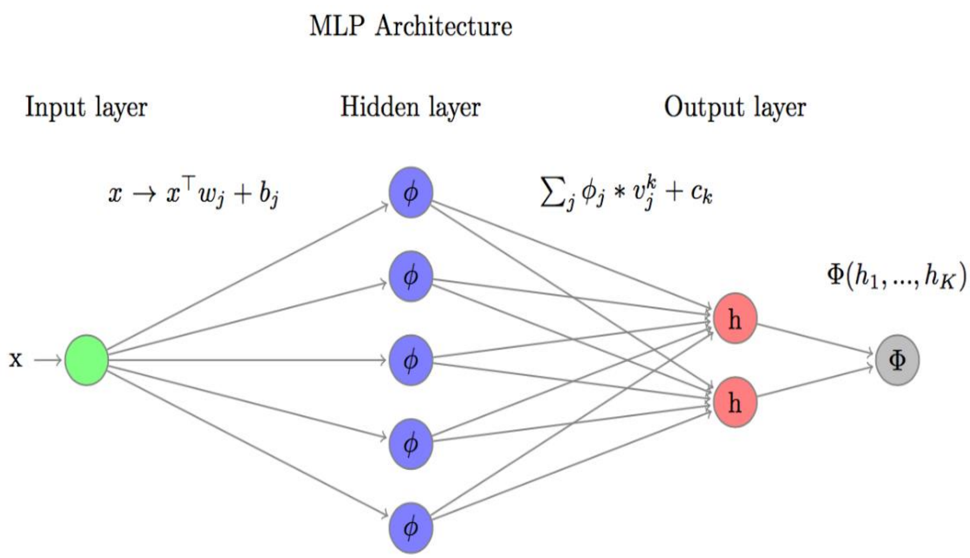


Figure 3: Visualization of a Neural Network architecture (multi-layer perceptron)

In the first layer of the MLP, we apply linear transformations to the data point *x*:

$$f_j(x) = x^T w_j + b_j \quad \text{for } j = 1, \ldots\ldots, J \tag{10}$$

where, the number of transformations is the number of hidden nodes in the first hidden layer. Next, we apply a non-linear transformation of outputs using what is called an activation function. We use a rectifier activation function, known as *ReLU* (rectified linear unit) as given by:

$$\emptyset(x) = \max(0, x) \tag{11}$$

Next, the outputs of activation function are again combined using linear transformation:

$$h_k(x) = \sum_j \emptyset\left(f_j(x)\right) * v_j^k + c_k \tag{12}$$

At this point, we repeat the activation step and extend the network with another activation layer (hidden layer 2) and then apply final transformation of the outputs to fit the algorithm objective of predicting sales from the given set of input parameters. We used the Adam (adaptive moment estimation) optimization algorithm (Kingma and Ba, 2015), which is an extension of the stochastic gradient descent in training our MLP. This optimization technique updates network weights iterative based on training data. We use the Adam optimization algorithm because it is computationally efficient, has low memory requirement, is invariant to diagonal rescale of the gradients, and is well suited for problems with large data set (we have about 6.1M transaction records).

3.2.5.2 Sensitivity Analysis Results

Input layer to hidden layer 1 input signal weights (weights of each of the 13 inputs to each of the 7 nodes in hidden layer 1) are given in Table 12. Hidden layer 1 to hidden layer 2 input signal weights (weights of each of the 7 inputs in hidden layer 1 to each of the 4 nodes in hidden layer 2) are given in Table 13.

Hidden layer 2 to output layer input signal weights (weights of each of the 4 inputs of hidden layer 2 to the single node in the output layer) are given in Table 14. The results of the sensitivity analysis of the input factors in the NN model and average signal weight from each input parameter in the first layer of the model are presented in Table 15.

Table 12: Weights by which (Node) Signals are Multiplied from Input Layer to Hidden Layer 1

	HL1(1)	HL1(2)	HL1(3)	HL1(4)	HL1(5)	HL1(6)	HL1(7)
nutrition promotion	.183	-.031	.0759	.113	.122	.820	.345
category nutrition promotion	.074	-.029	.082	.030	.157	.206	.187
cross-category nutrition promotion	4.914	.178	-6.854	-1.404	-1.251	-.517	.252
monthly spending	-.014	.187	.608	-.132	-.149	.884	.525
nutrition consciousness	-.189	-.419	.235	-.049	.077	-.627	.251
high nutrition category							
nutrition consciousness × nutrition promotion	.223	.136	.067	-.192	-.089	.612	-.275
nutrition consciousness × category nutrition promotion	.125	.188	-.009	-.080	-.089	.358	-.164
nutrition consciousness × cross-category nutrition promotion	4.847	-2.285	2.816	-.017	.309	.209	.524
monthly spending × nutrition promotion	-.059	.075	-.213	.076	.007	-.310	.184
monthly spending × nutrition promotion	-.029	-.175	-.089	.028	.018	-.186	-.058
high nutrition category × nutrition promotion	2.208	.124	-2.171	-1.104	0.104	.582	.166
high nutrition category × category nutrition promotion	.280	.026	-.119	.083	1.773	.390	.029
price per unit	.184	.976	1.181	1.131	-.017	.222	-.643

Table 13: Weight by which (Node) Signals are Multiplied from Hidden Layer 1 to Layer 2

	HL2(1)	HL2(2)	HL2(3)	HL2(4)
HL1(1)	.181	-1.993	0	-1.374
HL1(2)	-2.841	8.767	0	.854
HL1(3)	.113	.387	0	1.107
HL1(4)	1.275	.039	0	-.035
HL1(5)	-.997	.353	0	.209
HL1(6)	-.048	3.987	0	3.799
HL1(7)	-.226	-.109	0	-.166

Table 14: Weight by which (Node) Signals are Multiplied from Hidden Layer 2 to Output Layer

	Output Layer Node
HL2(1)	0.793
HL2(2)	1.837
HL2(3)	0
HL2(4)	1.504

Table 15: Sensitivity Analysis of Proposed MLP Architecture

	Average weight in layer 1 of MLP	Normalized Feature Importance	HLM coefficients
nutrition promotion	0.233	0.154	2.915***
category nutrition promotion	0.101	0.125	2.673***
cross-category nutrition promotion	0.273	0.094	-1.738*
monthly spending	0.049	0.058	.132**
nutrition consciousness	-0.087	0.047	.028**
high nutrition category	-0.070	0.066	.256***
nutrition consciousness x nutrition promotion	0.056	0.137	2.212***
nutrition consciousness x category nutrition promotion	0.047	0.209	1.051***
nutrition consciousness x cross-category nutrition promotion	0.434	2.158	.006*
monthly spending x nutrition promotion	0.669	1.966	-7.142***
monthly spending x category nutrition promotion	-0.915	6.181	-5.520***
high nutrition category X nutrition promotion	0.013	1.662	-2.558***
high nutrition category X category nutrition promotion	0.352	0.141	-1.791***

The attained results of the sensitivity analysis reveal that interactions of shopper's average monthly spending with both product level and category level nutrition promotions are more significant than the interactions of nutrition consciousness with either product or category level nutrition promotions. The model fit is improved, but the direction of effects and interaction effects in the HLM model results for product-level, category-level and cross-category level effects on product level sales still hold. Overall, there is an increase in net sales with featuring NuVal score on products as well as other products in the same category. We find that featuring a NuVal score on promotions reduces sales among shoppers with higher average monthly spending at the retailer store and increases sales among shoppers with higher nutrition consciousness. But overall the moderation effect is more sensitive on shopper monthly spending level than nutrition consciousness. This may be due to the fact that nutrition information display is more novel for shoppers with lower spending record at the retailer store than shoppers who spend more and have more extensive knowledge of product nutrition or shoppers who are more nutrition consciousness and have more knowledge when seeking out products with different nutrition level. Hence, the positive spill-over effect of products in a given category with featured nutrition score on sales of products in the same category is strongest for shoppers who shop less at the grocery retailer store. Hence, when selectively targeting shoppers for distributing flyers with featured nutrition promotions, less frequent or light shoppers should be the priority target for retailers to reap maximum positive spill-over of category-level nutrition promotion on sales of all products in the given category. Also, consistent is the result that these positive spill-over effects are stronger in lower nutrition categories than the already perceived higher nutrition categories. The spill-over effects of cross-category promotions are overall negative.

3.3 Impact of Nutrition Promotions on Category level Weekly Sales

In this section, we examine the main effect of nutrition promotions on net weekly sales of products at the category level, controlling for category type. We also test the moderating effects of category nutrition on category-level nutrition promotion impact on total category sales.

3.3.1 Econometric Analysis

Model [13] tests the impact of having one or more weekly category level price promotions and weekly category level nutrition promotions on the net weekly category level sales**.** Therefore, the dependent variable is the sum of dollar amount spent in week *j* by shoppers on all products belonging to category *i* (meat, produce, seafood or bakery category). There is a total of 494 weekly category level observations for dollar spent on 4 categories in 111 weeks. The model is specified as follows:

$$\begin{aligned} category\ sales_{ij} &= \beta_0 + \beta_{1ij} category\ price\ promotion_{\mathrm{ij}} \\ &+ \beta_{2ij} category\ nutrition\ promotion_{\mathrm{ij}} \\ &+ \beta_{2ij} higher\ nutrition\ category_{ij} \\ &+ \beta_{2ij} category\ nutrition\ promotion_{\mathrm{ij}} X\ higher\ nutrition\ category_{ij} \\ &+ \beta_{5ij} week_{\mathrm{j}} + \sum_{i=1}^{3} \beta_{6ij}\, category_i \end{aligned} \qquad [13]$$

where,

$category\ sales_{ij}$: total $ sales in category *i* in week *j*

$category\ price\ promotion_{\mathrm{ij}}$: 1/0 variable indicating whether there is a price promotion in category *i* in week *j*

$category\ nutrition\ promotion_{ij}$: 1/0 variable indicating whether there is a price promotion in category *i* in week *j* with NuVal score

$higher\ nutrition\ category_{ij}$: 1/0 variable indicating high vs low average nutrition with 1: produce or seafood category; 0: meat or bakery category

$category_i$: whether category *i* is meat, produce or seafood as compared to bakery

$week_j$: sequential number of week *j* out of 111 weeks

3.3.2 Results

Table 16 summarizes result of category level sales as specified in model [13]. Featuring weekly category level price promotion significantly increases average weekly sales in the category by $7487, while adding nutritional information on price promotion significantly improves average weekly sales in the category by around $3357. So besides significant positive effect of category level promotion on total weekly sales in the category, there is indeed a significant positive effect of category level promotion with NuVal information on total weekly sales in the category, consistent with the nutrition promotion impact on individual product sales.

Table 16: Effect of category level promotions on weekly net sales of all products in a category

Parameter	Parameter Description	Coeff (B)
constant		335.20***
category price promotion	1= category has one or more product on price promotion, 0= category has no product on price promotion	7487.07***
category nutrition promotion	1= category has product on nutrition promotion, 0= category has no product on nutrition promotion	3356.72**
high nutrition category	1= high nutrition category (produce or seafood), 0 = low nutrition category (meat or bakery)	65770.04***
category nutrition promotion × high nutrition category	effect of nutrition promotion in a high nutrition category on sales of product in the given category	-1270.01**
produce	1 = if category is produce, 0 = otherwise	120500.00***
seafood	1 = if category is seafood, 0 = otherwise	18620.00***
meat	1 = if category is meat, 0 = otherwise	88950.00***
week	sequential number of week over the given time period	39.30*

significance level: * $p < .05$, ** $p < .01$, *** $p < .001$; $R^2 = 0.735$

The interaction effect of category nutrition with featuring nutrition promotions in the category, yields a significant negative coefficient of b = 1270, indicating that the increase in total category sales from featuring weekly nutrition promotions is higher in lower nutrition categories of meat and bakery than the higher nutrition categories of produce and seafood. Thus, similar to product level sales, retailers should pay attention to the finding that featuring nutrition promotions improves overall sales in low nutrition categories by a higher margin than in high nutrition categories. Controlling for product category, compared to the base category of bakery, average weekly sales in the meat category was higher by $88950, average weekly sales in the produce category was higher by $120500, and average weekly sales in the seafood category was higher by $18620. Controlling for week, average weekly total sales in a category went up by $39 each week.

3.4 General Discussions

3.4.1 Findings and Contributions

Grocery retailers have been increasingly implementing ways to do their part in fighting against obesity by offering diverse health and wellness programs at the point of sale and consumers have placed their trust in food retailers to support their goal of eating healthy. Our objective in this research has been to examine how consumers react to nutritional information in retailer promotions and take that into account, while making purchase decisions. We specifically focus on the use of NuVal scores and examine consumer responses after the nutrition scoring system has been in place for a while and its novelty has worn off. Specifically, we look at the impact of featuring the NuVal score in the product's price promotion piece in the weekly grocery promotion flyers. at the POS. The NuVal scoring system combines all the nutritional in- formation into a single summary indicator of the relative healthiness of the product and it makes it easy for shoppers to read and process to make informed healthy purchases. Our research makes the following key contributions. First, using frequent shopper purchase data of 40,000 shoppers across a twenty-seven month period we test our central proposition that featuring NuVal score on the price promotion appearing in weekly grocery promotion flyers, heightens evaluation of the product promoted. This effect is strongest in products in lower nutrition categories. It dispels shoppers' perceived concerns with the quality of products in lower nutrition categories and increases favorability for purchase. The effect is also stronger for healthy shoppers as well as light shoppers with lower average monthly spending at the retail store by providing more novel information through nutrition promotions. Most significantly, the positive impact of the products promoted with featured NuVal score, spills over to other products in the category. The positive spill-over effect is particularly significant in lower nutrition categories. However, the spill-over effect of nutrition promotion to products in other categories is negative, although this negative spill-over effect is lower for healthier shoppers. Additionally, we also find that featuring category level promotions with NuVal score on weekly promotion flyers increases the net weekly sales of all products in the category. This effect is found to be stronger for "price type" type promotions than "free with" type price promotions.

Finally, we find the direction of all these effects to be replicated for quantity of products purchased. A sensitivity analysis reveals that shopper average monthly spending and interaction with nutrition promotions is more significant factors affecting sales than shopper nutrition consciousness and the corresponding nutrition promotions, although the latter predictors do significantly impact sales. Thus, when selectively targeting consumers for exposing to nutrition promotions, the retailer should target light shoppers with lower average spending at the retail store, since nutrition information of products is relatively novel information for such shoppers.

3.4.2 Managerial Implications

Our research has important practical implications for grocery retailers. Given that grocery retailers are increasingly implementing a wide range of health and wellness initiatives at the, it is essential for them to understand the programs' effectiveness in promoting shoppers' understanding and product sales. Since, grocery retailers are always putting out product promotions, a simple act of just putting out NuVal information for at least the healthier products in the category brings attention to the entire category and can help improve sales of not only individual products in the category but also the overall sales of all products in the given category. Our results provide evidence that featuring NuVal scores on promotions has a "win-win" benefit for both consumers and grocery retailers. Such a practice presents novel information to the shoppers regarding relative nutritional information of the product as well as perceived nutritional quality of similar products in the category. This translates into higher dollar spent per product transaction in the promoted product category, which means more profit incurred by the grocery retailer. Consumer targeting can also be effective when mailing out product promotions selectively. Especially mailing product promotion flyers with NuVal information to shoppers with lower average monthly spending at the retail store can grab attention of such shoppers because of novelty of the information and can help convert more purchases from this class of shoppers. Also, it is important that shoppers with more nutrition consciousness be reached out with NuVal scores featured on product promotions because this group of shoppers seek out nutrition information more actively from others.

The best practice is for grocery retailers will be to put out NuVal scores for all category promotions, especially on the healthier items in the category to draw attention and increase sales of all products in the category. But under constraints of the costs to do so, retailers should at least tap into our findings that NuVal score featured on promotions in lower nutrition categories grab more attention than NuVal score featured on promotions in higher nutrition categories. Thus, retailers should prioritize featuring NuVal scores or any other easily communicated nutrition information on product promotions in categories such as bakery or meat which are perceived by shoppers as lower nutrition categories. Thus, targeting on the basis of consumer characteristics and product promotion types should help retailers draw in more returns on promotions.

3.4.3 Future Research

Our research sets the stage for several future research opportunities. First, we acknowledge that while our research provides evidence of effectiveness of featuring NuVal score on product promotions, our data precludes a causal test of the processes driving these effects. Therefore, moving forward, a possible series of causal experiments with a retailer would add to the research by finding exactly which factors mediate the effect of nutrition promotions on sales. A further research direction is looking at product types and finding out promotions, especially ones with NuVal score featured, on which type of products, apart from the nutrition level of the individual product, drive category sales higher? Is it cost of products or seasonal demand of products or any other significant product feature that contributes to the retailer's higher share of profits, that drives the heightened category sales from NuVal score featured on price promotions?

Frequency of promotions with NuVal scores is a further area of interest. Though we find that featuring NuVal scores on promotions helps, how much is too much information? Should all promoted products have featured NuVal scores or does that result in the novelty factor wearing off? Should all weeks have promotions accompanied by NuVal scores or will that have adverse impact on shoppers? These are some of the questions and research directions that we will work on to supplement our current findings.

Appendix A

This appendix describes the StubHub data variables of interest as well as discusses the classifications of the StubHub pages. The data variables that are of interest for the analysis of the StubHub data are listed as follows:

I. Device used: PC, smartphone and tablet.
II. Page type (with detailed categorization).
III. Time spent in each user session: measured in terms of average number of pages per session.
IV. Number of pages logged in from PC as well as mobile in the user path.
V. Average ticket price.
VI. Number of tickets purchased.
VII. Seat zone classification: premium, medium or nose-bleed seats.
VIII. Time to event: measured in terms of days remaining to event.
IX. Team popularity: whether playing teams are part of the perennially Top 25 ranked conference member. This classification is considered due to the university being a member of this conference.
X. Game type: Whether game is a football game or basketball or women’s basketball game.
XI. Game week: whether game is played on a weekend or not.

We categorize StubHub pages into the following broad page classes:

a. Event: consisting of StubHub web page containing all listings of events consistent with user's search keyword, e.g., events in a city or sports events, etc. This was the most common landing page logged in by the user.

b. Event Details: web page detailing information about a specific event clicked on by the user, such as game type, opponents, time and location of game, game duration, etc.

c. Seat-Map: seat chart and corresponding ticket prices for specific tier seats; here users spend time on locating desired seats on interactive maps showing seat sections and analyze the cost associated with each seat category.

d. Cart: StubHub page where user is directed to when he/she chooses a ticket; users add an event (here game) to their digital shopping cart.

e. Check-out: users either directly check out without putting event in cart or check out from the cart and input card details, verify shipping information, shipping window, etc.

f. Order confirmation: consisting of the order placement or confirmation details pages and also pages related to the retrieval of placed order.

Appendix B

This appendix contains the Markov Transition Probability calculations for switching probabilities between different web pages for consumers surfing StubHub's wen pages from Personal Computer vs Smartphone vs Tablet.

Order confirmation pages appear higher number of times in the overall user search than check out pages because order confirmation leads to various pages as mentioned above; that does not mean total orders placed > check outs. In a way check-out can signal at order being placed. Maximum time of the purchase sessions are spent on the Event details page. Events page is viewed the most on smartphone, while the events details, cart, check out and order confirmed pages are viewed on the PC more than on any other device: indicating more purchases made on PC, while events are viewed more on Smartphone (and then on Tablet).

Some logged in purchase session patterns:

User 1: E ED M M M M ED ED CH CH CH CH O

User 2: E E C C C C C C O CH Ch ED Ch

User 3: E ED ED ED C M M M C M C Ch C Ch O O M

User 4: ED C Ch Ch Ch Ch C Ch Ch Ch C Ch C Ch Ch C Ch C Ch O

User 5: M M M M M M M M C C M M M M M C Ch Ch O

where,

E: event landing page

ED: event details page

M: seat map page

Ch: check-out page

O: order confirmation page

The following table contains the average transition probabilities of a user switching from one-page type to the other page type for sessions that are part of the user path that end in a purchase.

Table 17: Markov Transition Table for Purchase Sessions

	Events	Event Details	Seat Map	Cart	Checkout	Order Confirmation
Events	D1*0.4184+	D1* 0.2837+	D1*0.2589+	D1*0.0035+	D1* 0.011+	D1*0.0106+
	D2*0.4943+	D2*0.2641+	D2*0.2341+	D2*0.0001+	D2*0.0036+	D2*0.0007+
	D3*0.5270	D3*0.1922	D3* 0.2780	D3*0.0000	D3* 0.0008	D3* 0.0004
Event Details	D1*0.0061+	D1*0.7485+	D1*0.0084+	D1*0.0024+	D1*0.0031+	D1* 0.2312+
	D2*0.3316+	D2*0.4974+	D2*0.0919+	D2*0.0018+	D2* 0.0042+	D2*0.0701+
	D3*0.3299	D3*0.4716	D3*0.1102	D3*0.0027	D3*0.0034	D3*0.0801
Seat Map	D1*0.0353+	D1* 0.0454+	D1*0.7183+	D1*0.1009+	D1*0.0316+	D1*0.0679+
	D2* 0.5088+	D2*0.1516+	D2* 0.3306+	D2* 0.0030+	D2*0.0025+	D2*0.0011+
	D3* 0.4989	D3*0.1191	D3*0.3768	D3*0.0007	D3*0.0007	D3*0.0029
Cart	D1*0.0016+	D1*0.0607+	D1*0.2959+	D1*0.2025+	D1*0.1713+	D1*0.2679+
	D2* 0.0366+	D2* 0.1829+	D2* 0.1463+	D2*0.4390+	D2*0.1219+	D2*0.0731+
	D3*0.0000	D3* 0.1818	D3*0.0909	D3*0.1818	D3* 0.0909	D3*0.4545
Checkout	D1*0.0089+	D1*0.0668+	D1*0.1492+	D1*0.2405+	D1* 0.1782+	D1*0.3563+
	D2*0.3248+	D2*0.2906+	D2*0.0940+	D2*0.0342+	D2*0.1367+	D2*0.1111+
	D3*0.1667	D3*0.0833	D3*0.2500	D3*0.1667	D3*0.1667	D3*0.1667
Order Confirmation	D1*0.0004+	D1*0.6238+	D1*0.0379+	D1*0.0330+	D1*0.0319+	D1*0.2728+
	D2*0.0141+	D2*0.7730+	D2*0.0113+	D2*0.0128+	D2*0.0113+	D2*0.1759+
	D3*0.0059	D3*0.7456	D3* 0.0059	D3*0.0118	D3*0.0295	D3*0.2011
Initial probability	D1*0.0136+	D1*0.6039+	D1*0.1053+	D1*0.0310+	D1*0.0217+	D1*0.2240+
	D2*0.4263+	D2* 0.3341+	D2*0.1981+	D2*0.0034+	D2*0.0049+	D2*0.0299+
	D3*0.4512	D3*0.2618	D3* 0.2482	D3*0.0020	D3*0.0043	D3*0.0303

D1/D2/D3: Indicator Var for PC/Smartphone/Tablet

We find that the probability of transition from Event page, Event details page, Seat Map page, Cart page and Che Probability of transition from Events page to Cart page as well as Events page to Checkout page is also higher for PC than Smartphone or Tablet. Check-out page to Order Confirmation page transition probability is higher on PC than on Smartphone or Tablet. Probability of transition from Event Details page to Seatmap page is lower for PC than Smartphone or Tablet:

more search in mobile device. Probability of transition from Seatmap page to both Cart and Check-out pages are higher for PC than Smartphone or Tablet.

The following table contains the average transition probabilities of a user switching from one-page type to the other page type for sessions that are part of the user path that does not end in a purchase.

Table 18: Markov Transition Table for Non-Purchase Sessions

	Events	Event Details	Seat Map	Cart	Checkout
Events	D1*0.4250+	D1* 0.2996+	D1*0.2664+	D1*0.0024+	D1* 0.0033+
	D2*0.4580+	D2*0.2590+	D2*0.2682+	D2*0.0018+	D2*0.0044+
	D3*0.4805	D3*0.2102	D3* 0.3014	D3*0.0008	D3* 0.0045
Event Details	D1*0.0234+	D1* 0.9392+	D1*0.0308+	D1*0.0055+	D1*0.0006+
	D2*0.4585+	D2*0.3747+	D2*0.1470+	D2*0.0043+	D2* 0.0056+
	D3*0.4347	D3*0.3928	D3*0.1623	D3*0.0024	D3*0.0047
Seat Map	D1*0.0694+	D1* 0.1010+	D1*0.8036+	D1*0.0251+	D1*0.0004+
	D2* 0.5161+	D2*0.1614+	D2* 0.3122+	D2* 0.0016+	D2*0.0023+
	D3* 0.5243	D3*0.1329	D3*0.3375	D3*0.0009	D3*0.0028
Cart	D1* 0.0154+	D1*0.2519+	D1*0.4115+	D1*0.2673+	D1*0.0538+
	D2* 0.0366+	D2* 0.3251+	D2* 0.0861+	D2*0.3887+	D2*0.0133+
	D3* 0.1967	D3* 0.3443	D3*0.3115	D3* 0.1311	D3* 0.0164
Checkout	D1* 0.0800+	D1*0.2667+	D1* 0.0533+	D1*0.3200+	D1* 0.2800+
	D2*0.3943+	D2*0.2625+	D2*0.0929+	D2*0.0178+	D2*0.2192+
	D3*0.3920	D3*0.2311	D3*0.1206	D3*0.0201	D3*0.2311
Initial probability	D1*0.0561+	D1*0.7099+	D1*0.2176+	D1*0.0138+	D1*0.0020+
	D2*0.4705+	D2* 0.2665+	D2* 0.2440+	D2* 0.0041+	D2*0.0055+
	D3*0.4813	D3*0.2313	D3*0.2779	D3*0.0016	D3*0.0052

D1/D2/D3: Indicator Var for PC/Smartphone/Tablet

Following are the plots for average Markov transition probabilities for computer (PC) and mobile (smartphone and tablet combined) sessions ending in a purchase:

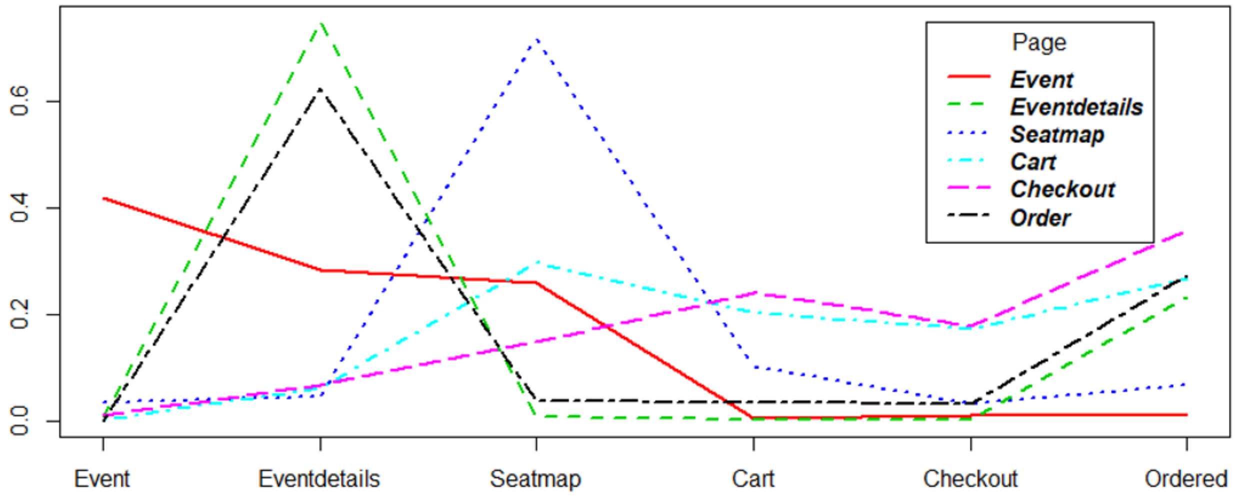


Figure 4: Transition Probability Plot for Page Switching on Computer

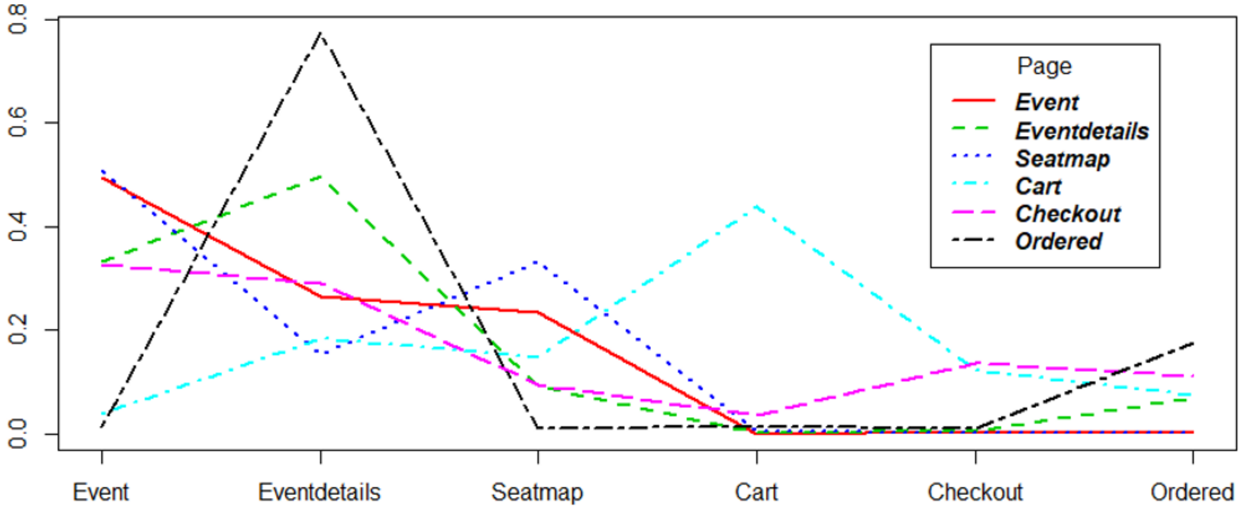


Figure 5: Transition Probability Plot for Page Switching on mobile devices

Appendix C

This appendix contains the list of questions asked in the mediation analysis device experiment. It was administered on Amazon Mechanical Turk and the appendix presents the questions as they were seen by survey takers on their randomly assigned PC or smartphone screens.

Impact of Device Selection on Purchase Likelihood

Start of Block: Welcome

Thank you for your interest in our survey. In this survey, we want to learn how Americans feel about searching and purchasing online. Your honest and thoughtful responses to this survey are invaluable to us. It should take only a few minutes to complete this survey. Thank you in advance for your contribution.

End of Block: Welcome

Start of Block: Participant consent

By participating in this study, you are agreeing that your survey responses may be used by the researchers for analysis and the analysis results may be published. However, response data is anonymous.

Do you consent to these terms?

○ Yes (1)

○ No (2)

Do you live in the United States?

○ Yes (1)

○ No (2)

Skip To: End of Survey If Do you live in the United States? = No

End of Block: Participant consent

Start of Block: PC (desktop or laptop)

Please go to www.ticketmaster.com from Personal Computer (desktop or laptop) You are visiting New York city next month with two friends. You have time and money to go somewhere for fun one evening. You are interested in checking out some tickets to shows, games or events in the area. You decide to look on ticketmaster.com. Please visit www.ticketmaster.com from your Personal Computer (desktop or laptop) to complete the search for an event that the 3 of you can attend, as you normally would. Once you are done searching, please answer the following questions to the best of your ability.

Timing

First Click (1)

Last Click (2)

Page Submit (3)

Click Count (4)

Page

Break

Please go to www.ticketmaster.com from your smartphone.

(*<u>Random assignment to Personal Computer or Smartphone</u>*)

You are visiting New York city next month with two friends. You have time and money to go somewhere for fun one evening. You are interested in checking out some tickets to shows, games or events in the area. You decide to look on ticketmaster.com.

Please visit www.ticketmaster.com from your smartphone to complete the search for an event that the 3 of you can attend, as you normally would. Once you are done searching, please answer the following questions to the best of your ability.

First Click (1)

Last Click (2)

Page Submit (3)

Click Count (4)

Q1 How long did you search?

	No time	10+
	0 2 3 5 7 8 10	
Minutes		

Q2 Which website did you visit?

○ www.stubhub.com (1)

○ www.ticketmaster.com (2)

○ www.amazon.com (3)

Q3 How many events did you consider?

	None	10+
	0 1 2 3 4 5 6 7 8 9 10	
Shows you considered attending		

Q4 How do you feel about the search process for tickets?

	Not true at all	Very true

	0	1	3	4	5	6	8	9	10
The search was easy for me.									
The search process was inconvenient.									
I was confident in searching on this website from the assigned device.									

Q5 You searched for tickets to an event in which of the following cities?

○ Chicago (1)

○ Boston (2)

○ New York City (3)

○ San Francisco (5)

End of Block: Search block questions

Start of Block: Purchase

The day is getting closer to your trip. Take one more look at a possible event ticket for 3 adults. Assume you are making a purchase decision (you don't have to actually buy a ticket but just imagine you are making a purchase decision). Once done making a purchase choice (i.e., you either decide to buy 3 tickets for a specific event on ticketmaster.com or decide to not buy a ticket), please answer the following questions.

Timing

First Click (1)

Last Click (2)

Page Submit (3)

Click Count (4)

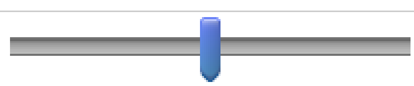
End of Block: Purchase

Start of Block: Purchase questions block

Q6 If you were in this actual situation, how likely would you be to purchase the tickets?

Not at all likely Very likely

0 1 2 3 4 6 7 8 9 10

Likely to buy the tickets?	

Q7

What was the individual ticket price for the event you were considering?

	Cheaper tickets $200 or more each 0 20 40 60 80 100 120 140 160 180 200
Individual ticket price	

Q8 Which device did you use to search ticket and make purchase decision?

- ○ PC (desktop or laptop) (1)
- ○ Smartphone (2)
- ○ Tablet (3)

Q9 How do you feel about the purchase process for tickets on Ticketmaster?

Not true at all Very true

0 1 3 4 5 6 8 9 10

The search was risky for me.	
The purchase process was convenient.	
I was confident in buying tickets from this website on the device assigned.	

Q10 For how many adults did you look for an event ticket?

- ◯ 1 adult (1)
- ◯ 3 adults (2)
- ◯ 5 adults (3)

End of Block: Purchase questions block

Start of Block: Online bahavior

Q11 **Do you own a Personal Computer (desktop or laptop)?**

◯ Yes (1)

◯ No (2)

Q12 **Do you own a Smartphone?**

◯ Yes (1)

◯ No (2)

Q13 When you shop online, to what extent do you prefer to use a Personal Computer (desktop or laptop) for:

	Do not prefer … Strongly prefer 0 1 2 3 4 5 6 7 8 9 10
Searching for items to buy	
Making online purchases	

Q14 When you shop online, to what extent do you prefer to use a smartphone for:

	Do not prefer	Strongly prefer
	0 1 2 3 4 5 6 7 8 9 10	
Searching for items to buy		
Making online purchases		

Q15 How often do you use www.ticketmaster.com or other ticket booking websites such as StubHub to search and purchase event or game tickets?

	Never	Frequently
	0 1 2 3 4 5 6 7 8 9 10	
Search on Ticketmaster		

End of Block: Online bahavior

Start of Block: Demographics

A little about you...

Q16 How many years have you resided in the U.S.?

▼ 0 (4) ... 30+ (34)

Q17 Gender:

- Man (1)
- Woman (2)
- Gender non-conforming or gender non-binary (3)
- Something else not listed above (4)
- Prefer not to answer (5)

Q18 What is your race?

- White (1)
- African-American or Black (2)
- Latino/a/x or Hispanic (3)
- Native American/American Indian or Alaskan Native (4)
- Asian (5)
- Pacific Islander (6)
- Bi- or Multi-Racial (7)
- Something else not listed above (8)
- Prefer not to answer (9)

Q19 What is your year of birth?

____

Q20 What is your highest academic qualification?

- Less than high school (1)
- High school/GED (2)
- 2 year college degree (3)
- 4 year college degree (4)
- Professional degree (5)
- Doctorate (6)

Q21 What is your marital status?

- Single (never married) (1)
- Married/Partner (2)
- Single (separated, divorced or widowed) (3)

End of Block: Demographics

Start of Block: Feedback

Q22 **How realistic was the ticket search and purchase scenario?**

	Extremely realistic	Fairly realistic	Neither realistic nor unrealistic	Fairly unrealistic	Extremely unrealistic
	1 2	3 4	5 6 6	7 8	9 10
Realistic					

Q52 **How interesting was this survey for you to complete?**

	Extremely interesting	Fairly interesting	Average	Fairly dull	Extremely dull
	1 2	3 4	5 6	7 8	9 10
Interest in survey					

End of Block: Feedback

Bibliography

Ailawadi, K.L. and B. Harlam (2004), “An Empirical Analysis of the Determinants of Retail Margins: The Role of Store-Brand Share,” Journal of Marketing, 68 (1) 147–165.

Ailawadi, K. L., B.A. Harlam, J. César, and D. Trounce (2006), “Promotion profitability for a retailer: the role of promotion, brand, category, and store characteristics,” Journal of Marketing Research, 43, 518–535.

Ailawadi, K. L., B.A. Harlam, J. César, and D. Trounce (2007), “Practice prize report-quantifying and improving promotion effectiveness at CVS,” Marketing Science, 26, 556–575.

Ailawadi, K. L., J.P. Beauchamp, N. Donthu, D.K., and V. Shankar (2009), “Communication and promotion decisions in retailing: a review and directions for future research,” Journal of Retailing, 85(1), 42–55.

Andrews, J. Craig, Scot Burton, and Jeremy Kees (2011), “Is Simpler Always Better? Consumer Evaluations of Front-of-Package Nutrition Icons,” Journal of Public Policy & Marketing, 30 (2), 175–90.

Andrews, J. Craig, Richard G. Netemeyer, and Scot Burton (1998), “Consumer Generalization of Nutrient Content Claims in Advertising,” Journal of Marketing, 62 (4), 62–75.

Andrews, Michelle, Xueming Luo, Zheng Fang, and Anindya Ghose (2016), “Mobile Ad Effectiveness: Hyper-Contextual Targeting with Crowdedness,” Marketing Science, 35 (2), 218–33.

Ansari, Asim, Carl F. Mela, and Scott A. Neslin, (2008), “Customer Channel Migration,” Journal of Marketing Research, 45(1), 60-76.

Asadi, Shahla , Rusli Abdullah, Mahmood Safaei, and Shah Nazir (2019), “An Integrated SEM-Neural Network Approach for Predicting Determinants of Adoption of Wearable Healthcare Devices,” Mobile Information Systems, 9 pages.

Ataman, M. Berk, Harald J. Van Heerde, and Carl F. Mela (2010). “The Long-Term Effect of Marketing Strategy on Brand Sales,” Journal of Marketing Research, 47(5), 866–882.

Balasubramanian, Siva K. and Catherine Cole (2002), "Consumers' Search and Use of Nutrition Information: The Challenge and Promise of the Nutrition Labeling and Education Act," Journal of Marketing , 66 (July), 112-27.

Bart, Yakov, Andrew T. Stephen, and Miklos Sarvary (2014), “Which Products Are Best Suited to Mobile Advertising? A Field Study of Mobile Display Advertising Effects on Consumer Attitudes and Intentions,” Journal of Marketing Research, 51(2), 270-285.

Bell, D., D. Corsten, and G. Knox (2011), “From point of purchase to path to purchase: How preshopping factors drive unplanned buying,” Journal of Marketing, 75(1), 31-45.

Bellman, Steven, Robert F Potter, Shiree Treleaven Hassard, Jennifer A Robinson, and Duane Varan. (2011), “The Effectiveness of Branded Mobile Phone Apps,” Journal of Interactive Marketing, 25(4), 191-200.

Berning, Joshua P. and David E. Sprott (2011), “Examining the Effectiveness of Nutrition Information in a Simulated Shopping Environment,” Journal of Food Distribution Research, 42(3), 60-76.

Bilgicer, Tolga, Kamel Jedidi, Donald R. Lehmann R., and Scott A Neslin (2015), “The Long-Term Effect of Multichannel Usage on Sales,” Customer Needs and Solutions, 2(1), 41-56.

Blattberg, Robert. C., and Scott Neslin (1990), “Sales promotion: Concepts, methods, and strategies,” Englewood Cliffs, NJ: Prentice Hall.

Blattberg, Robert C. and Edward I. George (1991), “Shrinkage Estimation of Price and Promotional Elasticities: Seemingly Unrelated Equations,” Journal of the American Statistical Association, 86 (414) 304–315.

Brinker, Mike, Kasey Lobaugh and Alison Paul (2012), “The Dawn of Mobile Influence-Discovering the Value of Mobile in Retail,” Deloitte Digital.

Bucklin, Randolph and Catarina Sismeiro (2003), “A Model of Web Site Browsing Behavior Estimated on Clickstream Data,” Journal of Marketing Research, 40(3), 249-267.

Burford, Sally and Sora Park (2014), "The impact of mobile tablet devices on human information behavior," Journal of Documentation, 70(4), 622-639.

Chan, F. T. S. and A. Y. L. Chong (2012), “A SEM-neural network approach for understanding determinants of interorganizational system standard adoption and performances,” Decision Support Systems, 54(1), 621–630.

Chandon, Pierre, Brian Wansink, and Gilles Laurent (2000), “A Benefit Congruency Framework of Sales Promotion Effectiveness.” Journal of Marketing, 64(4), 65–81.

Chang, Po-Chien (2010), “Drivers and moderators of consumer behavior in the multiple use of mobile phones,” International Journal of Mobile Communications, 8(1), 88-105.

Chu, J., M. Arce-Urriza, J.-J. Cebollada-Calvo, and P. K. Chintagunta (2010). “An empirical analysis of shopping behavior across online and offline channels for grocery products: The moderating effects of household and product characteristics,” Journal of Interactive Marketing, 24 (4), 251–268.

Chung, Tuck Siong, Roland T. Rust and Michel Wedel (2009), “My Mobile Music: An Adaptive Personalization System for Digital Audio Players,” Marketing Science, 28(1), 52-68.

Danaher, Peter J., Michael S. Smith, Kulan Ranasinghe, and Tracey S. Danaher (2015), “Where, When, and How Long: Factors That Influence the Redemption of Mobile Phone Coupons,” Journal of Marketing Research, 52(5), 710-725.

Dawes, J. (2004), "Assessing the impact of a very successful price promotion on brand, category and competitor sales", Journal of Product & Brand Management, 13(5), 303-314.

Dhar, Sanjay K., and Stephen J. Hoch (1997), “Why store brand penetration varies by retailer,” Marketing Science, 16(3), 208–227.

Dennis, Charles, Eleftherios Alamanos, Savvas Papagiannidis and Michael Bourlakis (2016), “Does social exclusion influence multiple channel use? The interconnections with community, happiness, and well-being,” Journal of Business Research, 69(3), 1061-1070.

Dinner, Isaac M., Harald J. van Heerde, and Scott Neslin (2015), “Creating Customer Engagement Via Mobile Apps: How App Usage Drives Purchase Behavior,” Tuck School of Business Working Paper No. 2669817.

Dubin, Jeffrey A and Daniel L. McFadden (1984), “An Econometric Analysis of Residential Electric Appliance Holdings and Consumption,” Econometrica, 52(2), 345-362.

Fong, Nathan M., Zhang, Yuchi, Luo, Xueming and Wang, Xiaoyi (2016), “Targeted Promotions and Cross-Category Spillover Effects,” Fox School of Business Research Paper No. 16-035. Available at SSRN: https://ssrn.com/abstract=2847635 or http://dx.doi.org/10.2139/ssrn.2847635.

Fong, Nathan M., Zheng Fang, and Xueming Luo (2015), “Geo-Conquesting: Competitive Locational Targeting of Mobile Promotions,” Journal of Marketing Research, 52(5), 726-735.

Food Marketing Institute (2018), FMI (2012a), “U.S. Grocery Shopper Trends 2018,” (September 6), [available at https://www.fmi.org/docs/default-source/webinars/trends-2018-webinar-3-final94d6250324aa67249237ff0000c12749.pdf?sfvrsn=547c426e_0].

Frederick, Shane, George Loewenstein, and Ted O Donoghue (2002), "Time Discounting and Time Preference: A Critical Review," Journal of Economic Literature, 40 (2), 351—401.

Garretson, Judith and Scot Burton (2000), “Effects of Nutrition Facts Panel Values, Nutrition Claims, and Health Claims on Consumer Attitudes, Perceptions of Disease-Related Risks, and Trust," Journal of Public Policy & Marketing, 19(2), 213–227.

Ghose, Anindya, Avi Goldfarb and Sang Pil Han (2013), “How Is the Mobile Internet Different? Search Costs and Local Activities,” Information Systems Research, 24(4), 613-631.

Ghose, Anindya and Sang Pil Han (2014), “Estimating Demand for Mobile Applications in the New Economy,” Management Science, 60(6), 1470-1488.

Gill, Manpreet, Shrihari Sridhar, and Rajdeep Grewal (2017), “Return on Engagement Initiatives: A Study of a Business-to-Business Mobile App,” Journal of Marketing, 81(4), 45-66.

Haan, Evert de, P.K. Kannan, Peter C. Verhoef, and Thorsten Wiesel (2015), "The Role of Mobile Devices in the Online Customer Journey," Marketing Science Institute Working Paper Series, Report No.15-124.

Haan, Evert de, P.K. Kannan, Peter C. Verhoef, and Thorsten Wiesel (2018), "Device Switching in Online Purchasing: Examining the Strategic Contingencies," Journal of Marketing 82(5), 1-19.

Hackleman, Edwin C. and Jacob M. Duker (1980), "Deal Proneness and Heavy Usage: Merging Two Segmentation Criteria," Journal of the Academy of Marketing Science, 8 (Fall), 332-344.

Haghirian, P., M. Madlberger and A. Tanuskova (2005), "Increasing Advertising Value of Mobile Marketing - An Empirical Study of Antecedents," Proceedings of the 38th Annual Hawaii International Conference on System Sciences, 32.3.

Hayes, A. F. and K. J Preacher. (2014). "Statistical mediation analysis with a multicategorical independent variable," British Journal of Mathematical and Statistical Psychology, 67, 451-470.

Heaton, Jeff (2008), "Introduction to Neural Networks for Java", 2nd edition book published by Heaton Research, Inc.

Hoban, Paul R. and Randolph E. Bucklin (2015), "Effects of Internet Display Advertising in the Purchase Funnel: Model-Based Insights from a Randomized Field Experiment," Journal of Marketing Research, 52(3), 375-393.

Hoch, Stephen J. and George Loewenstein (1991)." Time Inconsistent Preferences and Consumer Self-Control," Journal of Consumer Research, 17 (4), 492-507.

Hoch, Stephen J., Xavier Dreze, and Mary Purk (1994), "The EDLP, Hi-Low, and margin arithmetic," Journal of Marketing, 58, 16–27.

Hodkinson, Chris (2019), "'Fear of Missing Out' (FOMO) Marketing Appeals: A Conceptual Model." Journal of Marketing Communications, 25 (1), 65–88.

Hruschka, H., M. Lukanowicz, and C. Buchta (1999) "Cross-category sales promotion effects," Journal of Retailing and Consumer Services, 6, 99–105.

Hu, Ye, Rex Yuxing Du, and Sina Damangir (2014), "Decomposing the Impact of Advertising: Augmenting Sales with Online Search Data," Journal of Marketing Research, 51(3), 300–319.

Huang, L., X. Lu, and S. Ba (2016). "An empirical study of the cross-channel effects between web and mobile shopping channels," Information & Management, 53 (2), 265–278.

Hui, Sam K., J. Jeffrey Inman, Yanliu Huang and Jacob Suher (2013), “The Effect of In-Store Travel Distance on Unplanned Spending: Applications to Mobile Promotion Strategies,” Journal of Marketing, 77(2), 1-16.

Husson, Thomas, Julie A. Ask, Carrie Johnson, Melissa Parrish and Emily Kwan (2014), “Mobile Trends for Marketers,” Forrester Research.

Kannan, P. K., Rosellina Ferraro (2018), “Dark Side of Mobile App Adoption: Examining the Impact on Customers ’ Multichannel Purchase,” Conference Proceedings.

Keller, Scott B., Mike Landry, Jeanne Olson, Anne M. Velliquette, and Scot Burton (1997), “The Effects of Nutrition Package Claims, Nutrition Facts Panels, and Motivation to Process Nutrition Information on Consumer Product Evaluations,” Journal of Public Policy & Marketing, 16 (2), 256–69.

Kim, S. J., R. J.-H. Wang, and E. C. Malthouse (2015). “The effects of adopting and using a brand’s mobile application on customers’ subsequent purchase behavior,” Journal of Interactive Marketing, 31, 28–41.

Kingma, Diederik P. and Jimmy Ba (2015), “Adam: A Method for Stochastic Optimization,” Seventh International Conference on Learning Representations, 69-80.

Kirby, Kris N. and Nino Marakovic (1996), "Modeling Myopic Decisions: Evidence for Hyperbolic Delay-Discounting Within Subjects and Amounts," Organizational Behavior and Human Decision Processes, 64 (1), 22-30.

Kozup, John C., Elizabeth H. Creyer, and Scot Burton (2003), “Making Healthful Food Choices: The Influence of Health Claims and Nutrition Information on Consumers’ Evaluations of Packaged Food Products and Restaurant Menu Items,” Journal of Marketing, 67 (2), 19– 34.

Kumar, V., and Robert P. Leone (1988), "Measuring the Effect of Retail Store Promotions on Brand and Store Substitution," Journal of Marketing Research, 25(2), 178-85.

Kivetz, Ran (2005), “Promotion Reactance: The Role of Effort-Reward Congruity,” Journal of Consumer Research, 31(4), 725-736.

Lee, Young Eun and Izak Benbasat (2003), “A Framework for the Study of Customer Interface Design for Mobile Commerce,” International Journal of Electronic Commerce, 46(3)

Leeflang, P. S. H., & Parreno-Selva, J. (2012), “Cross-category demand effects of price promotions,” Journal of the Academy of Marketing Science, 40(4), 572-586.

Levy, Alan S. and Sara B. Fein (1998), "Consumers' Ability to Perform Tasks Using Nutrition Labels," Journal of Nutrition Education, 30 (4), 210-17.

Levy, Michael, and Barton A. Weitz (1998), Retailing management (3rd ed.), New York: Irwin/McGraw-Hill.

Li, Chenxi, Xueming Luo, Zhang Cheng, and Xiaoyi Wang Sr. (2017), “Sunny, Rainy, and Cloudy with a Chance of Mobile Promotion Effectiveness,” Marketing Science, 36 (5), 762–79.

Li, Hongshuang (Alice) and P.K. Kannan (2014), “Attributing Conversions in a Multichannel Online Marketing Environment: An Empirical Model and a Field Experiment,” Journal of Marketing Research, 51(1), 40-56.

Luo, Xueming, Michelle Andrews, Zheng Fang, and Chee Wei Phang (2013), “Mobile Targeting,” Management Science, 60(7), 1738-1756.

Manchanda, Puneet, Asim Ansari, Sunil Gupta (1999), “The “Shopping Basket”: A Model for Multicategory Purchase Incidence Decisions,” Marketing Science, 18(2), 95-192.

Mandel, N. and E. J. Johnson (2002), “When Web pages influence choice: Effects of visual primes on experts and novices,” Journal of Consumer Research, 29(2), 235-245.

Manzano, Joaquín Aldás, Carla Ruiz Mafé and Silvia Sanz Blas (2009), "Exploring individual personality factors as drivers of M-shopping acceptance," Industrial Management & Data Systems, 109(6), 739-757.

Mathios, A. (2000), “The Impact of Mandatory Disclosure Laws on Product Choices: An Analysis of the Salad Dressing Market.” The Journal of Law & Economics, 43(2), 651-678.

Melumad, Shiri, J. Jeffrey Inman and Michel Tuan Pham (2019), “Selectively Emotional: How Smartphone Use Changes User-Generated Content,” Journal of Marketing Research, published online.

Moe, Wendy W. and Fader, Peter S. (2004), “Dynamic Conversion Behavior at E-Commerce Sites,” Management Science 50(3), 326-335.

Montgomery, Alan L., Shibo Li, Kannan Srinivasan and John C Liechty (2003), “Modeling Online Browsing and Path Analysis Using Clickstream Data,” working paper, Graduate School of Industrial Administration, Carnegie Mellon University.

Moorman, Christine (1996), "A Quasi Experiment to Assess the Consumer and Informational Determinants of Nutrition In- formation Processing Activities: The Case of the Nutrition Labeling and Education Act," Journal of Public Policy & Marketing, 15 (Spring), 28-44.

Newman, Christopher L., Scot Burton, J. Craig Andrews, Richard G. Netemeyer, and Jeremy Kees (2018), “Marketers’ Use of Front-of-Package Nutrition Symbols: An Examination of Effects on Product Evaluations,” Journal of the Academy of Marketing Science, 46 (3), 453–76.

Nielsen (2012), "A Nielsen Report: Battle of the Bulge and Nutrition Labels: Healthy Eating Trends Around the World," research report, available at http://silver- group.asia/wp-content/uploads/20 1 2/02/Nielsen-Global-Food- Labeling-Report-Jan2012.pdf.

Nikolova, Hristina Dzhogleva and J. Jeffrey Inman (2015), “Healthy Choice: The Effect of Simplified POS Nutritional Information on Consumer Choice Behavior.” Journal of Marketing Research, 52 (6), 817-835.

O’Brien, Michelle C., Aine McConnon, Lynsey E Hollywood, Geraldine J Cuskelly, Julie Barnett, Monique Raats, and Moira Dean (2013), “Let’s talk about health: shoppers’ discourse regarding health while food shopping,” Public Health Nutrition, 18(6), 1001-1010.

Ozturk, Ahmet Bulent, Anil Bilgihan, Khaldoon Nusair, and Fevzi Okumus (2016), “What Keeps the Mobile Hotel Booking Users Loyal? Investigating the Roles of Self-Efficacy, Compatibility, Perceived Ease of Use, and Perceived Convenience,” International Journal of Information Management, 36, 1350–59.

Park, Young-Hoon and Peter S. Fader (2004), “Modeling Browsing Behavior at Multiple Websites,” Marketing Science, 23(3), 280-303.

Raghubir, Priya & Inman, J. & Grande, Hans (2004), “The Three Faces of Consumer Promotions”, California Management Review, 46, 23-42.

Raju, Jagmohan S. (1992), “The Effect of Price Promotions on Variability in Product Category Sales,” Marketing Science, 11(3), 207-220.

Rapp, A., T.L Baker, D. G. Bachrach, J. Ogilvie, and L.S. Beitelspacher (2015), “Perceived customer showrooming behavior and the effect on retail salesperson self-efficacy and performance,” Journal of Retailing, 91(2), 358-369.

Roe, Brian, Alan S. Levy, and Brenda M. Derby (1999), “The Impact of Health Claims on Consumer Search and Product Evaluation Outcomes: Results from FDA Experimental Data,” Journal of Public Policy & Marketing, 18(1), 89-105.

Rusonis, Shana (2015), “Organized Ideation: How Hotwire Runs 120+ Experiments Per Year,” Blog .Optimizely.com, April 28, Retrieved 3/26/19 from https://blog.optimizely.com/2015/04/28/organized-ideation-hotwire-travel-experiments/.

Shankar, Venkatesh and Sridhar Balasubramanian (2009), “Mobile Marketing: A Synthesis and Prognosis,” Journal of Interactive Marketing, 23(2) ,118-129.

Shu, Suzanne B, and Ayelet Gneezy (2010), “Procrastination of Enjoyable Experiences,” Journal of Marketing Research, 47 (5), 933–44.

Sismeiro, Catarina and Randolph E. Bucklin (2004), “Modeling Purchase Behavior at an E-Commerce Web Site: A Task-Completion Approach,” Journal of Marketing Research, 41(3), 306-323.

Song, Inseong and Pradeep K. Chintagunta (2006), “Measuring Cross-Category Price Effects with Aggregate Store Data”, Management Science, 52(10), 1594-1609.

Spangler, Todd (2018), "Are Americans Addicted to Smartphones? U.S. Consumers Check Their Phones 52 Times Daily, Study Finds," Variety.com, November 14. Retrieved 3/26/19 from https://variety.com/2018/digital/news/smartphone-addiction-study-check-phones-52-times-daily-1203028454/.

Strom, R., M. Vendel, and J. Bredican (2014), "Mobile marketing: A literature review on its value for consumers and retailers," Journal of Retailing and Consumer Services, 21, 1001-1012.

Tam, Kar Yan and Shuk Ying Ho (2006), "Understanding the Impact of Web Personalization on User Information Processing and Decision Outcomes," MIS Quarterly, 30(4), 865–890.

Van Heerde, Harald J, Peter S H Leeflang, Dick R Wittink (2004), "Decomposing the Sales Promotion Bump with Store Data," Marketing Science, 23(3), 317-334.

Variyam, Jayachandran N. and John Cawley (2006), "Nutrition Labels and Obesity," NBER Working Paper 11956, National Bureau of Economic Research.

Venkatesan, R., V. Kumar, and N. Ravishanker (2007). "Multichannel shopping: Causes and Consequences," Journal of Marketing, 71 (2), 114–132.

Verhoef, Peter C., P.K. Kannan, and, J. Jeffrey Inman (2015), "From Multi-Channel Retailing to Omni-Channel Retailing: Introduction to the Special Issue on Multi-Channel Retailing," Journal of Retailing, 91.2, 174-181.

Vroegrijk, Mark, Els Gijsbrechts, and Katia Campo (2013), "Close Encounter with the Hard Discounter: A Multiple-Store Shopping Perspective on the Impact of Local Hard-Discounter Entry," Journal of Marketing Research, 50, 606-626.

Wakefield, Lane T. and Kirk. L. Wakefield (2018). "An Examination of Construal Effects on Price Perceptions in the Advance Selling of Experience Services," Journal of Service Research, 21(2), 235–248.

Walters, R. G., and S. Mackenzie (1988), "A structural equations analysis of the impact of price promotions on store performance," Journal of Marketing Research, 25, 51–63.

Walters, Rockney G. (1991), "Assessing the Impact of Retail Price Promotions on Product Substitution, Complementary Purchase, and Interstore Sales Displacement," Journal of Marketing, 55(4), 16-28.

Wang, Rebecca Jen-Hui, Edward C. Malthouse and Lakshman Krishnamurthi (2015), "On the Go: How Mobile Shopping Affects Customer Purchase Behavior," Journal of Retailing, 91(2), 217-234.

Wedel, M., and J. Zhang (2004), "Analyzing brand competition across categories," Journal of Marketing Research, 41, 448–456.

Xu, Kaiquan, Jason Chan, Anindya Ghose, and Sang Pil Han (2017), “Battle of the Channels: The Impact of Tablets on Digital Commerce,” Management Science, 63 (5), 1469–92.

Ye Hu, Rex Yuxing Du, and Sina Damangir (2014), “Decomposing the Impact of Advertising: Augmenting Sales with Online Search Data,” Journal of Marketing Research, 51(3), 300-319.

Zabukovˇsek, S. Sternad , Z. Kalinic, S. Bobek, and P. Tominc (2018), “SEM–ANN based research of factors’ impact on extended use of ERP systems,” Central European Journal of Operations Research.

Zauberman, Gal, B. Kyu Kim, Selin A. Malkoc, and James R. Bettman (2009), "Discounting Time and Time Discounting: Subjective Time Perception and Intertemporal Preferences," Journal of Marketing Research, 46 (8), 543-56.

Zhao, Zhenzhen and Christine Balague (2015). “Designing branded mobile apps: Fundamentals and recommendations,” Business Horizons, 58, 305-315.

Zhou, Tao (2011), "The impact of privacy concern on user adoption of location-based services," Industrial Management & Data Systems, 111(2), 212-226.

Zhou, Tao, and Yaobin Lu (2011), “The Effects of Personality Traits on User Acceptance of Mobile Commerce,” International Journal of Human-Computer Interaction, 27 (6), 545–61

Zubcsek, Peter Pal, Zsolt Katona and Miklos Sarvary (2017), “Predicting Mobile Advertising Response Using Consumer Colocation Networks,” Journal of Marketing, 81(4), 109-126.