ABSTRACT

ZHU, YUXIN. An Examination of Shopper Conversion among U.S. Online Retail Formats. (Under the direction of Dr. Marguerite Moore).

E-commerce channels have been recognized for continuing increases in market share among many consumer markets, including the apparel and footwear sector (Love, 2016). Therefore, e-commerce is expected to represent a significant portion of the apparel business moving into the future. As a first step toward understanding consumer purchasing behavior within the apparel e-commerce context (i.e., online apparel retailing), the current study focuses on the actual conversion of consumers from browsers to shoppers during the online experience.

Specifically, four objectives are addressed in this research: 1) Determine the conversion rate among six online retailer formats in the domestic market: fast fashion, value department, traditional department, upscale department, specialty and pure-play internet; 2) Compare shopper conversion rates among six online formats; 3) Examine differences within online retail formats among consumers who are active online apparel buyers versus those who only browse; 5) Analyze demographic and shopping behavior predictors simultaneously of active online apparel buyers versus consumers who only browse. The demographic predictors include: income, household size, education level, and presence of children. The shopping behavior predictors include: duration at site in minutes and total number of pages viewed per session.

Data for the study are accessed from a secondary source which tracks online consumer behavior, ComScore, from September to December, 2014. The final sample size resulted in 46,667 individual browsing sessions, of which 1,543 indicated purchases across the eight selected retail sites.

The secondary data were analyzed using a variety of tools. Objective one was measured descriptively, objective two employed a chi-square analysis, objective three used t-tests and objective four employed a logistic regression model.

Findings suggest a range of conversion rates by format between two percent and five percent which is consistent with previous findings. The specialty retail formats indicated the highest conversion rates. Chi-square tests also suggest significantly higher associations between the specialty formats and shopper conversion. Conversely, the analysis indicated significantly less association between conversion among shoppers in fast fashion and the value department store format. In terms of predicting conversion, the logistic regression model indicated that both shopping behavior variables (i.e., duration at a site and pages-viewed) and a single demographic (i.e., household income) are positively associated with likelihood of the purchase (conversion). Additionally, the results suggest that the highest education level in household negatively impacts the likelihood of conversion.

The findings suggest differences in retail formats and conversion of shoppers to purchasers online. This research demonstrates that specialty formats indicate the strongest shopper conversion among the examined formats, while the fast fashion and value department store formats indicate the lowest conversion of online purchasers. Additionally results suggest that active purchasers, regardless of format, spend more time online and visit more web pages within a session. Discussion, limitations and future research association with the study's findings are presented to conclude the thesis.

An Examination of Shopper Conversion among U.S. Online Retail Formats

by
Yuxin Zhu

A thesis submitted to the Graduate Faculty of
North Carolina State University
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APPROVED BY:

Dr. Marguerite Moore
Committee Chair

Dr. A. Blanton Godfrey

Dr. Yingjiao Xu

DEDICATION

♥

For my mother and grandfather who unconditionally support me to accomplish my dream and inspired me to be a better person.

BIOGRAPHY

Yuxin Zhu was born in Shanghai, China in October of 1989. Before she came to the U.S., she has gotten her bachelor degree in fashion design from Shanghai Donghua University in 2014, and accumulated years of experience working in Shanghai, China, especially in sales management and market planning area. She possesses a strong drive, relentless intellectual curiosity, and the desire to create innovative ways on problem solving. Her work experience has enabled her to understand the importance of collaboration with other people, and has also cultivated leadership potential, along with strong analytical and interpersonal skills. She has worked with and managed over 300 people in retail stores and also got chance to work with Fitbit and Ford in Chinese market as a junior planner, those high intense work environment also force her to absorb information and knowledge quickly.

She continued her further study as a full-time graduate student in NC State University majoring in textile and apparel technology management in Fall 2015. Yuxin has huge passions on analyzing marketing environments in both America and China, and she aims to build e-commerce integrated business model for apparel brands. In 2016, she got the first prize in AATCC C2C® Student Merchandising Competition. She also stood out during the study abroad program in Hong Kong, and built industrial relationships with some leading apparel companies.

Yuxin plant to complete the requirements to graduate in the spring of 2017 with a Master of Science in Textile and Apparel Technology Management. And she will join American & Efird Shanghai branch after her graduation.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Introduction and Background

Academics and trade professionals widely agree that traditional trade environments are increasingly complex and consistently changing along with technological innovation and savvy consumers (Blázquez, 2014; Ha & Stoel, 2012; Luo, Fan, & Zhang, 2016). Though this dynamic marketing environment provides potential opportunity, the market also introduces challenges for industry practitioners who have to satisfy evolving consumer wants and needs. Thomas, Miller and Simmons (2015) note that the Internet has been transformative in shifting power downstream in supply chains, resulting in increased consumer knowledge, and subsequently consumers' greater sense of individual market empowerment. As such, it is not surprising that E-Commerce channels continue to increase market share among many consumer sectors (Global connected commerce report, 2016). The US Department of Commerce reported an estimated annual increase in domestic E-Commerce of 14.6 percent ($341.7 B USD) for 2015 compared to 2014. In contrast, the same report indicated that annual domestic retail sales overall grew only 1.4 percent (Denale & Weidenhamer, 2016). Therefore, growth in many sectors of the domestic retail industry appears to be occurring in E-Commerce channels. As a result, retailers are likely to focus future efforts on this increasingly popular channel of distribution.

Although the recent U.S. Department of Commerce report indicates growth in e-commerce and supply chains are increasingly focusing on this channel, a great deal of uncertainty remains regarding consumers' online purchase behavior (Delucchi, 1993; Ha & Stoel, 2012; Kim & Krishnan, 2015) Futher e-commerce drives an increasingly competitive environment where competition is only a few mouse clicks away, which appears erode brand loyalty and increased price competition for some products (Srinivasan, Anderson, & Ponnavolu, 2002).

The challenge of e-commerce is particularly notable within the apparel industry due to the importance of tactile experience (i.e., touch and feel) (Workman & Cho, 2013) with the material attributes of these products (Yu, Lee & Damhorst, 2012) A recent industry report suggests the overall trend towards greater growth in E-Commerce versus traditional retail sales indicated by the U.S. Department of Commerce report for 2015 is clearly presented in the U.S. apparel market. Specifically, Love (2016) reports that e-commerce continues to increase its share of apparel sales, accounting for 14.8 percent in 2014 and 17 percent in 2015. The increasing competitive importance of e-commerce within the apparel industry further underscores the importance of understanding consumer interactions within this unique technological market environment.

Purpose of the Study

As a first step toward understanding consumer purchasing behavior within the apparel e-commerce context, the current study focuses on the actual conversion of consumers from browsers to shoppers during the online experience. According to the Web Analytics Association (2007), conversion can be defined as a method of segmenting behavior as visitors interact with a web property. Generally speaking, a visitor completing a target action that may indicate 1) potential for future behavior such as clicking on an advertisement, or registering for more information, or starting a check out process; or 2) completion of a purchase on-line or quote. The former (1) are sometimes referred to as step, support, mini, or micro conversions, and the latter (2) are sometimes defined as target or goal conversions. The purpose of this study is to establish a cursory understanding of online shopper conversion among market leading E-Commerce channels for apparel in the United States. To address this purpose, the following research objectives are proposed:

> Research Objective 1 (RO1): Determine the conversion rate among online retailers, representing six different formats in the domestic market: fast fashion, value department, traditional department, upscale department, specialty and pure-play internet.

> Research Objective 2 (RO2): To compare conversion rates among retailers representing six different online formats in the domestic market: fast fashion, value department, traditional department, upscale department, specialty and pure-play internet.

> Research Objective 3 (RO3): To examine differences within online retail formats among consumers who are active online apparel buyers versus those who only browse in terms their online purchasing behavior (duration at a set and number of pages-viewed).

> Research Objective 4 (RO4): To analyze the demographic and shopping behavior predictors simultaneously of active online apparel buyers versus consumers who only browse. The demographic predictors include: household income, education level, age of oldest head of the household and household size. The shopping behavior predictors include: duration at site in minutes and total number of pages viewed per session.

Though the online shopping behaviors of apparel consumers are increasingly important to profit generation in this market, little evidence of industry wide shopper conversion rates exists for researchers in the field. This research aims to establish an empirical foundation which identifies shopper conversion rates among different online retail formats using a robust dataset of actual consumption behavior from the U.S market. Further, by determining conversion rates within specific retail format types, the research aims to provide greater understanding of format specific online shopping conversion.

The research also seeks to understand within format behaviors to broaden understanding of shopper conversion within the apparel industry. The literature indicates several potential influences on online shopper conversion including variables related to online shopping behaviors (e.g., duration at a site and pages viewed) as well as demographics (e.g., household income, most education of head of household, oldest age of head of household and household size). The study considers the impact of online shopping behavior within each retail format to uncover potential patterns of behavior that may differ based on these formats. Further the study considers the impact of both demographic and shopping behavior on the likelihood of shopper conversion. This is an empirical research on relation to consumers' actual online purchases rather than online shopping intention, which is more relevant to real business applications.

Operational Definitions

Clickstream Analysis− Clickstream analysis, also referred to as clickstream analytics, is the process of collecting, analyzing and reporting aggregate data about website users' browsing patterns and purchase activities. A clickstream may include: pages visited, sequence of browsing activities, product selected, items purchased, total time online, etc. (Rouse, 2016).

Conversion Rate-The general definition of conversion is the completion of a task or process. For the purposes of this research, conversion rate is defined as whether or not a single consumer browsing session results in a purchase. For example, a given online retailer's conversion rate is determined by the number of active sessions resulting in a purchase divided by total number of active sessions undertaken during the data collection period. This is also referred to as 'shopper conversion.'

Machine Identifier-The ComScore clickstream data are collected from a random sampling of more than two million Internet users who gave the permission to ComScore on online shopping behavior observation and capture. This chunk of data is collected at the individual household level. Each household is assigned a unique identity number referred to as the machine identifier in this research.

Retail Format- Retail formats is the overall merchandising and presentation that a retailer offers to the customer or client, either as a retail storefront or as an online experience. Retailers that belong to a common format tend to share similar physical characteristics including store size, layout, selling capacities as well as similar product lines. For example, Nordstrom which is considered to be within the upscale department store format shares this format with retailers such as Saks Fifth Avenue and Bloomingdales.

Session Identifier-A session is defined as a period of sustained web browsing or a sequence of page viewings that is established at a certain point and ends at a later point. Each session was assigned a unique number referred to as a 'session identifier' in this research.

Summary

The thesis is organized as follows. In Chapter Two relevant literature is reported to provide a current understanding of the study's context which is e-commerce in the apparel industry, followed by incorporation of academic and trade literature to inform the study's objectives. Chapter Three delineates the research methods used to address each of the four research objectives: including sampling procedures, data collection and measurement and analytical procedures. Chapter four presents the findings, presented in terms of each objective and Chapter Five presents general conclusions of the study, provides a discussion of the findings' implications, identifies the study's limitations as well as future research directions.

CHAPTER 2

LITERATURE REVIEW

In order to better address the research objectives, several literatures in which relevant hypotheses and research methodologies are tested have been reviewed. The scope covers e-commerce development status, the evaluation on e-commerce performance, clickstream analysis. Meanwhile, consumer shopping behavior and the influence on demographic drivers will also involve.

E-Commerce in the Apparel Industry

'E-Business' is a broad term that encapsulates numerous business functions and activities including: customer service, electronic order processing, supply chain management and electronic purchasing in the value chain (Thomas, Miller, & Simmons, 2015). E-Business operations facilitate integration of business processes that rely on information, thereby directly benefitting decision makers with relevant, timely data (Bakos, Miller, Packham, Pickernell, & Thomas, 2016).

'E-Commerce' is a narrower term that focuses on the transaction process. It is defined as the buying and selling of goods and providing the services over the Internet (Thomas, 2010). Described another way, E-Commerce is any transaction completed over a computer-mediated network that involves the transfer of ownership or rights to use goods or services (Fraumeni, Manser, & Mesenbourg, 2000). Liu, Krasnoproshin & Zhang (2012) suggest a broader definition of E-Commerce s that moves beyond buying and selling behavior, to incorporate the entire online process: product development, marketing, selling, delivery, service and payment activities.

As noted in Chapter One recent growth in apparel sales has been fueled by e-commerce (Denale & Weidenhamer, 2016). Researchers have focused on internet shopping as a general field of inquiry since the early dissemination of online shopping activities in the late 1990's. Among this stream of research, inquiry commonly focuses on the drivers of e-commerce adoption as a purchasing tool among consumers (Chang & et al , 2005). Research demonstrates the following reasons consumer adoption of the internet as a shopping tool: efficiency, ease of transaction (Blázquez, 2014), privacy and security(Han & Maclaurin, 2002), perceived value (Szymanski and Hise, 2000), website design, and the provision of relevant information (Breitenbach and Van Doren, 1998). Young, Kim and Kim (2004) reiterate the influence of consumers' time efficiency as a positive driver of internet shopping, increasingly computer proficient consumers.

Apparel has become an online success due largely to easy and free returns, innovative visualization tools and the presence of customer reviews (Blázquez, 2014; Flanagin, Metzger, Pure, Markov, & Hartsell, 2014; Jang & Davis Burns, 2004). Those advantages have several effects on observed behavior. First, because the access costs are much lower, online shoppers may be more likely to visit a store without any intention of buying (Moe & Fader, 2004). Nie and Erbring (2000) suggest that 52 percent of the consumers use the Internet for product information, 42 percent for travel information, and 24 percent for buying. Particularly, apparel online shopping cannot meet consumers' needs on physically touching and examining the products to assess color, size, design, and fabric, which prevents them making purchasing decisions. Second, due to the low cost of visiting website, online shoppers tend to extend the checkout process and come back later to buy (Moe & Fader, 2004). That's the reasons why online shoppers make multiple trips to the same store for a single purchasing decision. In the clickstream data, we can see multiple secession IDs appear under the same machine identifier within a close time period.

On the other positive side, purchasing on-line is gradually becoming a more acceptable concept. However, apparel e-retailers are still straggling in find business models that can ensure stable profits. Currently, Internet retailers generally fall into one of the four categories: virtual e-retailers, bricks-and-mortar retailers, catalog companies, and multi-channel retailers that use the Internet(Jang & Davis Burns, 2004). And each e-retailer develops their own business strategy, which brings the market fierce competition.

Website Performance Measurement

Along with the expansion of Internet usage among consumers, corporations, political groups and organizations are constantly pursuing ways to improve their websites' communication capacities. Central to this purpose is the goal to ensure that webpages effectively communicate with users while serving the strategic mission of the organization. According to Beri Bhavna (2013), a website's communication capacity can be gauged from its ease of use and ability to convert shoppers from browsers to purchasers (conversion rate). To date, ease of use and conversion rate represent the two common criteria for website performance evaluation.

Website Usability

From an overall perspective, The International Standards Organization [ISO9241-11: Guidance on Usability (1998)] defines usability as the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use. In 2001, Hartson, Andre, & Williges found that effort put into usability design greatly improved website performance. The research suggests that userfriendly website navigation is important for website usability. This finding suggests that a clean and clear layout with a logical structure will shorten a user's learning curve and help them achieve their goal in a shorter time, which improves the user's experience.

In their 2003 book on customer centered web design, Chandler and Hyatt suggest that poor performing e-commerce websites tend to be more database-driven than customer-driven, which can result in customer frustration, dissatisfaction, and lost sales. They further suggest that the online retailer should not be considered as a traditional catalog or retail store, but a combination of both formats. Thus the factors, such as navigation, channel of communication, customer interaction, and supply chain support, play a vital role in the customer's purchasing decision.

In 2009, Jaspers provided several methods for usability measurement, which he categorized into two major groups: 1) the expert-based inspection method, and; 2) the user-based inspection method. In general, expert-based methods aim to uncover potential usability problems by having evaluators inspect a user interface with a set of guidelines, heuristics or questions in mind or by performing a step-wise approach derived from knowledge of how humans process tasks. User-based testing methods include examples such as user performance measurements, log-file and keystroke analyses, cognitive workload assessments, satisfaction questionnaires, interviews and participatory evaluations (Nielsen, 1994; Molich, R. & et al., 1999; Gray, W.D. & et al., 1998). In summary, Jaspers (2009) asserts that a combination of both the expert and user inspections is the most comprehensive approach to understanding usability by incorporating the unique user experience.

Conversion Rate

Conversion rate represents the second measurement commonly used to determine website performance. In a general sense, conversion refers to the completion of a task or process, and in the context of online commerce is not strictly used to describe a purchase but may also include additional outcomes including lead generation, registration, etc. (Burby & Brown, 2007). Therefore, the outcome of conversion can vary by perspective.

Traditionally, within online retailing, conversion rate is commonly expressed as the percentage of consumers who purchase from the store's website per visit (Moe & Fader, 2004). A number of researchers explore the relationship between consumer purchase intention and conversion rate. Gudigantala, Bicen and Eom (2016) modeled the impact of purchase intention and website satisfaction on conversion rate and found that both predictors positively impact conversion. Numerous researchers have reported conversion rates for online retailers and the percentages are consistently low, with some results as low as two percent and few exceeding five percent conversion rates (Chaffey, 2016; Holzwarth, Janiszewski, & Neumann, 2006; Sismeiro & Bucklin, 2004; Sohrabi, Mahmoudian, & Raeesi, 2012).

Kohavi (2003) suggests ten supplementary analyses to improve an e-commerce website. He categorizes these analyses into four sections: data audit, operational analyses, tactical analyses and strategic analyses. Kohavi's operational analysis category suggests using 'micro-conversions analysis' to improve performance. Micro-conversions are the intermediate steps of an online shopper's conversion to a purchaser (Lee, Podlaseck, Schonberg, & Hoch, 2001). The micro-conversion rate disaggregates the conversion measure into four steps including: 1) 'Product Impression'- the view of hyperlink to a webpage presenting a product 2) ‘Clickthrough’- the click on the hyperlink and view the webpage of the product. 3) ‘Basket Placement’- the placement of the item in the shopping basket, and 4) ‘Purchase’-the purchase of the item-completion of a transaction.

Clickstream Data Analysis

In the electronic commerce environment, consumer actions can be tracked by following their ‘clickstream’. Clickstream is a term used to describe visitors' paths through one or more websites (Rouse, 2016). Clickstream data are derived from raw page requests, often referred to as ‘hits’, and information associated with the visitor (e.g., timestamp, IP address, URL, number of transferred bytes, referring site, cookie data) that is recorded in web server log files (Lee, Podlaseck, Schonberg, & Hoch, 2001). Given their insight into the consumer’s online activities, clickstreams provide information that can be useful to marketers and merchandisers, such as how customers locate the store, the products they view, and the products they buy (Lee et al., 2001). Further, clickstream analysis can provide insight into the way a website is navigated and used by its visitors (Lee et al., 2001). Clickstream data are also unobtrusive, collected in the users’ natural environment with no artificial interruptions (Bucklin & Sismeiro, 2009). This feature makes clickstream analysis relatively objective and unbiased. Clickstream analysis is considered as one of the most effective evaluation methods on E-commerce due to its enormous data volume, real-time collection and accuracy.

There are two levels of clickstream analysis: traffic analytics and e-commerce analytics (Rouse, 2016). Traffic analytics focuses on server level data (i.e., log files) to track visitor browsing paths through the site. Traffic analysis can also capture page-loading time, and data transmission time as the shopper moves through a site. E-Commerce analytics is used to determine the effectiveness of the website as a sales format through clickstream data.

This approach records the activity related to consumer purchasing process, such as the duration time on the specific website, the product the shopper puts in or takes out of a shopping cart, the final payment and the consumer's personal information.

Online Shopper Demographics

Demographic variables have been considered by researchers to investigate online consumer behavior including browsing and purchasing outcomes. Many of these studies suggest that demographics can impact online behavior (Brown, Pope, & Voges, 2003; Birtwistle, Moore, Goldsmith, & Flynn, 2005; Leeflang & Wittink, 2000). Within this stream of research, demographics are predominantly treated as either moderators or control factors (Brown & Venkatesh, 2005). Research that clearly builds model based on predictive power of demographic variables is inadequate. An extensive review of the online shopping literature (Chang, Cheung, & Lai, 2005) also indicates no study that is solely dedicated to examining demographic variables as behavioral predictors. Moreover, except for age, gender, income and educational level, the other demographics on online shopping are rarely tested and result in inconsistent findings (Schibrowsky, Peltier, & Nill, 2007).

Early demographic research into Internet shopping suggests that mature, affluent consumers shop online due to their relatively higher purchasing power and access to credit, while younger consumers tended to primarily use the Internet for information acquisition (Donthu & Garcia, 1999). According to the Mathwick et al. (2002) study, online shoppers tended to be younger than 44 years of age, educated and more affluent. The same research suggested that online shoppers are typically from single-income households exceeding US $75,000 (Mathwick, Malhotra, & Rigdon, 2002). More recently Jeong et al. (2009) conducted a study to explore the relationship between web site features, consumer emotional components of pleasure and arousal and 4Es (educational, entertainment, escapist, and esthetic experiences) as originally conceptualized by Pine and Gilmore (2011). Their findings suggest that entertainment and esthetic experiences significantly impact arousal as mediating variables. Educational experience did not influence consumer emotional components.

Brown (2005) examined demographics within her study which examined retail channel choice behavior using the technology adoption model. Brown's research suggested that income and socio-economic status (SES) are positively related to apparel purchasing among three channels: in-store, online and catalog. In terms of age, their results did not indicate a significant relationship.

Retail Formats and Online Shopping Behavior

Based on the literature review of current apparel industry on e-commerce, it's clear that consumers nowadays have multiple choices on shopping channels. Workman and Siwon (2013) differentiate the apparel shopping outlets into two, one is touch shopping channels (i.e. brick-and-mortar stores) and the other is non-touching channels (i.e. catalog, television and internet)

Researches (Mokhtarian, 2004) show there's huge difference between in-store shopping behavior and online shopping behavior. Traditional brick-and-mortar store dominant the apparel industry because this sales channel can provide consumer sensory gratification, such as touching and feeling on the product and the store atmosphere. (Peck & Childers, 2003; Blázquez, 2014) Although there are obstacles to completely transfer in-store shopping experience to online, the fast development of high technology gradually shortens the gap between two shopping outlets.

Shim (2000) along with Young (2004) believe the rise of the ecommerce decreases the time consuming for product searching and transportation, thus it's a more cost-effectiveness format. Nowadays, many consumers tend to do an information research online before they drive to the retail store(Ward & Morganosky, 2002). Some of them even combine e-commerce and in-store shopping to maximize their benefit. They acquire product information online, check out the product in store, enjoy the shopping environment and service, and finally purchase online (Farag, Schwanen, Dijst, & Faber, 2007).

There are two important measures of consumer online engagement widely used in the researches of online shopping behavior. One is duration at a site (Danaher, Mullarkey, & Essegaier, 2006), and the other one is pages-viewed (Huang, Lurie, & Mitra, 2009). Related research incorporates browsing characteristics as covariates to predict consumer's online purchase behavior (Bucklin & Sismeiro, 2003; Mallapragada, Chandukala, & Liu, 2016). Bucklin and Sismeiro (2004) study browsing characteristics, such as duration at a site and pages viewed within browsing session. And they found repeat visit might lead to reduce propensities of pages viewed, but not to reduce the duration. Their results also reveal browsing patterns that consumers tend to show the propensities of timesaving, which also supports Shim (2000) and Young's (2004) founding.

CHAPTER 3

METHODOLOGY

In order to address the four research objectives, the study employs a large secondary dataset accessed from ComScore during the last four months of 2014. These data provide realistic insight into actual online browsing and purchasing behaviors through the use of unobtrusive observation technology. Due to its realism and broad sampling scope, these data are effective for answering the research objectives.

Sampling Method

The ComScore Web Behavior Data include both browsing and purchasing behaviors of online users in the United States. ComScore uses random sampling from a panel of more than two million Internet users who have granted the firm permission to access and capture their online activity. The data are captured at the household level based on a single machine identifier.

By following machine identifier activity the following behaviors are captured: website visited, page views, the duration of time at website and purchase activity during a single website visit, referred to as a session. For the purposes of this study, the data are organized at two levels: 1) The session identifier level which includes all sessions undertaken by a single household over the four month period; and 2) the machine identifier level which aggregates all session activities associated with the household over the four month period into a single unit of analysis. These two levels of data specification are necessary to appropriately measure the study's objectives and are discussed in detail later in this chapter. Use of ComScore data for both academic and marketing research is evident in the academic literature (Bailey & et al., 2008; Jiang & Tuzhilin, 2006; Lin & et al., 2010; Moe & Fader, 2004).

The final sample for this analysis was constituted based on the following criteria: session occurred between September and December 2014, session included a website visit to one of eight predetermined retail sites that represent six unique retail formats: 1) fast fashion, 2) value department store, 3) traditional department store, 4) upscale department store, 5) specialty store (three retailers) and 6) pure-play internet retailer (Table 1). Additionally, all sessions included in the sample exceeded a duration of one minute, or users viewed two web pages or more. The final sample size resulted in 46,667 individual browsing sessions, of which 1,543 indicated purchases across the eight selected retail sites. Retailers for the study were selected to represent each of the six formats based on their nationwide brick and mortar market coverage, as well as their distinction as unique retail formats. Data availability for each of the formats during the last four months of 2014 was also a requirement for inclusion. Each retail format includes a single retailer as its representative, with the exception of the specialty format which incorporates three different retailers who cater to different market segments (Table 1)

Table 1

Format, Retailers, Market Coverage and Target Market Description

Formats	Specific E-tailers	#Stores in USA	Target Market
Fast fashion	Forever 21	723	"Focuses on making trendsetting apparel accessible to fashion lovers of all ages, sizes and styles (Alex Ok, President Forever 21)."[1]
Value department store	Kohl's	1,155	"Kohl's target marketing strategy focuses on middle-class women ages 25-45 who shop for their families and enjoy deals and rewards."[2]
Traditional department store	Macy's	850	"Macy's, Inc. is a premier omnichannel retailer with iconic brands that serve customers through outstanding stores, dynamic online sites and mobile apps."[3]

Continuing to the next page

Table 1 Continued

Formats	Specific E-tailers	#Stores in USA	Target Market
Young adult specialty brand	American Eagle	935	A youth specialty retailer focusing in young adult wear for men and women.[5]
Middle market specialty brand	Gap	915	Gap brand targets individuals, male and female from 3 to 45, interested in American casual style
Aspirational specialty brand	J-Crew	287	"J. Crew's target market was young, educated, and affluent, with a median age of 32, some postgraduate education, and an annual household income above $62,000."[6]
Pure-play channel	6 p.m.	1	6 p.m. is an online shopping outlet on which discount apparel, shoes, bag and accessories from popular brands are available. It targets to the online shoppers who seek great deal.

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Measures

Research Objective 1

To determine conversion rate for RO1, for each of the eight online retailers, the following simple calculation was used:

Conversion rate = number of sessions that result in purchase / total number of sessions

Therefore, each of the eight unique sites generated a single ratio for conversion rate to be compared in the analysis.

Research Objective 2

The measures used to address RO2 include two nominal variables. A categorical variable for format is used to identify each of the eight retailers while a simple binomial yes/no variable is used to measure whether or not a shopper purchased during a session (conversion).

Research Objective 3

Three measures were employed to analyze RO3 which focused on examining online shopping behaviors among purchasers compared to browsers. The independent variable is represented by a binomial classification variable for those who purchased and those who only browsed. Two continuous dependent variables for online shopping behavior are examined: duration of minutes per session and total number of pages viewed per session.

Research Objective 4

RO4 examines shopping behavior and demographic predictors on the likelihood of conversion (i.e., purchase) based on the entire sample of households. The measures used to address RO4 include: two shopping behavior measures and four demographic measures. In contrast to the previous research objectives which were measured based on each session, these measures are based on each household as a unit of analysis. The shopping behavior measure for duration at site is constituted by the sum to all sites over the four-month period. The measure for number of pages viewed is also summed to reflect this behavior in total over the four month period. Demographic variables including: income, most education level (head of household), oldest age (head of household), household size were captured on ordinal scales (Table 2).

Table 2

Measures for Demographic Predictors

Variables	Level	Description
Household Income	11	Less than 25k
	12	25k~39.999k
	13	40k~59.999k
	14	60k~74.999k
	15	75k~99.999k
	16	100k~149.999k
	17	150k~199.999k
	18	200k+
	99	Unknown
Most Education Head of the Household	0	Less than a high school diploma
	1	High school diploma or equivalent
	2	Some college but no degree
	3	Associate degree
	4	Bachelor's degree
	5	Graduate degree
	99	Missing

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Table 2 Continued

Variables	Level	Description
Age of Eldest Head of the Household	1	18~20
	2	21~24
	3	25~29
	4	30~34
	5	35~39
	6	40~44
	7	45~49
	8	50~54
	9	55~59
	10	60~64
	11	65 and over
	99	Unknown
Household Size	1	1
	2	2
	3	3
	4	4
	5	5
	6	6+
	99	Unknown

Analysis

Research Objective 1

Additional analysis beyond the calculation of conversion rates described in the measurement section was not required to identify conversion rates across the eight retail sites which is the purpose of objective one. The conversion rates are examined directly to identify differences within formats. No additional statistical testing is employed for RO1.

Research Objective 2

To analyze RO2, the study employs a chi-square test to examine whether specific retail sites and the incidence of purchase are significantly associated. A Pearson chi-square test was performed for the full contingency table (i.e., omnibus test) with an alpha of .05. In cases of significance at the omnibus level, post hoc testing was undertaken. Post hoc testing for a significant chi-square test requires the following steps: 1) acquire the adjusted residuals associated with each cell in the original contingency table, 2) square the adjusted residuals to form z-scores, 3) calculate p-values based on a chi-square distribution from the z-scores associated with each cell (GarcIa-pErez & Nunez-Anton, 2003). Due to the increased chance of making a Type 1 error, we used a Bonferonni adjustment to reduce this potential threat. The Bonferonni adjustment was calculated by dividing alpha (.05) by the total number of cells in the contingency table (16), resulting in an adjusted alpha of .003125.

Research Objective 3

T-tests are used to address RO3, which compares the purchasers and browsers in terms of two dependent variables for online shopping behavior: duration onsite per session and total number of pages viewed per session. Levene's test of homogenous subsets is also considered. In cases that Levene's test indicates non-homogenous subsets, the t-tests will be performed on an edited sample. Although a t-test can be robust to non-homogenous subsets, this test may not be robust enough to mitigate the variance present in the extremely different sample sizes in this data (i.e., browsers, N=6,170 and purchasers N=161). For non-homogenous subsets, the following sampling adjustment will be made prior to the t-test. To address the uneven sample sizes, the larger browser group will be randomly sampled to generate an equivalent sample size to the purchasers (N=161) in order to compare the two groups.

Research Objective 4

A logistic regression model is used to analyze RO4, which examines the shopping behavior and demographic predictors for the likelihood of conversion. Due to the binomial dependent variable for conversion, Logistic Regression appropriate for examining the impact of the predictor variables. A forward logistic regression method is used with an alpha of .05. Beta estimates are evaluated to determine significant predictors.

CHAPTER 4

RESULTS

Sample Description

The sample data is organized into two levels: 1) the session level and 2) the household level. The session data include 46,667 individual browsing sessions among the six online retail formats (i.e., eight retail sites) from September to December, 2014, of which 1,543 indicated purchases. The household level data is aggregated from the session data and includes 8,352 households, 1,098 of which purchased at least once during the sessions (Table 3).

Table 3

Transaction Distribution by Household

Retail Formats	Total Transactions	Range	Mode (percent)
Forever 21	130	4	1(0.84)
Kohl’s	238	6	1(0.76)
Macys	259	16	1(0.79)
Nordstrom	83	30	1(0.75)
American Eagle	125	2	1(0.82)
Gap	168	8	1(0.78)
JCrew	26	15	1(0.77)
6 p.m.	69	4	1(0.84)

The data indicate that most households only purchased once during the four-month interval. In terms of ranges, Nordstrom indicated the widest range of household transaction frequency (30), followed by Macy's (16), JCrew (15), Gap (8), Kohl's (6), Forever21 & 6 p.m. (4) and American Eagle (2). In terms of total number of transactions per retailers Macy's indicated the highest number (N=259), followed by Kohl's (N=238), Gap (N=168), Forever 21 (N=130), American Eagle (N=125), Nordstrom (N=83), 6 p.m. (N=69) and JCrew (N=26).

Research Objective One

The conversion rates for each of the eight online retailers ranges from .0253 to .0561 (Figure 1). Specialty formats indicated the highest conversion rates (from .0510 to .0561), followed by the traditional department store (Macy's, 0.0314), pure-play internet store (6 p.m. 0.0300) and the upscale department store (Nordstrom, 0.0291). The lowest conversion rate was indicated by the fast fashion format (Forever 21, 0.0253) and the second lowest was indicated by the value department store format (Kohl's, 0.0272) (Table 4).

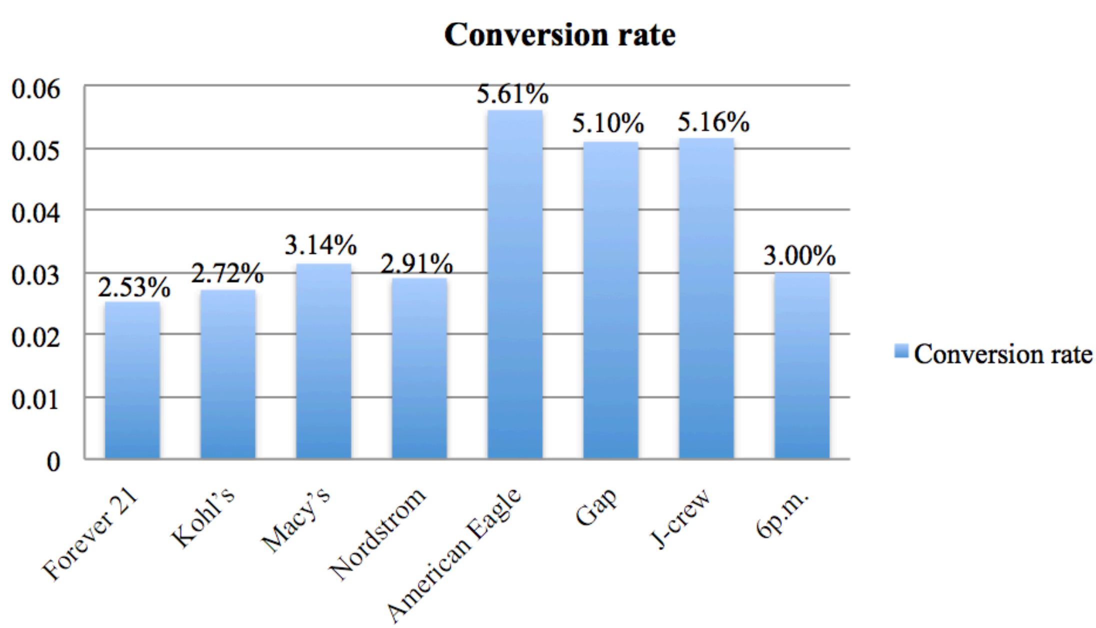

Figure 1: *Online Retailers' Conversion Rate*

Table 4

Online Retailers' Conversion Rate (based on Session ID)

Ecommerce format	Online retailer	Total transaction/total session	Conversi on rate	Rank
Fast fashion	Forever 21	161/6331	0.0253	8
Value department store	Kohl's	331/12157	0.0272	7
Traditional department store	Macy's	359/11421	0.0314	4
Up-scale department store	Nordstrom	153/5261	0.0291	6
Specialty-young adult	American Eagle	153/2727	0.0561	1
Specialty-middle market	Gap	238/4670	0.0510	3
Specialty-aspirational	J-crew	60/1163	0.0516	2
Pure-play channel	6 p.m.	88/2937	0.0300	5

Research Objective Two

For Research Objective 2, we compared the frequency of purchasers and browsers among each retail format using a two-way contingency table based on the session data (Table 5). The accompanying Chi-Square test, indicates a significant statistic (Pearson 133.509, p-value > .000, alpha .05) (Table 6). Based on this result, post-hoc tests are performed to further investigate the sources of association among format type and shopper conversion.

Table 5

*Two-way Contingency Table: Domain ID * Transaction Flag Crosstabulation*

			Transaction Flag		
			No	Yes	Total
Domain ID	Forever 21	Count	6170	161	6331
		Expected Count	6121.7	209.3	6331.0
		% within Domain ID	97.5%	2.5%	100.0%
		% within Transaction Flag	13.7%	10.4%	13.6%
	Kohl's	Count	11826	331	12157
		Expected Count	11755.0	402.0	12157.0
		% within Domain ID	97.3%	2.7%	100.0%
		% within Transaction Flag	26.2%	21.5%	26.1%
	Macy's	Count	11062	359	11421
		Expected Count	11043.4	377.6	11421.0
		% within Domain ID	96.9%	3.1%	100.0%
		% within Transaction Flag	24.5%	23.3%	24.5%
	Nordstrom	Count	5108	153	5261
		Expected Count	5087.1	173.9	5261.0
		% within Domain ID	97.1%	2.9%	100.0%
		% within Transaction Flag	11.3%	9.9%	11.3%
	American Eagle	Count	2574	153	2727
		Expected Count	2636.8	90.2	2727.0
		% within Domain ID	94.4%	5.6%	100.0%
		% within Transaction Flag	5.7%	9.9%	5.8%
	Gap	Count	4432	238	4670
		Expected Count	4515.6	154.4	4670.0
		% within Domain ID	94.9%	5.1%	100.0%
		% within Transaction Flag	9.8%	15.4%	10.0%
	JCrew	Count	1103	60	1163
		Expected Count	1124.5	38.5	1163.0
		% within Domain ID	94.8%	5.2%	100.0%
		% within Transaction Flag	2.4%	3.9%	2.5%
	6 p.m.	Count	2849	88	2937
		Expected Count	2839.9	97.1	2937.0
		% within Domain ID	97.0%	3.0%	100.0%
		% within Transaction Flag	6.3%	5.7%	6.3%

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Table 5 Continued

		Transaction Flag		
		No	Yes	Total
Total	Count	45124	1543	46667
	Expected Count	45124.0	1543.0	46667.0
	% within Domain ID	96.7%	3.3%	100.0%
	% within Transaction Flag	100.0%	100.0%	100.0%

Table 6

Chi-Square Tests (retail format by browsers vs. purchasers)

	Value	DF	Asymptotic Significance (2-sided)
Pearson Chi-Square	133.509*	7	.000
Likelihood Ratio	119.555	7	.000
N of Valid Cases	46667		

* 0 cells (0.0%) have expected count less than 5. The minimum expected count is 38.45.

According to post-hoc test (Table 7), American Eagle (6.94), Gap (7.21) and JCrew (3.58) have positive adjusted residual values, indicating that there are more purchasers than would be expected by chance. Conversely, Forever 21 (-3.65), Kohl’s (-4.19), Macy’s (-1.12), Nordstrom (-1.71) and 6 p.m. (-0.97) have negative adjusted residual values, indicating that there are fewer purchaser completed the shopping on these formats than would be expected by chance.

In terms of P-value, three specialty stores: American Eagle (<0.001), Gap (<0.001) and JCrew (0.00034), along with Forever 21 (0.00026) and Kohl’s (0.00003) indicate significant differences between browsers and purchasers. P-values associated with the remaining department stores, Macy's (0.26271) and Nordstrom (0.08727), along with 6 p.m (0.33205) did not indicate significant differences in the two groups.

Table 7

*Post-hoc Test for Purchaser among Retail Formats**

Retail Formats	Adjusted Residual	Chi-Square	P-value
Forever 21	-3.65	13.32	0.00026**
Kohl's	-4.19	17.56	0.00003**
Macys	-1.12	1.25	0.26271
Nordstrom	-1.71	2.92	0.08727
American Eagle	6.94	48.16	< 0.00001**
Gap	7.21	51.98	< 0.00001**
JCrew	3.58	12.82	0.00034**
6 p.m.	-0.97	0.94	0.33205

Note: *The Bonferroni adjustment is calculated by dividing alpha (.05) by the total number of cells in the contingency table (16), resulting in an adjusted alpha of .003125.

**indicates statistical significance at the adjusted level ($p < .003125$)

Research Objective Three

The t-tests that examined whether there are differences in browsers and purchasers within each of the eight formats in terms of number of duration at a site and pages viewed (Table 8). Descriptive statistics suggest that purchasers' average duration at a site ranges from 20.4 to 44.6 minutes. In terms of format, consumers indicated the longest duration online (mean=44.61) and the highest frequency of webpages (mean=75.79) among the fast fashion format (Forever 21). In contrast, the shortest average duration (mean=20.40) and least number of pages-viewed (mean=18.74) occurred among shoppers in the upscale department store format (Nordstrom).

Table 8

Group Statistics

Retail Formats		Behavior	N	Mean	Std. Deviation	Std. Error Mean
Forever 21	Pages Viewed	Browser	161	17.14	25.520	2.011
		Purchaser	161	75.79	69.610	5.486
	Duration at a Site (minutes)	Browser	161	12.34	19.593	1.544
		Purchaser	161	44.61	45.984	3.624
Kohl's	Pages Viewed	Browser	331	10.84	19.258	1.059
		Purchaser	331	41.71	38.186	2.099
	Duration at a Site (minutes)	Browser	331	8.76	14.836	.815
		Purchaser	331	37.89	35.704	1.962
Macy's	Pages Viewed	Browser	359	9.90	13.178	.696
		Purchaser	359	38.42	29.244	1.543
	Duration at a Site (minutes)	Browser	359	9.51	17.627	.930
		Purchaser	359	37.24	33.834	1.786
Nordstrom	Pages Viewed	Browser	153	4.99	5.743	.464
		Purchaser	153	18.74	13.738	1.111
	Duration at a Site (minutes)	Browser	153	5.52	9.169	.741
		Purchaser	153	20.40	18.468	1.493
American Eagle	Pages Viewed	Browser	153	7.49	11.834	.957
		Purchaser	153	30.83	25.868	2.091
	Duration at a Site (minutes)	Browser	153	7.10	12.994	1.050
		Purchaser	153	30.41	27.275	2.205
Gap	Pages Viewed	Browser	238	10.59	18.610	1.206
		Purchaser	238	34.51	28.514	1.848
	Duration at a Site (minutes)	Browser	238	8.16	14.853	.963
		Purchaser	238	28.70	25.733	1.668

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Table 8 Continued

Retail Formats		Behavior	N	Mean	Std. Deviation	Std. Error Mean
JCrew	Pages Viewed	Browser	60	13.87	17.850	2.304
		Purchaser	60	38.10	26.514	3.423
	Duration at a Site (minutes)	Browser	60	15.22	22.693	2.930
		Purchaser	60	38.40	40.458	5.223
6 p.m.	Pages Viewed	Browser	88	9.15	15.685	1.672
		Purchaser	88	31.26	32.068	3.418
	Duration at a Site (minutes)	Browser	88	8.24	21.424	2.284
		Purchaser	88	30.27	32.689	3.485

Levene's Tests for all retail formats are significant, which indicates that that the statistics associated with 'equal variances not assumed' must be used for interpretation. All six formats (eight retail sites) indicate significant values for number of pages viewed ($p<.05$) (Table 9) and significant differences for duration at a site ($p<.05$) (Table 10). For number of pages viewed, t-tests and associated p-values across all eight retail sites suggest that purchasers view significantly more pages during a shopping session compared to browsers. Likewise, for duration at site, purchaser groups across all eight retailers spent significantly longer durations per session compared to the browser only group.

Table 9

Two Independent Samples Test-Pages Viewed

Variables	Retail Formats		Levene's Test for Equality of Variances		T-test for Equality of Means				
			F	Sig.	T	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
Pages Viewed	Forever 21	Equal variances assumed	71.625	.000	-10.037	320	.000	-58.646	5.843
		Equal variances not assumed			-10.037	202.245	.000	-58.646	5.843
	Kohl's	Equal variances assumed	126.086	.000	-13.131	660	.000	-30.867	2.351
		Equal variances not assumed			-13.131	487.658	.000	-30.867	2.351
	Macy's	Equal variances assumed	192.040	.000	-16.849	716	.000	-28.524	1.693
		Equal variances not assumed			-16.849	497.633	.000	-28.524	1.693
	Nordstrom	Equal variances assumed	91.570	.000	-11.418	304	.000	-13.745	1.204
		Equal variances not assumed			-11.418	203.548	.000	-13.745	1.204
	American Eagle	Equal variances assumed	50.629	.000	-10.149	304	.000	-23.340	2.300
		Equal variances not assumed			-10.149	212.953	.000	-23.340	2.300
	Gap	Equal variances assumed	60.233	.000	-10.838	474	.000	-23.920	2.207
		Equal variances not assumed			-10.838	407.899	.000	-23.920	2.207
	JCrew	Equal variances assumed	8.823	.004	-5.873	118	.000	-24.233	4.126
		Equal variances not assumed			-5.873	103.369	.000	-24.233	4.126
	6 p.m.	Equal variances assumed	23.686	.000	-5.811	174	.000	-22.114	3.805
		Equal variances not assumed			-5.811	126.373	.000	-22.114	3.805

Table 10

Two Independent Samples Test-Duration at a Site

Variables	Retail Formats		Levene's Test for Equality of Variances		T-test for Equality of Means				
			F	Sig.	T	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
Duration at a Site (minutes)	Forever 21	Equal variances assumed	38.643	.000	-8.193	320	.000	-32.273	3.939
		Equal variances not assumed			-8.193	216.244	.000	-32.273	3.939
	Kohl's	Equal variances assumed	122.775	.000	-13.710	660	.000	-29.136	2.125
		Equal variances not assumed			-13.710	440.659	.000	-29.136	2.125
	Macy's	Equal variances assumed	112.124	.000	-13.772	716	.000	-27.730	2.013
		Equal variances not assumed			-13.772	539.000	.000	-27.730	2.013
	Nordstrom	Equal variances assumed	44.224	.000	-8.928	304	.000	-14.882	1.667
		Equal variances not assumed			-8.928	222.641	.000	-14.882	1.667
	American Eagle	Equal variances assumed	62.887	.000	-9.542	304	.000	-23.307	2.442
		Equal variances not assumed			-9.542	217.616	.000	-23.307	2.442
	Gap	Equal variances assumed	49.027	.000	-10.668	474	.000	-20.546	1.926
		Equal variances not assumed			-10.668	379.142	.000	-20.546	1.926
	JCrew	Equal variances assumed	8.269	.005	-3.871	118	.000	-23.183	5.989
		Equal variances not assumed			-3.871	92.782	.000	-23.183	5.989
	6 p.m.	Equal variances assumed	22.263	.000	-5.289	174	.000	-22.034	4.166
		Equal variances not assumed			-5.289	150.098	.000	-22.034	4.166

Research Objective Four

The omnibus test for the logistic regression which examines demographic and behavioral predictors of purchase incidence, indicates a significant statistic ($p< .000$) (Table 11). The final model suggests that two demographic predictors and two behavioral predictors are significantly influential on the binomial dependent variable for purchase (Table 13). Specifically, household income (X^2=22.928, p<.0001), highest household education level (X^2=7.003, p=.008), duration at a site (X^2=35.486, p<.0001) and total number of pages viewed (X^2=35.460, p<.0001) are significant predictors of the occurrence of purchase (conversion). The logistic regression model indicates no significant relationships between the remaining predictor variables and the likelihood of purchase: age of oldest member in household (X^2=.406, p=.524) and household size (X^2=1.430, p=.232). Additionally, the models r-square (R^2, Nagelkerke, .236), suggests a somewhat weak model for predicting conversion overall (Table 12).

Table 11
Omnibus Tests of Model Coefficients

	Chi-square	df	Sig.
Step	1050.038	6	.000
Block	1050.038	6	.000
Model	1050.038	6	.000

Table 12
Model Summary

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
4735.143*	.118	.236

Note: *Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

In terms of the beta estimates generated from the logistic regression model, household income (B=.089), time spent on the site (B=.004) and pages viewed (B=.004) are positively related with likelihood of the purchase (conversion). In contrast, the beta coefficient associated with household education level (-.003) suggests that this demographic predictor decreases the likelihood of purchase.

Table 13
Variables in the Equation

	B	S.E.	Wald	df	Sig.
Household Income	.089	.019	22.928	1	.000
Most Education -- Head of Household	-.003	.001	7.003	1	.008
Oldest Age -- Head of Household	-.009	.014	.406	1	.524
Household Size	-.033	.027	1.430	1	.232
Duration at a Site (minutes)	.004	.001	35.486	1	.000
Pages Viewed	.004	.001	35.460	1	.000
Constant	-3.737	.290	166.182	1	.000

Note: Model tests likelihood of purchase.

CHAPTER 5

CONCLUSIONS, DISUCSSION, LIMITATIONS AND FUTURE RESEARCH

Conclusions

Research Objective 1

The findings related to RO1, which are based on the clickstream data for each of the retailers examined suggest a range of metrics from approximately two percent for the fast fashion format to six percent for the young-adult specialty format. This finding is generally consistent with previous findings in the related literature which indicates an approximate range of conversion rates between two and five percent (Sismeiro & Bucklin, 2004; Holzwarth et al., 2006; Sohrabi et al., 2012; Chaffey, 2016). Therefore overall, the results did not suggest any anomalies among the data, in comparison to published conversion rates.

Research Objective 2

The results for RO2 which analyzed the association between each of the eight online retailers and the incidence of purchasing vs. browsing only suggest that consumers among the specialty formats (i.e., American Eagle, Gap and JCrew) are more likely to purchase apparel online. Conversely, fast fashion shoppers and the value department store shoppers were significantly less likely to indicate purchasers. This finding is consistent with RO1 and suggests that the specialty formats likely enjoy higher relative conversion compared to the other formats examined in the study. Further, fast fashion and the value department store format suggest the lowest online conversions among the formats examined.

Research Objective 3

The findings for RO3 suggest that active purchasers and pure browsers differ significantly in their online shopping behaviors. The results suggest that active purchasers visit more web pages and spend more time on each online retail format compared to the browsers. This finding is consistent across the eight online retailers in the study. On average, active purchasers visit 39 pages compared to browsers who visit eleven pages. Also, active purchasers' average duration at a site is approximately 34 minutes compared to ten minutes for browsers.

Interestingly, among the formats, fast fashion consumers who purchased products spent the most time and browsed most webpages overall (Forever 21). In contrast, active purchasers who spent least time browsing and visited the fewest webpages was the up-scale department store (Nordstrom).

Research Objective 4

The logistic regression indicated that two shopping behavior variables (i.e., duration at a site and pages viewed), household income and highest level of education in household influence the outcome of conversion to an active purchaser. Oldest age of head of household and household size did not impact the likelihood of conversion. This finding provides further evidence that age does not influence online purchasing (Brown, 2005).

Interpretation of the logistic regression model suggests that shoppers who view more webpages, and spend more time online and live in relatively higher income households are more likely to present active purchasers among apparel formats. The finding related to household education as a predictor suggests that as education increases, the likelihood of a household member's conversion to active purchaser decreases. Again, our finding that income is positively related to online apparel purchasing is consistent with the findings of an earlier study also performed in the apparel context (Brown, 2005).

Discussion

When considering the results holistically, the research suggests that online shopper conversion rates differ among different types of retail formats. Though the previous literature suggests consistent findings in terms of range of conversions suggested in this study, much of that research was performed in contexts outside of the apparel industry. The three online retailers that represent the specialty format indicated the highest overall shopper conversion rates as well as the strongest association between format and active purchase incidence. In contrast the two formats that consistently indicated the lowest conversion or active purchase incidence are the fast fashion format and the value department store format.

The higher conversion rate among specialty retailers in the study may be due to brand loyalty among their target consumers. In contrast to the other formats in the study with the exception of the fast fashion format, specialty retailers tend to own their brand and predominantly offer their store brand with only occasional offerings of outside brands. Through this relatively narrower marketing focus, it is possible that the brand relationship mitigates online purchasing risk among specialty formats' consumers when buying online. In other words, their expectations are likely based on experience and in turn give them greater confidence in purchasing apparel from these known entities. Further, these stores have relatively narrower and more clearly defined target markets with which they have established both online and offline relationships.

Conversion rates were consistently lowest among the fast fashion format and the value department store format. In terms of fast fashion, though our findings showed the lowest relative rate of active purchasing and conversion, the means associated with the small group of active purchasers among this format for online shopping behaviors indicated the greatest duration of time spent online per session and the most pages viewed per session. The focus of fast fashion retailing is the rapid introduction of new products with short life cycles. Additionally, the products are generally viewed as disposable and of poor quality. The target consumer for fast fashion seeks newness and is likely less loyal than specialty consumers. Therefore, the nature of the fast fashion environment appears to be well suited for physical retailing where consumers seek newness and bargains and can evaluate quality in the buying environment.

The study also found that all purchasers, regardless of retail format, spent longer on a retail website per visit and, subsequently viewed more pages compared to the browsers. This consistent finding suggests that active purchasers are capable and willing to spend comparatively more time online than browsers. Therefore, variables such as personal resources, web accessibility and degree of involvement may also influence conversion rate.

Additionally, recent research suggests that the duration of an online visit is positively related to the decision to purchase, but does not impact basket value. Whereas, number of pages viewed is positively related to both the decision to purchase and the basket value (Mallapragada et al., 2016). Their findings are more comprehensive than the findings of this study, however they can be considered as consistent. The same study found that the scope of a given website in terms of product variety positively impacts the duration of a browsing session, but negatively impacts the number of pages viewed. This finding is partially consistent with this study's findings, particularly considering the noticeably high average durations observed among the fast fashion purchasers.

The logistic regression model that examined household level data (i.e., by machine ID) suggested that the two behavioral variables (i.e., duration of visit, number of pages viewed) were more likely to predict the presence of a purchaser by household, followed by the two significant demographic predictors related to income and education. The demographic predictors though significant, indicated smaller effects compared to the behavioral variables. Income is a positive predictor of purchase, while highest level of education per household is a negative predictor of likelihood of purchase by household. Mentioned in the previous section, income has been recognized as a predictor for online apparel purchasing (Brown, 2005). A clear barrier to online purchasing is a lack of credit or means to complete a transaction which would be more likely among lower income households. Households with higher reported levels of education were less likely to engage in active online purchasing. This finding could be interpreted a number of ways. Households with highly educated members, could potentially have more than one computer, compared to less educated households. Also, individuals with more education are more likely to have access to a work computer which could imply that their online purchasing behaviors are misrepresented in the clickstream data. This potential measurement bias arises from the secondary data which is addressed in the Limitations Section.

Limitations

There are a number of limitations to consider when interpreting the results of this study. The limitations are presented in terms of issues related to the conceptual approach of the study as well as the methodology. The directions for future research as presented following discussion of the limitations.

Conceptual Limitations

The purpose of the study was to capture a general understanding of the conversion of browsers to purchasers within the e-commerce channel for apparel. A number of researchers have taken different approaches to identifying and understanding the online environment for apparel, textiles and other relevant products. Though access to the clickstream data clearly facilitates the analysis, the conceptual framework is limited to the variables present in this dataset. Therefore a number of potential variables which may influence conversion such as those related to individual consumers, brands and household characteristics and website usability are not measured within the current design.

Further, the practical implications of measuring conversion as a binomial, yes/no response are limited. The current research uses this approach to measuring conversion, which is consistent with other studies in this stream. This is both a conceptual and a methodological limitation. Marketers are likely more concerned with repeat purchasers, thereby focusing targeting efforts on these consumers to maximize investment. Therefore, identifying simple conversion, though consistent with peer research, is not as useful in practice as more sensitive purchasing measures.

Methodological Limitations

Though the study gains unique insight through the use of a relevant and broad secondary data source, methodological limitations associated with secondary data as well as limitations associated with clickstream data are present in the research design. The data are limited to one representative online retailer per format type, with the exception of the specialty format which includes three unique retailers that cater to different markets. The data are also accessed from a discrete time period in 2014, and arise from households who have opted into the consumer panel. Though the study benefits from the geographic breadth of the data as well as its capture of natural behaviors, generalizing beyond the scope of the sample should be considered cautiously. Further, the household level data cannot be linked to any individual consumer, thus diluting the ability to generalize the findings related to demographics beyond the household level. An additional limitation, recognized during data analysis, is the potential for households to own and use more than one computer and mobile devices that would not capture all online shopping behaviors per household during the data collection period.

Future Research

This research used an exploratory approach to examine shopper conversion from browser only to active purchasers online. The benefit and the drawback of the study are derived from the secondary dataset. The findings suggest directions for future research based on demographic measurement, website usability factors, consumer brand relationships with retailers, examination of repeat purchasers, and additional methodological approaches that draw on practices in the field of Computer Science. This research as well and other studies that examine household level demographic are not ideal for marketers who need to accurately target their efforts. Therefore individual level demographics would provide more useful data for practitioners.

Again, as noted in the literature, website usability factors likely impact an online retailers' performance (Beri & Singh, 2013; Sohrabi, Mahmoudian & Raeesi, 2012). Future study of conversion could be enriched by incorporating website usability data with clickstream data to provide insight into the consumer's perceptions along with their actions. The current research considered actions only and could not provide insight into any dimension of consumer attitudes regarding the online experience.

An additional path for future research is an exploration of brand relationships including the dimensions of brand loyalty (i.e., attitudinal and behavioral) and the likelihood on online purchasing from a given retailer. The results suggested a clear advantage among specialty formats, which may indicate that their relationship building efforts provide them with competitive advantage in online channels. This assumption should be addressed through empirical research.

Research that considers online purchasing can benefit by moving beyond simple yes/no measures for conversion. Future studies should consider consumers based on their online shopping frequency, thereby providing insight into segments that are more or less likely to purchase online.

The field of Computer Science is continuously advancing analytical techniques for secondary data (Bucklin & Sismeiro, 2009; Lee, Podlaseck, Schonberg & Hoch, 2001; ÖĞÜdÜcÜ & Özsu, 2006). Capitalizing on the processes from Computer Science researchers can combine clickstream data with additional data such as sales data, call center data, server log files, customer comment data to provide a more comprehensive understanding of today's online apparel consumer.

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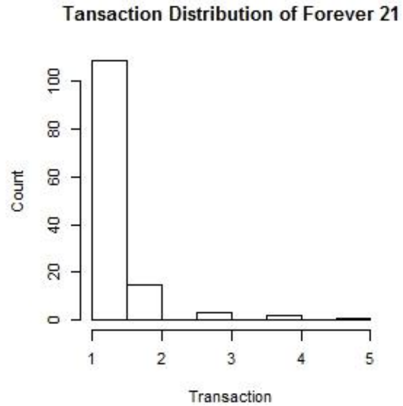
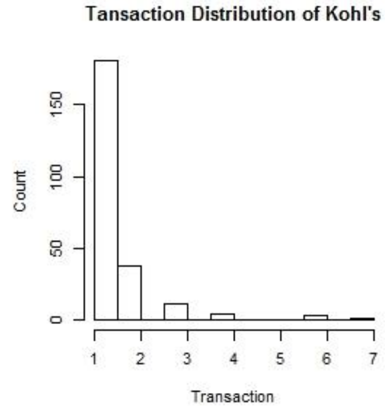
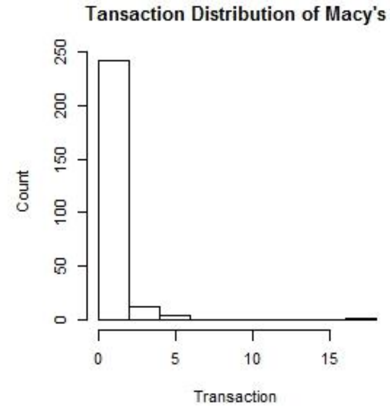
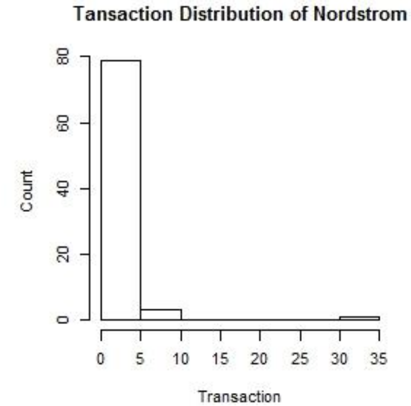
APPENDICES

Appendix A: Transaction Distribution Among Online Retail Formats







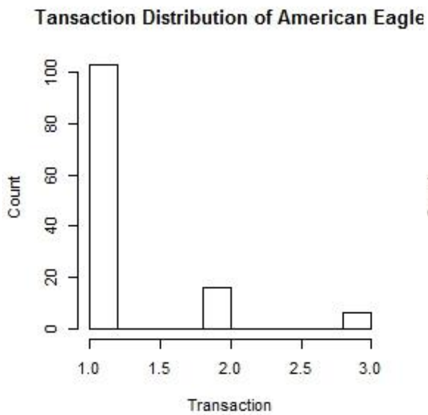


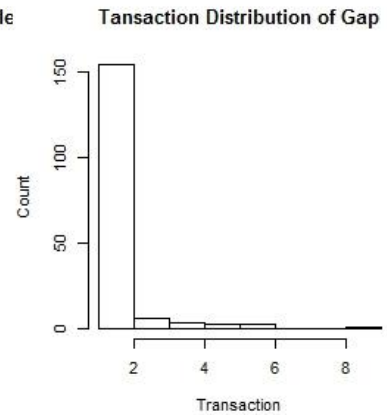
Frequencies		
level	count	prob
1	109	0.83846
2	15	0.11538
3	3	0.02308
4	2	0.01538
5	1	0.00769
total	130	1.00000
Quantile		
Min.	1	
1st qu.	1	
Median	1	
Mean	1.238	
3rd qu.	1	
Max.	5	

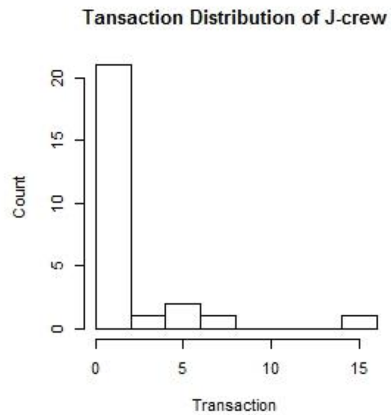
Frequencies		
level	count	prob
1	181	0.76050
2	38	0.15966
3	11	0.04622
4	4	0.01681
6	3	0.01261
7	1	0.00420
total	238	1.00000
Quantile		
Min.	1	
1st qu.	1	
Median	1	
Mean	1.391	
3rd qu.	1	
Max.	7	

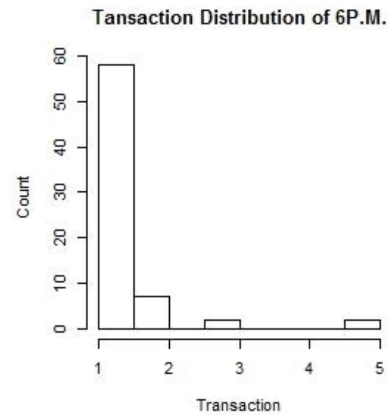
Frequencies		
level	count	prob
1	205	0.79151
2	37	0.14286
3	8	0.03089
4	4	0.01544
5	1	0.00386
6	3	0.01158
17	1	0.00386
total	259	1.00000
Quantile		
Min.	1	
1st qu.	1	
Median	1	
Mean	1.386	
3rd qu.	1	
Max.	17	

Frequencies		
level	count	prob
1	62	0.74699
2	11	0.13253
3	5	0.06024
5	1	0.01205
6	3	0.03614
31	1	0.01205
total	83	1.00000
Quantile		
Min.	1	
1st qu.	1	
Median	1	
Mean	1.843	
3rd qu.	1.5	
Max.	31	









Frequencies		
level	count	prob
1	103	0.82400
2	16	0.12800
3	6	0.04800
total	125	1.00000
Quantile		
Min.	1	
1st qu.	1	
Median	1	
Mean	1.224	
3rd qu.	1	
Max.	3	

Frequencies		
level	count	prob
1	131	0.77976
2	23	0.13690
3	6	0.03571
4	3	0.01786
5	2	0.01190
6	2	0.01190
9	1	0.00595
total	168	1.00000
Quantile		
Min.	1	
1st qu.	1	
Median	1	
Mean	1.417	
3rd qu.	1	
Max.	9	

Frequencies		
level	count	prob
1	20	0.76923
2	1	0.03846
3	1	0.03846
5	1	0.03846
6	1	0.03846
8	1	0.03846
16	1	0.03846
total	26	1.00000
Quantile		
Min.	1	
1st qu.	1	
Median	1	
Mean	2.308	
3rd qu.	1	
Max.	16	

Frequencies		
level	count	prob
1	58	0.84058
2	7	0.10145
3	2	0.02899
5	2	0.02899
total	69	1.00000
Quantile		
Min.	1	
1st qu.	1	
Median	1	
Mean	1.275	
3rd qu.	1	
Max.	5	