U.PORTO

FEP FACULDADE DE ECONOMIA
UNIVERSIDADE DO PORTO

# MEASURING INTERNET COMMERCE EXPERIENCE AND VALUING NETWORKED CUSTOMERS: A STRUCTURAL MODELING APPROACH

Ana Isabel Torres

Orientador: Professor Doutor Francisco Vitorino Martins

**TESE DE DOUTORAMENTO EM CIÊNCIAS EMPRESARIAIS**

Porto, 2012

# Biography

Ana Isabel Torres is graduated in Marketing Management from the Instituto Português de Administração de Marketing (IPAM), Porto, in 1995. She holds a Master of Science in Business Management from the Faculdade de Economia da Universidade do Porto, 2003. She has been a Ph.D. student at the Faculdade de Economia da Universidade do Porto since 2006. She participated as a scholar in doctoral seminars on managerial issues in marketing, at University of Groningen, (The Netherlands), and on research methods in marketing: structural equation models, at European Institute of Advanced Studies in Management, Brussels, (Belgium) in 2009.

She was invited Assistant of Marketing at the University of Aveiro, in 2005, invited lecturer at University Fernando Pessoa, Porto in 2008, and presently she teaches at University Portucalense, Portugal. Her previous work experience was in market research and marketing consultancy, and she worked with several industries and services. She has published a book chapter and presented several papers at international conferences on the Internet and leading technologies, since 2004.

## Acknowledgements

To my supervisor Professor Francisco Vitorino Martins I am forever grateful for his time, effort, wisdom, and thoughtfulness in supervising this thesis, as well as for his permanent encouragement and support along this journey. Without his orientation this work would not be the same.

I am grateful to the seminar participants at the EIASM and University of Gronigen, professors Hans Baumgartner from Pennsylvania State University, Adamantios Diamantopoulos from University of Vienna, for their helpful advice on SEM analysis, as well as to professors Peter Verhoef, Peter Leeflang from University of Groningen, and Stefan Wuyts from University of Tilburg, the Netherlands, for their comments and suggestions that helped to improve the research project. It was a privilege to receive the comments of researchers whose work I have followed for many years.

I want to express my gratitude to professors Filipe Coelho, Arnaldo Coelho from Faculdade de Economia da Universidade de Coimbra, Cristina Rodrigues from Universidade do Minho, Cláudia Carvalho from Universidade Portucalence, and João Marôco from ISPA, for discussing the methodology and participating in the pre-test of the research questionnaire, as well as to my colleagues of the Ph.D. course and faculty for their help in the pre-test of the online questionnaire.

Also, I want to thank to Dr. Pedro Silva from Sonae Distribution, Dr. Luis Morais from Wook, and Dr. Ana Borges from Fnac Online, for debating some methodological issues and its implications on the research online context. I am especially grateful to Dr. Ana Borges for her cooperation that helped in the data gathering process. I am also grateful to all customers of Fnac online that voluntarily helped by replying to the questionnaire.

This research was made possible by financial support from several sources. My gratitude goes to Fundação para a Ciência e Tecnologia for the Ph.D. scholarship, with financial support from POPH-QREN – Tipologia 4.1– and from Fundo Social Europeu.

Finally, I am forever grateful to my family, husband João Paulo, and my two sons João and David for their tolerance, love and support throughout this journey.

## Summary

This thesis consists of three distinct essays that share the common goal of investigating the underpinnings of customer retention and attraction in the electronic commerce environment, within a customer-value orientation. The first and the second chapters deal with the customer retention concept, while the third chapter links the value that networked customers represent for both retention and new market attraction. The three essays involve empirical research examining a sample of 308 online consumers from a leading e-retail site.

Chapter 1 measures and validates a scale index (e-SEIndex) to assess customers' online shopping experience and to predict customer retention. Its aim is to measure the e-SEI at both overall and dimension levels, for which it develops a higher-order factor structure. It was found that the strength of "the big five" first-order dimensions on the second-order factor e-SEI was quite uniform. The second-order factor e-SEI performs particularly well in predicting the set of nomological variables e-satisfaction and site recommendation intention. This chapter also provides evidence of cross-validation of the scale measures in both sub-samples of e-experience and e-novice customers.

Chapter 2 develops and tests a dual model that considers the commitment- and constraint-base mechanisms of online customer retention and the interrelationships across the two mechanisms. The aim is to develop and implement an approach for measuring the determinants and the magnitudes of switching costs – e.g. constraint – and repurchase behavioral intention – e.g. commitment–. The dual model depicts that the commitment– and constraint–based mechanisms simultaneously, yet differentially, determine customers' reactions to the online retail provider that will potentially keep customers in the long run.

Chapter 3 develops and estimates a model to assess the interplay amongst the networked customers' motivations on recommendation diffusion and co-shopping influence, assessing the role of network externalities effects. Its aim is to examine how different aspects of customers' motivations to recommend a site or product impact their intentions, behaviors and influence others to co-shopping, and how customers' network structure moderates these differences. The implications of network externalities effects for customer and e-business value, customer retention and market attraction are discussed.

# Contents

# List of Figures

# List of Tables

# Introduction

The general aim of this doctoral thesis is to investigate the underpinnings of customer retention and attraction in the electronic commerce environment, within a customer-value orientation.

E-commerce arose after the turn of new millennium, and consequently increased competition (Brynjolfsson and Smith, 2000) put the shift in focus not only on how to attract and to satisfy customers, but also on how to retain them (Reibstein, 2002), in a value-based orientation (Petersen et al., 2009; Gupta and Zeithaml, 2006). Customer retention means the effort to keep our customers being stayed as ours, prohibiting them from changing their minds (Hwang et al. 2004, p.185). Accordingly, it is reasonable to consider that customer retention in the online business context is paramount in the way customers have low switching costs due to increased competitive intensity and decreased information asymmetry between customers and firms.

In particular, researchers claim that customer retention is difficult to maintain in Internet commerce due to several technological factors, e.g. human-computer interaction instead of people-delivery context (Zeithaml et al., 2002), the use of intelligent knowledge agents such as shopbots or pricebots (Smith, 2002; Smith et al., 2000), which potentially reduce customers' switching costs and consequently customer loyalty (Balabanis et al., 2006; Burke, 2002). As such, electronic migration has made customer retention, or more specifically customer erosion, a major concern of online business. The challenge was not simply to retain these customers for future purchases, but also to capitalize on the customers who bring in the most referrals (Kumar et al., 2007).

Recently, firms and scholars have come to recognize the potential benefits of actual cooperation with networked customers for market information diffusion, new customer attraction or co-value creation (Seraj, 2012; Kozinets et al., 2008; Van Den Bulte and Wuyts, 2007). Social networks are an interesting phenomenon, which are gaining business and researchers' attention. Many factors underlie this interest including the ability of online communities or social network influence on members' perceptions of products and prices (Rezabakhsh et al., 2006), on peer purchasing decisions (Wang et al., 2012), often through frequent social interactions (Chan and Li, 2010), to rapidly disseminate information and e-Wom (Gupta and Harris, 2010), to learn consumer evaluations about new offerings, to speed up market product novelty and so forth (Ho and Dempsey, 2010), using highly influential customers for product innovation diffusion (Van den Bulte and Joshi, 2007), embody opportunities in which firms can make profitable use of social media applications (Kaplan and Haenlein, 2010). The coexistence of multiple streams in social networks applications makes research endeavors challenging in new areas. Online social networks have proliferated in recent times, and consequently networked customer value for e-commerce is a young and developing research stream.

The increasing importance of customer cultivation and retention, especially for the e-retail industries selling consumer goods, which are in the middle of intense competition and rapid customer churn, becomes an economic necessity for e-retailing site survival (Reichheld and Schefter, 2000). For managers, understanding how customers experience and value e-commerce is necessary because monitoring customers' experiences makes it possible to direct resources more efficiently and design/improve e-commerce offerings and service in ways that generate value for the customer (Parasuraman and Zinkhan, 2002). As the author's point out, this places the focus of the unit of analysis not only on "goods-value" but also on "service-value" to enhance customer value and retention process. In a similar way, relating "customer asset value" in firms' acquisitions efforts (Kumar et al., 2007) it also creates value for firms, increasing sales and generates a stable pool of loyal customers, suggesting a positive link between customer profitability and firm value (Gruca and Rego, 2005; Gupta and Lehmann, 2003; Reinartz and Kumar, 2003).

The significance of customer retention value in e-commerce and the current state of networked customer research gives this thesis dissertation its mandate to deliberate on the conceptual foundations of e-consumer behavior literature, and to investigate how customer retention and attraction in e-commerce can be enhanced, within a firm-customer-value orientation. In particular, e-consumer behavior remains a mainstream area of research, since the fast changing environment of the Internet and e-commerce introduces new issues of influence and measurement. An early indication of the consequent need for scholarly research was the fact that the Marketing Science Institute (USA) released as research priorities for 2000-2002 "e-business, e-commerce, impact of the Internet", and for 2006-2008-2010 "The connected customer", as the highest priority topics suggesting an even greater sense of urgency for generating sound research-based knowledge pertinent to Internet-based marketing. These calls for research, as well as prior work developed on the theme, in which the author of this dissertation was involved (Torres and Martins, 2012, 2011, 2009, 2007a, 2007b, 2005), were the seeds that gave rise to this research. The reader may view the articles as reflections of the research interest of the time, and a path in the maturation of the research process.

## Problem definition

There are three main issues, or problems, within current research that form the core of this dissertation. Firstly, within e-commerce research, most studies have investigated either e-service or pure content-based e-service quality site navigation (Bressolles et al., 2007; Loiacono et al., 2007), whereas relatively little attention has been given to pure physical good content-based offerings, which typically include the exchange of a tangible product. Despite the proposed shift in the unit analysis from services to product purchasing experiences (Parasuraman et al., 2005), e-commerce literature is still largely focused on service characteristics since most research is done on the perceived characteristics of websites. Consequently there is a need to investigate customer purchasing experiences at pre- and post-transaction stages in e-commerce, since this type of e-retailing is still under researched.

Secondly, much attention has been given to studying the relationship between trust, satisfaction, loyalty, and switching costs in the online service context (Shin and Kim, 2008; Chen and Hitt, 2002) rather than investigating the retailing site context. Due to the duality with which customer retention has been conceptualized (e.g. commitment and constraints) in the online service contractual setting, it is worthwhile to subject e-customer reactions to scrutiny in order to identify which mechanisms are central to retain customers in a non-contractual e-retailing context.

Finally, an issue that is related to firm-customer-value literature in general, is the role of the “networked customer” in the new world of social media. More specifically how customers’ collaboration with online firms could be a proxy for recommendation diffusion, influence peers purchasing decisions and new market attraction. The central premises of network externalities theory give some insight into this aspect: mutual value for both customers and firms is thought likely increase as a customer’s network expands. However, this relationship requires more investigation to guide further studies in e-commerce.

## Research scope and purpose

This doctoral dissertation contains three individual empirical papers, although linked by the same e-commerce setting. The three papers are the result of a long-term research process, and therefore they also reflect a maturation process regarding how online customer retention value could be investigated. The first and the second studies deal with the customer retention concept, while the third study links the value that customers represent for both retention and new market attraction.

The research purpose of the first study is to develop an “e-shopping experience index”, which implies selecting the relevant variables and testing and validating a set of e-commerce metrics, for customers’ assessment of their Internet shopping experiences from a specific retail website they currently purchase from. The proposed index serves to predict customer e-satisfaction and site recommendation intention. For online managers the e-shopping experience index will provide a standard and validated measurement instrument to monitor the impact of customers’ perceptions of online shopping experiences on e-satisfaction and recommendation intention, which is paramount to predict customer retention.

The second study investigates a dual model of customer retention: commitment-and constraint-based mechanisms that lead customers to remain with the incumbent online retailer, and examines the interplay amongst the mechanisms. One of the goals of this study is to identify the commitment and constraint factors that are effective, specifically in the context of online retail. For managers it is important to allocate firm-specific investments to the mechanism that enhances customer retention process.

The purpose of the third study is to develop and estimate a conceptual model to explain the motivations and consequences of virtual recommendation diffusion and co-shopping influence regarding online networked consumers. We aim to examine the network externalities effects by testing the moderator influence of customer network size among the set of construct relationships. Customers’ collaboration with online firms could be a proxy for recommendation diffusion and new market attraction can create mutual value for both customers and firms.

*The research delimitations*. The focal study is limited to investigating pure e-retail site offerings that embody exchange of tangible products. Although e-commerce may include trade between firms, organizations, or customers, this dissertation concentrates on business-to-consumer (b-to-c) e-commerce. The study was further limited to only one type of Internet retail site.

Since customer value is a broad concept, some choices had to be made when selecting literature relevant to customer retention in e-commerce. Literature on value of the customer to the firm, often termed as "customer lifetime value" (Gupta, 2009; Reinartz and Kumar, 2003), was excluded insofar as it explores the financial value of the customer to the firm. Furthermore, research referring to the forecasts about customer retention or defection (Fader and Hardie, 2009) was not included in the study as it requires extensive longitudinal data.

## Research methodology

In this section, the methodological choices made in this research are presented. This research adopts a methodological process which covers the three studies comprising this thesis. Specific research methods used in each study are described at the end of this section.

It was decided that an Internet retail company should be involved in the study to gather real-life data reflecting customer experiences. For this purpose interviews with online managers from most leading e-retail sites, selling different goods (e.g. Wook, Continente Online, Fnac Online) were conducted. The company that was chosen as a co-operator was suitable because it had a large and loyal customer base, a wide array of products, and showed willingness in cooperate in research. Its growth in sales demonstrates the value of its online business model and thus it provides a suitable research setting for researching real customers' online experiences. An online questionnaire was used to collect data and a banner (with a link to the survey) was posted on the company's website and its Facebook page requesting customers to participate in the online survey. Data gathering took place between June-July 2011.

From a total of 577 survey respondents, after deleting incomplete questionnaires, an effective sample of 308 customers was used.

The pretest of the initial questionnaire was performed in different ways. First, a qualitative approach was used through personal interviews with experts and e-marketing managers of a few leading retailing sites, with the aim of assessing the face validity of the constructs' measures and their fit to the specific context of a retail site. Secondly, the preliminary questionnaire including the initial set of construct measures was pre-tested with several academics of marketing. Then the script was refined according to their comments and judgments. Finally, the format and content of the online questionnaire (using the platform surveymonkey.com) were also pre-tested on doctoral students and faculties who are familiar with the issue of e-business/e-commerce, paying specific attention to question content, wording, sequence, layout, question difficulty, and instructions. On the basis of the problems identified by the respondents, minor adjustments were made to the questionnaire.

The research process began with a clear definition of the constructs involved, as a good measurement theory is a necessary condition to obtain useful and reliable results from structural relationships amongst the constructs (MacKenzie, 2003; Edwards and Bagozzi, 2000; Bollen and Lennox, 1991; Churchill, 1979).
During this initial research, the project was submitted to the Marketing Science Institute (MSI doctoral research awards). The comments and suggestions for improvement which were received from the MSI referees provided a valuable aid in clarifying the research goals. The process continued to model e-customer behavior to extract a deeper understanding of how customer retention in e-commerce could be enhanced. The choice was to study measures that impact the true value-adding elements of e-commerce experiences, instead of emphasizing technology-oriented issues. At this time, the research project was presented at a doctoral seminar (EIASM with University of Gronnigen, NL) and comments and suggestions for improvements from the faculty seminar, especially from Professors P.Verhoef, S. Wuyts and P. Leeflang were helpful to the extent that they showed how the research could be extended into new research streams. In particular, Professor Wuyts gave some insights about the relevance and the consequences of social networks for marketing practitioners.

The construct definition then provided the basis for selecting or designing individual indicator items to operationalize the constructs. Here, comments and advice from seminar participants on structural equation models, especially from Professors H. Baumgartner (Pennsylvania State University, USA), A. Diamantopoulos (University of Vienna, Austria), and T. Bijmolt (University of Gronnigen, NL) were very helpful to obtain a good measurement theory and reliable results from structural relationships among the constructs. The construct definitions and items were derived from two common approaches. First, a thorough and extensive literature review on the individual constructs was undertaken to identify scales that previously performed well. As such, in a few instances, constructs are defined and operationalized as they were in previous research studies (see e.g. e-satisfaction, recommendation intention, in Paper 1; switching costs, repurchase intentions, in Paper 2). Secondly, when scales were not available in prior research, we developed new construct measures or substantially modified an existing scale to fit the online context (i.e. online transaction, product value, and interactivity, in Paper 1; voluntary collaboration and co-shopping in Paper 3). The process ended with an extensive initial set of scale items, afterwards submitted to pretest to select the measures that suited the research goals. As such, the questionnaire design was one of the critical steps for the development of the research.

After data retrieval, the data was subjected to specific quantitative research methods. Since the aim in each paper is to analyze multiple dependence relationships, with latent variables, as well as their positioning in relation to each other, structural equation modeling, specifically using AMOS 19 (Arbuckle, 2010) was employed to analyze the data. Structural equation modeling is the technique which allows analyzing directly multiple dependence relationships with latent variables (Byrne, 2010; Hair et al., 2006). Since each paper also aims to analyze specific relationships between variables, further research methods that cover more advanced techniques in structural equation modeling are used.

Paper 1 analyses the relationship between e-shopping experience Index, as an independent variable, and e-satisfaction and site recommendation as dependent variables (i.e. multiple dependent variables), structural equation modeling was chosen as the applicable analysis method. This paper aims to develop an e-shopping experience index by developing and testing a second-order measurement model. The second-order confirmatory factor analysis is a suitable technique to represent a second-order latent factor (e-SEI) that causes multiple first-order latent factors. The study also performs a multi-group confirmatory factor analysis for cross-validation purpose of the scale measures. The most basic application of cross-validation is providing a second confirmation of measurement theory that enables us to understand if the results are the same across different characteristics of the population (i.e. e-experience).

Paper 2 uses multi-group analysis as a suitable technique for testing differences in latent construct means across sample characteristics, and to identify useful intervening moderator variables.

Paper 3, by seeking evidence of multi-group equivalence, examines whether certain paths in the causal structure are different across populations. Through the multi-group analysis, the study tests the effect of moderator variable (i.e. network size) in structural relationships in the model.

## Summary and contribution of the papers

This section briefly summarizes the three papers included in this thesis. In Table 1, the contribution of each paper is presented.

Paper 1 "Developing and validating an index for online shopping experience (e-SEI)".

The research purpose of the first paper is to develop an e-shopping experience Index (e-SEI), which implies testing and validating a set of e-commerce metrics, for customers' assessment of their Internet shopping experiences. In a two-stage study analysis we propose a hierarchical factor structure of the salient dimensions of e-SEI, as a second-order factor. The study also seeks to cross-validate the measures comparing sub-groups i.e. more e-experienced consumers with less e-experienced consumers, to test if the scale index measures are suitable for both populations of online consumers. The study also intends to examine the nomological validity of the e-SEI second-order factor, in terms of its capacity to predict e-satisfaction and site recommendation intention. The study aims to provide a validated instrumentation for e-retailers understanding and satisfying experienced e-consumers, and predict customer future behavior. Another way to use the e-SEIndex, is as a diagnostic tool, which will allow online retailers to determine e-business areas that are in need of improvement. It also represents a uniform and comparable system of measurement that allows for systematic benchmarking over time, and across e-business and retail sites.

Paper 2 “A dual mechanism of customer retention in the context of online commerce”.

The second study investigates a dual mechanism model of online customer retention: the constraint-and commitment-based mechanisms. One of the goals of this study is to identify the commitment and constraint factors that are operative specifically in the context of online retail, and test that both mechanisms are important to explain online customer retention. After the validation process of the construct measures, the study looks to analyze the relationships amongst the constructs of interest. We are interested in examining the relationships amongst personalization, loyalty rewards and repurchase intention, both representing the commitment-based mechanisms; and the relationships between personalization, search costs, and switching costs reflecting the constraint-based mechanism. The study is intended to carefully examine whether personalization is simultaneously an important measure of the effectiveness of both mechanisms. It also is intended to examine whether the constraint (e.g. switching costs) and commitment (e.g. repurchase intentions) outcomes have different antecedents. Finally, the study aims to examine the potentially differential effects on constraint and commitment, outcomes and antecedent, on different groups of customers (e.g. loyalty card holder versus no loyalty card holder).

Paper 3 “Virtual recommendation diffusion and online co-shopping influence: the role of network externalities”.

The purpose of the third study is to develop and estimate a conceptual model to explain the motivations and consequences of virtual recommendation diffusion and co-shopping influence regarding online networked consumers. For this purpose, we describe how the customers’ intrinsic and extrinsic motivations, i.e. voluntary collaboration and incentive seeking, respectively precede and contribute to his or her intentions to recommend the site/product. We also describe how recommendation intentions lead to positive consequences, such as behavior, and ultimately lead to co-shopping influence. Moreover, we consider the different interplay among co-shopping influence and customers’ intrinsic and extrinsic motivations. We also examine the moderating effect of customers' network size among the set of construct relationships to investigate network externalities effects.

Table 1 Contribution of the papers

| **Paper** | **Approach to value-retention** | **Theoretical Contribution** | **Managerial Implications** |
|---|---|---|---|
| Paper 1<br><br>Developing and validating an index for online shopping experience (e-SEI) | Studies e-SEI dimensions (webstore, online transaction, product value, customer support, delivery and returns and interactivity) which can be seen as perceptions of customer value around the exchanges of physical goods in Internet and antecedents of customer retention. | e-SEI is suitable to predict future customer behavior, e-satisfaction and site recommendation of both e-experienced and e-novice customers.<br>e-SEI big five dimensions reflects customers perceived value of e-commerce. | Need to monitor the impact of customers' perceptions of online shopping experiences on e-satisfaction and recommendation intention is paramount to predict customer retention behavior or to warn potential defection.<br>e-SEIndex provides a standard measurement as a diagnostic tool, that allows for systematic benchmark data regarding current levels of e-tail performance and across competitors, as well to identify e-tail areas in need for improvement. |
| Paper 2<br><br>A dual mechanism of customer retention in the context of online commerce | Proposes that personalization and loyalty rewards should be treated as perceived benefits for customer value creation and investigates how these in addition to switching costs (as sacrifices/ constraints to switch provider) impact customer retention process. | Proposes a dual mechanism of customer retention process in e-retailing. The findings suggest that customers do not remain with the online provider in a constraint manner, and only personalization and loyalty rewards as perceived benefits for customer value creation explain the retention process. | Online firm-specific investments: in sophisticated personalization tools (e.g. providing customers personal accounts in website for co-creation, co-design, intelligent agents tracking customer´s needs), and rewarding customers for frequent purchases will affect both, short-term performance by an immediate increase of sales, and long-term customer retention by offering ongoing incentives for repeated purchases. |
| Paper 3<br><br>Virtual recommendation and co-shopping influence: the role of network externalities | Investigate the customer's motivations and outcomes of site recommendation and the effect of customer's network for mutual value creation. | The network externalities effects, for both customers and firms: customer' recommendation value increases as network size expands, under customer incentives and co-shopping influence. | Managing and creating alliances with networked customers for cooperation, crowdsourcing, influence of peers' buying decisions, building a vibrant and exciting online brand community for social sales, will be determinant of co-value creation, increased market share and profitability. These issues lie at the heart of e-commerce transformation. |

## Structure of the dissertation

In this section, the structure of this dissertation is presented to give the reader a preview of what is to come. The introduction presents the background of this dissertation, explains the motivation and the research goals for taking up this research. It describes the research process and methodological choices applied in this research.

The first chapter presents study 1 “Developing and validating an index for online shopping experience (e-SEI)”. The second chapter presents study 2 “A dual mechanism of customer retention in the context of online commerce”. The third chapter presents study 3 “Virtual recommendation diffusion and online co-shopping influence: the role of network externalities”. The last chapter “Conclusion” summarizes and presents the findings of each paper. In addition, the contribution to the research community as a whole is presented, and managerial implications are discussed. The summary concludes with the limitations of this research and directions for future research as well are provided.

# Chapter 1

## Developing and validating an index for online shopping experience (e-SEI)

This study proposes an index scale for the online shopping experience which is tested empirically using a second order latent variable model. Since online shopping is an experience which is changing more rapidly due to Internet technology and due to more sophisticated and experienced customers, a new index for measuring customer online shopping experience index (e-SEI) is required. Thus, this paper is a first step towards proposing a higher-order factor structure to capture the dimensions which are important to online customers and propose an index for the e-retail context. Structural equation analysis, using the confirmatory factor technique and cross-validation using e-experienced as well as e-novice customer sub-samples support the validity of the measures. The e-SEI model was tested in the context of one of the largest online retailers where it was found to significantly predict customer satisfaction and intention to recommend the site to others. In this study we found that the predictive power of e-SEI on e-satisfaction and recommendation intention is considerably above the average of similar studies for behavioral sciences. The model performs particularly well in predicting the nomological constructs. This model allows the online retailer to understand the specific factors that significantly influence customers' e-satisfaction and site recommendation. The implications of e-SEI dimensions for practitioners and suggestions for future research are discussed.

***Keywords***: e-shopping experience index; online stores; customer satisfaction; site recommendation intention; scale validation.

## 1.1 Introduction

Internet shopping may gradually replace conventional retailing channels, mail-or phone-order stores, catalogs and sales forces. Consequently, competition among Internet shopping sites has been increasing, and the web store ability to satisfy and retain customers will be critical for the survival and success of online firms. Broadly speaking, electronic commerce (e-commerce) refers to goods and services purchased on the Internet, and includes digital goods and services delivered directly over the Internet. The importance of customer perceived value in e-commerce stems from the fact that electronic markets have more benefits to consumers than conventional markets due to the increased product offering, convenience, customization and the ability of consumers to discover and compare prices (Brynjolfsson and Smith, 2000). As Varian (2000) has said "E-commerce will undoubtedly change the way business is done" (pg. 137). In coming years electronic markets may dramatically change the way products are bought and sold. The shifting from traditional to electronic commerce retention practices such as cybersecurity, trust, on-time delivery, reasonable prices, product performance, and follow-up service and support seem to remain very important to customer loyalty in e-commerce (Smith, 2002).

Scholars have proposed several conceptual and empirical electronic service quality (e-SQ) models to capture the factors that affect customer perceptions of online service quality dimensions (Loiacono et al., 2007; Parasuraman et al., 2005; Zeithaml et al., 2002). A review of the extant literature suggests that prior e-SQ scales focus mainly on website-centric metrics and pure e-service settings. Whether most of e-scale dimensions and specific outcomes and findings on it can be generalized to online shopping settings needs to be re-examined (Zeithaml et al., 2002). Firstly, online shopping experience differs from e-service: each online transaction involves a number of third-parties such as credit card clearance firms and reverse logistics for delivery and returns. Secondly, the spatial and temporal separation between customers, e-retailers and suppliers that is imposed by electronic markets (e.g. there is no immediate gratification providing feedback from online purchases) creates different challenges for e-business in providing online customer support and assistance. The lack of personal contact with salespeople, constraints in physical access to product inspection, and the time lag between the purchase and delivery of products make the transaction and post-transaction more critical stages of the online shopping experience. Finally, Internet technology changes concerning Web 2.0, where interactivity is a relevant feature, create different challenges for e-business. Thus, developing and validating more accurate and robust measures that describe customers' evaluations of transaction and post-transaction online shopping experiences is imperative. The validity of robust (post) transaction measures (i.e. of quantitative studies) depends on respondent's online purchase experience. However, finding and targeting experienced online customers may be difficult. Given this difficulty, most prior studies use samples with students which provide biased inferences and limitations in the generalization of results. Validity of measurement instruments has thus become a challenge. Furthermore, as e-commerce becomes commonplace, e-retailers face the challenge of monitoring customers' online shopping experiences, satisfying and keeping existing customers.

In this study we synthesize previous research to obtain six major first-order dimensions that affect the overall online purchase experience: webstore functionality, transaction effectiveness, product value, customer support, delivery and returns, and interactivity; and two consequences of consumers' experience level: customer satisfaction and recommendation intention.

The rationale for a higher-order factor structure is as follows. Previous studies in which e-SQ scales have been developed found high intercorrelations among items across factors (Loiacono et al., 2007; Parasuraman et al., 2005). These instances are strongly suggestive of the presence of a higher-order factor model. The retail literature suggests that consumers form evaluations of retail quality both at the attribute and at the integrated level (Dabholkar et al., 1996). Based on these various sources, we propose that customers think of online shopping experience at a dimension level and an overall level, which makes it suitable for a higher-order factor structure to be investigated.

Since online shopping involves transaction and post-transaction evaluations, a new index for measuring electronic shopping experiences (e-SEI) of existing and experienced online customers is required. Hence, by reviewing existing e-scales this study attempts to propose an e-SEI for online retail environments which can serve as a predictor of customer e-satisfaction and intention to recommend the site to other people. Indeed, business-to-consumer (B-to-C) marketers have long capitalized on references from satisfied customers to achieve additional sales. In online shopping this is even more straightforward, as customers' referrals can be spread faster over the Internet, rather than with face-to-face media. So the e-SEI could also serve as a predictor of e-business profitability and future market value, for the potential to freely attract prospects (Kumar et al., 2009; Bolton et al., 2004; Fornell et al., 1996). Historically, the American customer satisfaction index (Fornell et al., 1996) has been applied in many countries and industries and being related to firm profitability and success. Moreover, the relevance of the customer retention value chain being generated for firms has been investigated in marketing literature and much research has documented the relationship between customer retention and firms' long term financial performance (Anderson and Mansi, 2009; Bolton, 2004; Reichheld and Sasser, 1990), and between customer profitability and firm value (Gruca and Rego, 2005; Gupta and Lehmann, 2003; Reinartz and Kumar, 2003).

Recent studies have also reported that customer behavior does not remain stable because the experience acquired from past e-purchases which means that customer's perceptions of e-commerce change with purchasing experience (Hernández et al., 2010). Therefore, this research also seeks to cross-validate the measures comparing more e-experienced customers with less e-experienced customers, to test if the e-SEI measures are suitable to assess online shopping experiences of both groups of customers.

This research presents important theoretical and practical contributions. On the theoretical side, we propose and empirically test an e-SEI model: a multidimensional higher-order measurement model to provide an index for the online retail context, using a sample of existing and experienced customers from a leading e-retail site. This study provides a set of validated measures for researchers to understand and satisfy experienced e-consumers. On the practical side, this model could serve at a dimension level as an online diagnostic tool that will allow online retailers to identify e-business areas which perform poorly and are in need of improvement. Another way to use the instrument as a useful diagnostic tool is by computing the overall index scores for e-retail, acting as a predictive tool of customer satisfaction and site recommendation, because online firms need a valid instrument to enhance customer retention and attraction. At the same time this index represents a uniform and comparable system of measurement that allows for systematic benchmarking over time and across e-business and retail sites. For managers, an index assessing systematic and over time customer reactions to online shopping experiences provides instrumental value to e-business, not only in identifying e-business areas that are weak and in need of improvement, but also to identify and understand (dis)satisfied customers, warning of potential defection. E-business firms report difficulty in creating and executing strategic systems responsive enough to changing circumstances to analyze customer defections (Chen and Hitt, 2002; Reichheld and Schefter, 2000). For example, customers who close their accounts and shift e-business to a competitor are easy to identify. Conversely, predicting churn or defection in a highly competitive and non-contractual setting such as online shopping is difficult. Therefore, the increasing importance of customer cultivation and retention, especially for the e-retail industries selling consumer goods, which are in the middle of intense competition and rapid customer churn, becomes an economic necessity for e-retailing site survival.

The organization of this paper is as follows. In section 1.2, we review the relevant literature and we describe the proposed e-SEI model structure and hypotheses. Then, in section 1.3, the description of the way the sample was derived and the definitions of measures are given. In section 1.4, the model validity and applicability are evaluated and statistical results analyzed. Finally, we conclude with a discussion and provide directions for further research.

## 1.2 Theoretical structure and hypotheses

The experience of successful e-business shows that customer satisfaction with the quality of service determines the success or failure of an e-commerce firm (Reichheld and Schefter, 2000). While price was initially considered to be the key driver for the success of e-businesses in attracting customers, it is not a determinant factor of customer retention (Reibstein, 2002). Researchers found that customers are willing to pay premium prices for books from online retailers that they have dealt with previously (Brynjolfsson and Smith, 2000). One possible explanation is that satisfactory customer e-purchase experiences, other than price, influence customers’ buying decisions.

Customers are willing to repurchase from e-retailers they believe to assure ongoing satisfaction levels (Anderson and Srinivasan, 2003; Srinivasan et al., 2002). This is even more important in the case of e-commerce, because customers do not deal directly with the company's staff and cannot judge whether a retailer is trustworthy (Gefen et al., 2008; Pavlou and Gefen, 2004). As e-commerce becomes more commonplace, more experienced customers are valuing other dimensions. For example, more experienced and existing customers are probably being more demanding on judging post-transaction evaluations. While the number of firms selling products online is rapidly increasing, many consumers have been disappointed with their online shopping experiences, and researchers pointed out that poor service quality is a key area of concern, particularly with regard to post-transaction services (Otim and Grover, 2006; Parasuraman et al., 2005). For example, the growth of consumers' reviews on the Internet (such as Gomez.com) frequently concerns complaints about: refund and billing, return and exchange policies, defective products and poor customer service. More problematic is the increase of consumer complaints on the Internet (e.g. site reviews, virtual networks) potentially disseminating negative WOM from dissatisfied customers which, in turn, can affect a firm's reputation and customers' repurchase intentions (Nitzan and Libai, 2011; Hsu, 2008). Actually, the most critical problems of retailing websites are related to inadequate customer service: for example, customers cannot find products, are not able to complete transactions, encounter a bad link, discover no phone number is included in the website, and products are not delivered on time, or at all; e.mails were not answered, and desired information could not be found, which become critical to the viability of Web channels. If electronic channels are a more convenient way of buying, they must be perceived by consumers as effective and efficient (Wolfinbarger and Gilly, 2003; Szymanski and Hise, 2000). While low price and web presence were initially thought to be the drivers of success of electronic commerce, customer service and recovery issues soon become pivotal (Reibstein, 2002). If a firm does not provide good service, customers will not come back. This suggests that to promote successful online shopping experiences a company should emphasize correctly processing the order and invoice, responding to customer queries and complaints promptly, accurately delivering goods to the customer's address, properly dealing with returned goods and maintaining its website well (Hsu, 2008). These elements should form the bedrock of a successful e-business.

For this reason, in the past decade, academic research has been focused on e-service quality (e-SQ), and has made progress, particularly in identifying its underlying dimensions and determining how it can be conceptualized and measured (Hsu, 2008; Loiacono et al., 2007; Parasuraman et al., 2005; Wolfinbarger and Gilly, 2003). Several new scales, therefore, have been developed to address this (e.g. E-S-QUAL; WebQual; PirQual; SiteQual; e.TailQ; .comQ). Zeithalm and colleagues' (2002) work based on an extant literature review on e-SQ suggests that its dimensions should include (1) information availability and content, (2) ease of use or usability, (3) privacy/security, (4) graphic style, and (5) fulfillment. These dimensions form the core of e-SQ, and although several researchers may use different construct taxonomies, in essence, they are quite similar to those proposed by Zeithalm et al. (2002). A review of these e-SQ scales is summarized in Appendix A.

Successful online shopping experiences are believed to affect customer satisfaction and the intention to recommend a website to other people. Customer satisfaction and loyalty concepts are well recognized in marketing literature as outcomes of customer value (Yang and Peterson, 2004; Parasuraman and Grewal, 2000). Previous research has often treated customer loyalty as a measure of customer retention (Tsai et al., 2006; Hwang et al., 2004). Customer retention means the effort to keep our customers being stayed as ours, prohibiting them from changing their minds (Hwang et al. 2004, p.185). Accordingly, it is reasonable to consider a circular logic when we consider the four concepts: customer value-satisfaction-loyalty-retention. According to Reichheld and Schefter (2000), acquiring customers on the Internet is extremely expensive. As a result, it is crucial for online companies to create not only a satisfied and loyal customer base, but also a customer referral chain for potential market attraction and additional sales that it may create (Kumar et al., 2007). Moreover, the Internet provides a structural route for customer recommendation diffusion and e-retailers are extensively including this tool on their websites. However, few e-retailers seem to succeed in creating truly satisfied customers willing to recommend the site, and little is known about the mechanism involved in generating it.

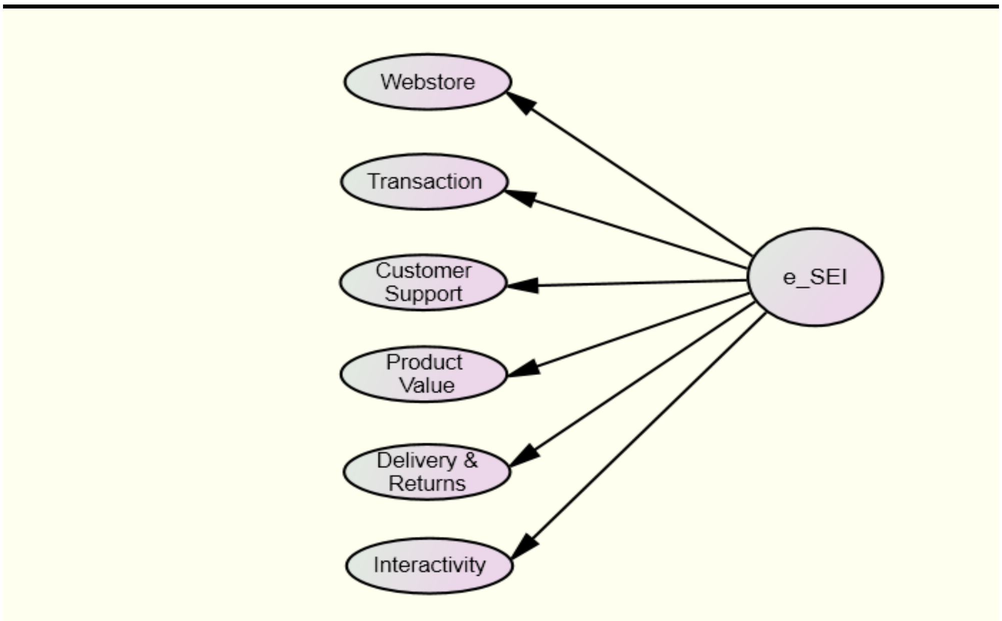
This study proposes that online shopping experience evaluations are an important predictor of customer satisfaction and recommendation intention. Given that, the proposed e-SEI model in this study is defined broadly to encompass all phases of customer interaction with a retail website, including all cues and encounters that occurred before, during and after the online transaction. Therefore, customers' overall evaluations of online shopping experiences should predict overall customer satisfaction and site recommendation intention. Following we will introduce the constructs employed in the e-SEI model.

### 1.2.1 e-SEI dimensions

The proposed online shopping experience (e-SEI) model focuses on six key first-order dimensions of the online shopping consumers' experience (webstore functionality, transaction effectiveness, product value, customer support, delivery and returns, and interactivity) and the second-order factor representing the relative importance of each dimension on the overall evaluation of e-SEI. Theoretically, many constructs in behavioral sciences can be represented at different levels of abstraction. In this case, e-SEI can be represented by numerous related first-order factors. Each one is measured using multiple item scales tapping a specific e-SEI dimension. As a result, the first-order factors can be viewed as indicators of a more abstract higher-order factor that reflects broader, more abstract online shopping experiences. For example, customer's satisfactory online shopping experiences could reflect more tangible factors such as customer support or product delivery and returns. In the end, e-retailers key decisions may be made on the more abstract e-SEI factor, and these decisions are better than relying only on the individual more specific factors. Thus, the individual factors are first-order factors and e-SEI could be thought as a second order-factor. Figure 1.1 shows the proposed e-SEI second-order model.

To identify the first-order e-SEI dimensions the current study builds on the research already conducted on the topic, and particularly on Hsu (2008), Parasuraman et al. (2005), and Wolfinbarger and Gilly (2003). Both scale measures developed in these studies demonstrate good psychometric properties, based on findings from a variety of reliability and validity tests, providing a validated baseline measure as a starting point of future measurement instruments. However, studying e-SEI requires scale development that extends beyond merely adapting other e-service quality scales. In this study we will focus on somewhat different issues, as we may need to develop one or more supplemental measures for e-SEI factor.

Figure 1.1 Proposed higher-order structure for the e-shopping experience index




Note: For the sake of brevity each factor's measurement indicators, error terms and disturbance terms are not included in the figure. Full measurement items that were used in the questionnaire are presented in Appendix B.

We did an extensive literature review on e-service quality validated measures (see Appendix A) and on Net-enable e-commerce metrics, and we suggest that these dimensions should form the core of e-SEI: (1) webstore functionality, (2) transaction effectiveness, (3) product value, (4) customer support, (5) delivery and returns, and (6) interactivity are the major dimensions that affect the online shopping experience. Understanding the relative importance of each of them is paramount for e-retailers in order to create value, satisfy and retain customers. This research explores customer value as embedded in the online purchasing experiences. Customers evaluate online shopping experiences in terms of the webstore functionality, transaction effectiveness, product value, customer support, interactivity, and delivery and returns. All the dimensions reflect the degree to which an individual customer feels that the online provider fulfills and satisfies his/her personal needs. The customers' assessments of retail site offerings and service provided can be viewed as customer perceived benefits or sacrifices (Zeithaml, 1988). An introduction to the six e-SEI dimensions follows.

**Webstore functionality**

An Internet purchase involves, in the first place, interaction with the website. Website design includes all elements of the consumer's experience at the website (except for customer service), including navigation, layout and graphic style, information search, and information content; It also involves ease of use, intuitiveness, user interface, and search facilities that minimize customer effort in online shopping (Hsu, 2008; Wolfinbarger and Gilly, 2003). Likewise, Zeithaml et al., (2002) emphasized the importance of search functions, download speed and navigation which also improve website usability.

Some authors highlight the importance of website informational content (Hausman and Siekpe, 2009): information is an important valuable resource for online consumers, because they can obtain it directly from a website rather than having to go through salespeople in an offline store; the value of information includes its relevance, timeliness (e.g., a continuous update), and accuracy (e.g., a detailed product description, product reviews and transparent price information).

Research also suggests that many customers abandon their shopping cards on the Internet because they are frustrated with the design of the website. Particularly, website design is especially important in judging quality for experiential users, i.e. who probably spend more time at a site than do goal-oriented users (Novak et al., 2000); and for purchasers of books, Cd's and videos (Iwarrden et al., 2004). Furthermore, website design is the most important factor in predicting quality for customers who are frequent purchasers at a particular website (Wolfinbarger and Gilly, 2003).

This research summarizes prior literature and propose the following key features of website design: (1) the website has logical layout and graphic style (Hsu, 2008; Wolfinbarger and Gilly, 2003); (2) the website has adequate search facilities (Hsu, 2008; Zeithaml et al., 2002) and, (3) the website provides in-depth and up-to-date information (Hsu, 2008).

**Transaction effectiveness**

Transaction effectiveness refers to the procedures and services of online shopping order that reduce consumer time, effort and risk in the transaction process. Transaction service features, such as shopping carts, that make placing an order easy and quick, and billing and payment options, can all reduce the time and effort consumers expend and consequently increase online purchase effectiveness. Taking a customer value orientation, transaction effectiveness indirectly measures customers' value perceptions as they are related to convenience value of e-commerce. For instance, online transaction can be perceived as a benefit if it is evaluated as high and a sacrifice if it is evaluated as low.

Another issue of major importance to online transactions is the role of security and privacy related to the security of credit card payments and the privacy of shared information to reduce the perceived risk of Internet shopping. Security refers to the confidentiality, integrity, authentication, and non repudiation of the e-transaction and online data (Turban et al., 2006). To ensure transaction security and to combat the lack of trust in the context of e-commerce, e-retailers frequently provide stated and authenticated policies of security (e.g., encryption and the use of seals of approval), and websites offer digital certificates to prove their identity and verify consumer identities (Chen et al., 2010). Researchers have regarded privacy as the ability of an individual to control, manage, and selectively reveal personal information (Eastlick et al., 2006). The protection of privacy is imperative for online transactions. To eliminate consumer privacy concerns, many online shopping websites have developed privacy policies to assure confidentiality of customers information (Hsu, 2008). Some authors suggested that a privacy statement can enhance the perceived trustworthiness of e-vendors (Schaupp and Belanger, 2005; Belanger et al., 2002) and, consequently, the protection of privacy signifies transaction integrity and thus influences transaction decisions (Chen et al., 2010). Likewise, Wolfinbarger and Gilly (2003) found that not having bad experiences, such as stolen credit card information, customer ratings of privacy/security improve significantly across interactions with a specific e-tail website.

Additionally, online retailers provide a variety of payment methods (for example, credit card, wire transfer, and online money transfer) to reduce customer constraints and facilitate online transactions. Schaupp and Belanger (2005) also pointed out that online shopping websites should not only minimize delivery time, but also to provide parcel tracking mechanisms of the order process to reduce consumer anxiety.

This research extends the scope of online transaction to incorporate five major features: (1) It is quick and easy to complete the online transaction (Wolfinbarger and Gilly, 2003), (2) the online store assures confidentiality of customer information (Hsu, 2008), (3) the online transaction is secure (Wolfinbarger and Gilly, 2003), (4) the online store has convenient payment methods, and (5) availability to track the order-delivery progress at the online store. Previous studies have not evaluated the latter two features but this research considers them to be important in reflecting the scope of online transaction effectiveness.

**Product value**

Zeithaml (1988) defines perceived value as the consumer's overall assessment of the utility of a product, based on perceptions of what is received and what is given. It is the trade-off between a received benefit (i.e., the benefits that a buyer derives from a seller's offering) and a cost or sacrifice (i.e., the buyer's monetary and non-monetary costs in acquiring the offering). The importance of customer perceived value in e-commerce stems from the fact that it is easy to compare product features and prices online (Anderson and Srinivasan, 2003). Product value directly measures customers' value perceptions, since the economic value and price information are included (Mathwick et al., 2001), which reflects the value compared to alternative competition choice. Moreover, adding product value to the e-SEI model increases the comparability of results across online business and sectors, because price information is added into the model (Anderson and Fornell, 2000). Past research has also shown that merchandising, quality of products, and product customization are major determinants of the customer online purchase decision. Arguably evaluation of the impact of product customization on online purchase intention is difficult. Product customization in the context of e-commerce may increase the possibility of perceived differences between consumer expectation about the purchased product and the actual, delivered product, and thus may increase consumer perceived uncertainty within an online transaction (Chen et al., 2010). Moreover, only a few brands allow customers' to fully customize and co-create products in their websites (e.g. "Nike ID.com"; "Dell.com" just to name two examples) which limits the empirical investigation. Hence, this research evaluates product value only in terms of matched product offer, merchandising and price. Merchandising refers to features of product offerings *per se*, for the sake of online shopping convenience (Szymanski and Hise, 2000). Schaupp and Belanger (2005) suggested that e-commerce should provide a great breadth and depth of product offer to impress the consumer. Product value also denotes that a match between the requested and the delivered product is a key element in online purchase decisions, and reasonable price and high quality are equally important for product value (Chen et al., 2010; Mathwick et al., 2001).

This research synthesizes the extant literature and evaluates the following features of product value: (1) an online store offers extensive product assortment, variety and exclusive products (Chen et al., 2010; Schaupp and Belanger, 2005; Szymanski and Hise, 2000); (2) product features should match customers' expectations (Chen et al., 2010); and, (3) competitive product pricing and, (4) product prices should provide good economic value (Chen et al., 2010; Mathwick et al., 2001).

**Customer support**

Customer service has been recognized as an important factor in the success or failure of an e-commerce enterprise because customers still suffer from low levels of service quality (Hsu, 2008; Parasuraman et al., 2005; Reichheld and Schefter, 2000). Unquestionably, customer service is a core element of a typical online purchase experience. One possible explanation is that customer satisfaction with service quality other than price influence online customers' buying decisions (Brynjolfsson and Smith, 2000). Given the lack of human contact with salespeople, in Internet shopping, a customer's experience with an online retailer is largely built via website interaction.

Research is converging towards post-purchase services, consisting of support of order tracking and customer support, which positively influence customer satisfaction and loyalty intentions (Pan et al., 2002; Reibstein, 2002). Wolfinbarger and Gilly (2003) found that customer service related to a company's willingness and readiness to respond to a customer's inquiries and needs quickly, and was one of the most important factors of e-retail quality having a great potential to increase satisfaction and e-loyalty intentions. Despite this, recovery service (e.g. handling complaints or problems) comes into play only when a customer problem occurs after the online transaction was made. However, online consumers sometimes need pre-purchase service (e.g. answer customer's queries), to help them with some difficulties with online purchases (Parasuraman et al., 2005). The authors argue that customer service and recovery, provided online, have a greater potential to increase satisfaction and loyalty intentions towards an online retailer. Furthermore, Belanger et al., (2002) suggested that the ability to handle online transactions and conduct e-commerce professionally may enhance consumer belief in an e-retailer.

This research argues that advances in information technology (e.g. website media richness, anthropomorphic systems to "humanize" the online environment) have enabled e-commerce websites to provide instantaneous explanations and online assistance to customers, which can improve satisfactory online shopping experiences. Therefore, this research proposes the inclusion of customer support in the e-SEI model which is likely to enhance customer e-satisfaction and the retention process. Taken together these arguments, this research evaluates the following features of customer support:

(1) The website provides online assistance to solve customer questions or needs (Parasuraman et al., 2005), (2) inquiries are answered promptly (Wolfinbarger and Gilly, 2003), (3) the site has a customer service representative online, and (4) it offers the ability to speak to a live person if there is a problem.

**Product delivery and returns**

Delivery refers to the total time spent in shipping and handling a product. An online company must be aware that e-business involves not only the front-end process (e.g. the design of the website) but also the back-end process (e.g. order fulfillment, delivery and returns) which is crucial to keep online customers and maintain them for future purchases. Delivery and returns indirectly measure customers' value perceptions related to convenience value of e-commerce when compared to the traditional retail. For instance, delivery and returns can be perceived as a benefit if it is evaluated as high and a sacrifice if it is evaluated as low, which reflects the degree to which an individual customer feels that the online provider fulfills and satisfies his/her personal needs. Accordingly, Hsu (2008) found that fulfillment with online transaction involves such back-end processes as on-time delivery, correctness of order fulfillment and billing accuracy, which were amongst the most important attributes of online companies for achieving the highest level of customer satisfaction. Likewise, Schaupp and Belanger (2005) pointed out that reliable and timely product delivery is essential to consumer satisfaction. The customer receives the right product they thought they ordered from the website; delivered by the time promised by the company, representing "fulfillment/reliability" in the e-tail quality model (Wolfinbarger and Gilly, 2003) was found to be the second strongest factor predicting loyalty intentions (e.g. telling others about the website and using the website again). Because shipping fees sometimes increases online transaction costs, researchers found that price information and transparency of the billing mechanism are among the most important factors of online transaction-related services that impact customer retention (Otim and Grover, 2006).

By observing the increasing number and complexity of product returns policies with the advent of online channels, forcing companies to outsource reverse service logistics to third parties, simplifying the return process for consumers (Bonifield et al., 2010; Petersen and Kumar, 2009; Guide et al., 2006), this research proposes to include product return policy. Accordingly, Bonifield et al. (2010) point out product return policies as a major issue of online shopping, as it can reduce consumers' perceived product uncertainty, which can affect the decision to purchase now or even future repurchase behavior. Moreover, there is evidence that product returns provide customers with an option value that is measurable (Anderson et al., 2009; Yu and Wang, 2008). More importantly, in online shopping a customer who returns a product satisfactorily will potentially be able to remove some additional uncertainty with online purchase by lowering the perceived risk of future purchases, knowing that products that do not fit can be returned without excess cost. For example, a free-based product return (meaning that the customer pays no cost to the store to return the product), relatively easy and hassle free, is frequently used by online firms to reduce customer perceived risk and uncertainty with ordered products (Petersen and Kumar, 2009). Therefore, this research proposes inclusion of delivery and returns in the e-SEI model, which is likely to enhance satisfactory online shopping. The former can increase consumers' perceived convenience value of online shopping while the latter reduces consumers' perceived product uncertainty.

According to the discussed issues this research evaluates the following major features of product delivery and returns: (1) correctness of order-delivery, (2) on-time delivery (Hsu, 2008), (3) online store offers meaningful guarantee and convenient options to return a product, and (4) the shipping and handling charges are reasonable (Parasuraman et al., 2005).

**Interactivity**

Previous studies on e-service quality have not evaluated interactivity features but this research considers them to be important in reflecting the scope of the online shopping experience. Interactivity represents an indicator of the efficiency, usability, and organization of the website interface to provide interactive real-time online communication, dedicated to customers' access to personal information and sharing consumption experiences. Research has suggested that well-developed, personalized content and interactive functions of websites tend to increase consumer satisfaction and consequently increase the return rate (Zviran et al., 2006; Palmer, 2002; Zhu and Kraemer, 2002). An interactive capability enabling customers to configure product features via the website, allowing products to be "built-to-order" and gain access to personalized accounts or private information is an important indicator of e-commerce capability to customers value creation (Zhu and Kraemer, 2002). In fact, researchers pointed out that the multimedia richness and interactivity of the web environment have the potential to engage users in ways not exhibited by other media (Agarwal and Venkatesh, 2002). Likewise, Hausman and Siekpe (2009) emphasized the importance of informational content provided by interactive features. For example, including product reviews of customer ratings on the website can decrease customer uncertainty and the risk of biased product information for potential customers displayed by e-vendors.

More recently, research has pointed to the role of virtual communities of transactions where most members tend to share and acquire information that is important in terms of achieving mutual understanding and moderating uncertainties or opportunism (Wu et al., 2010). This phenomenon appears particularly salient in virtual communities of consumption, that is, groups of consumers who continuously interact online because of their shared enthusiasm for/and knowledge about specific consumption activities which encourage resource sharing (Chan and Li, 2010). In observing the consumer's desire for information sharing, as a major issue of online shopping, this research proposes including online forums and communities as important and valuable interactive tools of online shopping websites. Previous studies have not evaluated these features in the context of B2C e-commerce, but this research considers them to be important in reflecting the scope of the interactivity dimension.

Taken together these arguments this research evaluates four key features of interactivity: (1) the interaction level of the website enables customers to configure product features to fit their needs, (2) the website enables customers to access personal accounts or private messages, (3) the site provides adequate interactive mechanisms, and (4) the website enables customers-to-customers to interact, and posting/sharing information in online forums or communities.

### 1.2.2 e-SEI outcomes

Prior studies suggest positive performances of critical dimensions of online shopping experience, previously described which are likely to foster customer satisfaction and other valuable behavioral outcomes, such as customer repeated buying, recommendation and referral intentions (Parasuraman et al., 2005; Srinivasan et al., 2002). When overall customer's shopping experiences are positive, this offers the e-retailer a chance to build the relationship with the customer and reap positive behavioral outcomes. This research includes customer satisfaction and site recommendation intention as behavioral outcomes of e-SEI. We discuss on each below.

Customer satisfaction is often defined, as a positive affective overall attitude regarding a product or service after its acquisition and use. Theoretically, overall satisfaction it can be considered an affective-based construct and is generally defined as a positive affective state resulting from a global evaluation of performance based on past purchasing and consumption experience (Szymanski and Henard, 2001; Oliver, 1999; Fornell et al., 1996). Overall satisfaction is often been used to measure e-business performance and can be judged broadly to encompass all phases of a customer´s interactions with a web site, including all cues and encounters that occur before, during, and after the transactions. Thus, customers perceive satisfaction with the online shopping experience as an overall process and outcome. Generally accepted that satisfaction is post-purchase response, cumulative and can vary over time (Szymanski and Henard, 2001) is a better predictor of customer loyalty (Shankar et al., 2003). Therefore this research uses customer overall satisfaction to assess the predictive power of e-SEI of customer future behavior.

Recommendation intention refers to a customer's willingness to recommend the site to other people. Along with repurchase intention, recommendation intention is considered one of the most important loyalty outcomes (Oliver, 1999). In particular, Oliver posits that advocacy behavior (e.g. customer referrals) is one of the most distinctive commitment outcomes toward a preferred vendor. Consistent with this argument, much research demonstrates that the greater the degree of commitment a customer has to an online provider, the more likely he or she is to say positive things about the service or product to others (Srinivasan et al., 2002). More important, recommendation intention as an outcome of customer loyalty is widely known as an essential component for the survival of an online firm, because recommendations and support from loyal customers can be spread faster across the Internet rather than face-to-face media (Gupta and Harris, 2010). In addition, online loyal customers are more likely to provide free word-of-mouth advertising (Kumar et al., 2007; Reichheld and Schefter, 2000). Therefore, positive changes in online shopping experiences should lead customers to "recommend to buy" or "strongly recommend to buy" from an online retailer, rather than unfavorable "don't buy" recommendations to potential new customers. A central part of our logic for e-SEI → recommendation value link is that customer satisfactory experiences provide information content of the prospects of firm future cash flows (Anderson and Mansi, 2009; Gruca and Rego, 2005). This reasoning suggests that customer's satisfactory online shopping experiences channeled by customer recommendation can serve as an indicator of more promising future firm profits.

Taken together these arguments we propose the following hypotheses:

$H_1$: Ratings in e-SEI positively influence customer e-satisfaction.

$H_2$: Ratings in e-SEI positively influence customer recommendation intention for the online firm.

Finally, as we mentioned earlier customer satisfaction is widely recognized as a key influence in the formation of customers' future behavioral intentions (Mithas et al., 2006; Shankar et al., 2003; Oliver, 1999; Fornell et al., 1996). Satisfied customers are more likely to tell others of their favorable online shopping experiences and, thus, engage in e-word-of-mouse advertising (Hsu, 2008; Kumar et al., 2007). Consistent with consumer behavior theoretic formulations, we also expect that higher levels of customer satisfaction lead to greater site recommendation intention. This path is not stated formally as hypothesis, because it has been well documented in the literature, but it is included in our model for the sake of completeness.

## 1.3 Method

### 1.3.1 Research site and data collection

The setting for the study was one of the most leading online retailers. Fnac online is one of the largest online retailer in Portugal since 2003; its customer base exceeded 90,000 consumers in 2010, and it sells a great variety of products, including electronic goods, computers, books, music, movies, gaming, etc. Fnac's growth in sales demonstrates the value of its online business model.

#### Quantitative online survey

The Fnac's website marketing manager provides permission to conduct the survey. The link to the formal questionnaire was posted on a survey Fnac website. A banner ad in Fnac website home page and its Facebook page requests buyers to participate in the online survey. When click the banner, the invitation to participate and complete the survey appeared, with an hyperlink to the questionnaire. The posting remains available from June to the first week in August 2011. All data came from survey respondents who have purchased a product from Fnac online before, since the identified dimensions for evaluating e-shopping experience cannot be assessed after a single visit to the website. After deleting incomplete questionnaires and cases with ambiguous values, out of the 577 respondents we obtained a final usable sample of 308 customers.

**Sample characteristics**

Among the 308 respondents 62,7% purchase from Fnac online for at least two years or more, 49,4% make purchases about three or four times a year and 23,7% at least once a month, and the most purchased products category are books (74,4%), computers (36,4%), music (29,5%), movies (22,1%), gaming (21,4%), and other consumer electronics (13,3%); 43,2% of the respondents have awareness of Fnac online from its physical stores, against 33,4% that search on Google or other Internet search engines.

The vast majority of the respondents were male (62,3%), and most were between 25 and 40 years old (54,8%). Most of the respondents had college degrees or higher (69,7%), and about more than a quarter had not gone beyond high school or professional degree. Besides a large number of these respondents were professionals from scientific, academic or business management positions (36%), and 48% having five years or more of Internet purchase experience.

A comparison of the sample demographics with known population data about Internet users (Hsu, 2008; Szymanski and Hise, 2000) reveals that the study respondents are relatively similar: young, with higher levels of education and income. These differences are reasonable, because the sample represents a set of consumers buying cultural, technological and entertainment products, a relatively high expenditure and educated segment. Table 1.1 summarizes the characteristics of these respondents.

### 1.3.2 Model constructs and measures

In this section, definitions of the constructs of interest and number of items used in this research are given. Scale measures used in this study were derived from IT and e-consumer behavior literature. A survey was designed to tap into the proposed e-SEI model (see Appendix B). Whenever possible, previously tested measurement items from existing scales found in related studies were adapted to fit the study context, with some exceptions.

Table 1.1 Characteristics of the respondents

| | | Frequency | Percent (%) |
|---|---|---|---|
| Gender | Male | 192 | 62,3 |
| | Female | 116 | 37,7 |
| Age | 18 below | 10 | 3,2 |
| | 18-24 | 70 | 22,7 |
| | 25-29 | 80 | 22,0 |
| | 30-39 | 101 | 32,8 |
| | 40-49 | 39 | 12,7 |
| | 50 above | 8 | 2,6 |
| Education level | Middle school or less | 13 | 4,2 |
| | High school or equivalent | 80 | 26,0 |
| | College degree | 115 | 37,3 |
| | Post-graduation | 34 | 11,0 |
| | Master's/ Doctoral degree | 66 | 21,4 |
| Occupation | Scientific and intellectual professionals | 70 | 22,7 |
| | Business managers | 41 | 13,3 |
| | Technicians | 49 | 15,9 |
| | Free-lancers and entrepreneurs | 18 | 5,8 |
| | Service personnel | 40 | 13,0 |
| | Student | 66 | 21,4 |
| | Other | 24 | 7,7 |
| Internet usage per day | Less than 1 hour | 2 | 0,6 |
| | 1 or 2 hours | 51 | 16,6 |
| | 3 or 4 hours | 101 | 32,8 |
| | 5 or 6 hours | 61 | 19,8 |
| | 7 or 8 hours | 45 | 14,6 |
| | 9 or 10 hours | 22 | 7,1 |
| | More than 10 hours | 26 | 8,4 |
| Online shopping experience /use | 1 year or less | 43 | 14,0 |
| | Between 2 – 4 years | 117 | 38,0 |
| | Between 5 – 8 years | 110 | 35,7 |
| | 10 years or more | 38 | 12,3 |
| First time purchase from Fnac online | 1 year ago, or less | 115 | 37,3 |
| | Between 2 – 4 years | 126 | 41,0 |
| | Between 5 – 8 years | 67 | 21,7 |
| Purchased product category [a)] | Books | 229 | 74,4 |
| | CD's and DVD's | 159 | 51,6 |
| | Gaming | 66 | 21,4 |
| | Software & hardware | 125 | 40,6 |
| | Photo, video & sound apparel | 74 | 24,0 |
| | Mobile communications | 34 | 11,0 |
| | Merchandising | 9 | 2,9 |
| | Other | 12 | 3,9 |

a) Multiple answer question (frequencies of responses could exceed 100%).
n= 308

First, the construct of interactivity develops new measures items based on information systems literature (Palmer, 2002; Zhu and Kraemer, 2002). Interactivity is defined as an indicator of the efficiency, usability, and organization of the website interface to provide interactive real-time online communication dedicated to customer's access to personal information, customized content and sharing consumption experiences. To investigate interactivity we used a multi-item scale measure consisting of four items. The assessment focuses on consumers' attitudes/perceptions about the convenience of the interactive level at website, enabling customers to customize product features to be "built-to-order", gain access to personalized accounts or private information and, whether the company offers an online community dedicated to customers' information sharing (e.g. discussion forums, message boards, etc).
Second, product value is defined as perceived benefits provided by a product purchased at the webstore, including product variety at competitive price and matching customer's expectations. The first two measures of the construct of product value were adapted from Chen et al., (2010) and Mathwick et al., (2001) respectively: "online store offers exclusive products", and "the prices of products offer economic value". Because the concept of product value has often been neglected in the context of e-SQ, we took special care in developing additional measures covering specific features of product value in the context of online retail. We developed three new measures based on the definition of the construct and from e-consumer behavior literature: "Products have competitive prices at this online store"; "The online store provides a wide range of product variety", and "Product features matching customer's expectations".
Webstore effectiveness is defined as the ease with which the customer can navigate the site, including the effectiveness of the layout, search tools and organization, quantity and quality of product information available at the webstore. To investigate the webstore dimension we use a multi-item scale measure consisting of five items; four of them were adapted from Hsu (2008) and Zhu and Kraemer (2002) questions and reworded them to fit our online retailer context. We developed one new measure (e.g. "the website offers reliable information provided by other customers about product reviews").
Transaction efficiency is defined as the fulfillment of the online order process, including the easy to order, payment options and transaction data security about private

information the customer provides. To examine online transaction dimension we use a multi-item scale measure consisting of five items; four of them were adapted from Hsu (2008) and Wolfinbarger and Gilly (2003) and we developed one new item (e.g. "I can track the order progress at this website".

The customer support construct is defined as the assistance provided by the website regarding questions, issues or problems with the products or services it is selling. The customer support consisted of four measures and were adapted from Parasuraman et al. (2005) and Wolfinbarger and Gilly (2003).

We define delivery and returns as the customer fulfillment with shipping and handling regarding product delivery fees, correctness, timeliness of order-delivery, and return options. To investigate delivery and returns we use a multi-item scale measure consisting of five items adapted from Hsu (2008) and Parasuraman et al. (2005) "modification" scale (i.e. questions were reworded to fit our online retailer context).

To examine customer satisfaction and customer behavioral intentions we use existing measures which have been extensively developed and validated in e-consumer behavior literature. We define customer satisfaction as a cumulative evaluation which encompasses all phases of a customer's interactions with an e-retail site, including all cues and encounters that occur before, during and after the transactions. For customer satisfaction we use four measures adapted from existing research (Tsai and Huang, 2007). Site recommendation intention is defined as an indicator of the likelihood of referring a friend, family member or acquaintance to a particular website, and the scale measure included five items: four of them were adapted from existing validated measures in the online context (Kim and Son, 2009) and we developed one new item to fit Internet retail potential features (e.g. I will refer product novelty and promotions that website send me that match my friends' needs).

The proposed model was then empirically tested by developing and using a questionnaire. Unless otherwise noted, for all the measurement items, a five-point Likert scale was adopted, with anchors ranging from strongly disagree (1) to strongly agree (5), in a way this format better conforms to linear models, thus providing higher criterion validity (Weijters et al., 2010). The Appendix B contains the specific measurement items details.

**Pilot test**

The preliminary questionnaire had 37 items and was tested with e-marketing managers and academics, altogether 15 subjects. We then refined the script according to their comments and judgments. The format and content of the online questionnaire were also pre-tested on doctoral students and individuals who are familiar with the issue of e-business, paying specific attention to question content, wording, sequence, layout, question difficulty, and instructions. On the basis of the problems identified by the respondents, we made minor adjustments to the questionnaire[1.] Based on preliminary survey items and pilot test results a list of 28 items (plus 9 items for dependent constructs) was identified. The final questionnaire written in Portuguese underwent back-translation to ensure conceptual equivalence. After data collection we perform several analyses in order to test empirically the e-SEI model, as following described.

### 1.3.3 Method to test the higher-order factor structure of e-SEI

Our research framework proposes a model in which perceptions towards e-shopping experience is constructed as a common latent variable or higher-order construct with reflective variables as the first-order dimensions. Figure 1.1 depicts the second-order factor e-SEI that explains six first-order factors, webstore, transaction, product value, customer support, delivery and returns and interactivity, each indicated by four or more reflective items. Each of these dimensions is in itself a factor reflecting multiple item scales to assess consumers' total e-shopping experience. However, they may all be driven by a higher-order factor that we label "e-SEI". Theoretically, the justification of using a higher-order factor is because it may be difficult to look at one's consumer e-shopping experience involving different dimensions and directly assess the likelihood of satisfactory experiences. However, it may be indicated quite well by more tangible indicators such as "transaction effectiveness" or "delivery and returns". As we mentioned before, the e-vendor key decisions may be made based on the more abstract "e-SEI" factor, and hopefully these decisions can be better than relying on the

[1] We clarified instructions, changed the wording of some ambiguous questions, and improved the layout increasing the user friendliness of the questionnaire.

individual more specific first-order dimensions. This rationale gives raise to the theoretical ground of a second-order factor configuration for a measurement theory.

Higher-order constructs, as their discussion and application is often limited to a second-order hierarchical structure, can be defined as constructs involving more than one dimension (MacKenzie et al., 2005; Jarvis et al., 2003; Netemeyer et al., 2003; Edwards, 2001; Law and Wong, 1999). The plausibility of hierarchical construct models is based on a number of theoretical and empirical grounds. Proponents of the use of higher-order constructs have argued that they allow for more theoretical parsimony and reduce model complexity (MacKenzie et al., 2005; Edwards, 2001; Law et al., 1998).

The conceptual grounds raised above are complemented by two empirical points: reliability and validity of measures of the multidimensional constructs (Edwards, 2001).

Typically, as the heterogeneity of the dimensions of the multidimensional construct increases, the internal consistency of the dimension scores will eventually be reduced. Moreover, the construct validity of the dimension measures has been questioned, as it contains large amounts of specific and group variance, which are generally treated as error variance (see Law et al., 1998). The second-order confirmatory factor analysis model is an appropriate technique for separating the confounding measurement error from specific variance (Bagozzi et al., 1991). For a detailed discussion of second-order models see also (Bagozzi and Heatherton, 1994; Gerbing et al., 1994; Rindskopf and Rose, 1988; Gerbing and Anderson, 1984; Hunter and Gerbing, 1982; Jöreskog, 1970).

Finally, proponents of higher-order constructs contend that such constructs exhibit a higher degree of criterion-related validity, especially if they serve as predictors.

Based on theoretical considerations described above, the six individual dimensions are first-order factors, and e-SEI the second-order factor can be operationalized as a higher level of abstraction that reflects broader, more abstract e-shopping experience. As such, this type of situation calls for the testing of a second-order confirmatory factor analysis - SOCFA model (Bagozzi et al., 1991). Following the author’s guidelines we begin with the CFA model because of its parsimony structure, its desirable features, and because it yields the restrictive assumptions of the second-order CFA model, i.e. at least three first-order factors per each second-order factor are required for model identification. In this approach, each measure loads directly on first-order trait and method factors, and the first-order factors load, in turn, on corresponding second-order trait and method factors (Bagozzi et al. 1991, p. 438).

To test the proposed e-SEI model we use second-order confirmatory factor analysis, a structural equation technique, allowing for multiple multidimensional variables, accounting for measurement error and testing for hierarchical factor structure. We foremost test the plausibility of higher-order factor model for construct validity and goodness-of-fit (GOF). We first, estimate a first-order measurement model, assessing construct validity and GOF indices. Secondly, we estimate a second-order factor model assessing both construct and nomological validity, as higher-order factors should be rigorously examined for criterion validity.  For example, in this study all the items measures use the same type of rating scale, there could be a common methods factor influencing all first-order constructs (MacKenzie et al., 2005) . The second-order factor could be interpreted as common measurement bias in this case. If the second-order factor reacts to other theoretical constructs as expected, the chance of being of this type is lower. More specifically, if the higher-factor e-SEI explains theoretically related outcomes such as e-satisfaction or intention to recommend the site, as well or better than does the combined set of first-order factors, then evidence in favor of the higher-order representation is provided (Hair et al. 2006, p. 818). Thus, a primary validation criterion becomes how well the higher-order factor explains the theoretically related constructs. To test the nomological validity, structural equation modeling (SEM) is used to test the hypothesized relationships among constructs in our research model. We use the software AMOS (version 19), maximum likelihood (ML) estimation method to conduct both, CFA to assess the reliability and construct validity, including convergent and discriminant validity, and SEM to test directly the multiple dependence relationships amongst constructs in our research model.

## 1.4 Results

### 1.4.1 Assessing the first-order measurement model

To assess the psychometric properties of the measures, we initially specified a measurement model for the first-order latent variables, in which no structural relationships were included. The first-order measurement model included six factors with their 28 corresponding reflective indicators, as listed in the Appendix B. We ran a CFA of the six factor structure not only to assess overall model fit, but also to assess the reliability of the measures and construct validity. We evaluated model fit through multiple fit criteria, each of which represents a different aspect of the model. In particular, four fit indices examined in this study were the comparative fit index (CFI), the normed fit index (NFI), the root mean square error of approximation (RMSEA), the goodness-of-fit index (GFI). For each index, an acceptable level of fit is indicated as follows: CFI > 0.95; NFI > 0.95; RMSEA < 0.08, and GFI > 0.90 (Hu and Bentler, 1999; Browne and Cudeck, 1993; Bentler, 1990).

We ran the first-order measurement model, and the results indicated that the model fit the data poorly in terms of all the fit indices considered in this study: $\chi 2(335)$= 1147,90, $p< 0.000$, chi-square normalized by degrees of freedom (CMIN/DF)= 3.43, CFI=0.855, NFI=0.809, RMSEA=0.089 with the 90% confidence interval [.083;.095].

We first assess the distributional properties of the manifest variables. Kline (2005) considers the standardized kurtosis index rescaled ($\beta 2$ ) values equal to or greater than 7 to be indicative of early departure from normality. Using this value of 7 as a guide, an examination of the univariate kurtosis values reveals no item indicating excessive kurtosis (the highest kurtosis value of 4.223 observed for delivery and returns - De1 measure label in Appendix B). We also check for observations farthest from the centroid using Mahalanobis distance**.** After delete potential outliers, altogether 10 observations, the model fit improve significantly.

Several diagnostic measures are made to assess items reliability of each construct including standardized loadings > 0.5, standardized residuals ǀ 2.5 - 4ǀ and modification indices (Lagrange Multipliers > 11). First, by looking at the completely standardized loading estimates of the items are above the threshold of 0.5 and were all significant ($p<0.001$). Although, only the estimates for De1 (0.461) fall the 0.5 cutoff.

When examining the standardized residual values, that exceeds the cutpoint of 2.58 (Jöreskog and Sörbom, 2001), we observe the largest residuals for De1, De2, Pv4, Pv5, Web5, and Tra4 covariance discrepancy between several other items, and modification indices suggest (beyond its standardized loading falls below the less conservative .7 cutoff) that those variables need to be dropped. Therefore, from this information we excluded those variables in further analyses, assuring at least three items indicators for each construct, as models with sample size greater than 200 that adhere to the three indicator rule are unlikely to produce problems with model identification (Hair et al., 2006; Kline, 2005; Jöreskog and Sörbom, 2001). Guided by both theoretical and empirical considerations, the respecified model shows better fit statistics. CFA results suggest a reasonably overall good fit: $\chi 2$ (189) = 397,48, p =.000, CMIN/DF = 2,1 which is less than the maximum of 3, and the CFI, the NFI, and the RMSEA were satisfactory (.954, .917 and .061, respectively). Using the 90% confidence interval we conclude the true value of RMSEA is between .053 and .069 (even the upper bound is lower than the threshold of 0.08) which is acceptable.

We assess construct validity examining convergent, discriminant and nomological validity[2]. The reliability (CR) of these measures was over the threshold of 0.7 and the average variance extracted (AVE) exceeded the recommended value of 0.5 (Fornell and Larcker, 1981). To assess discriminant validity, Fornell and Larcker (1981) suggest the use of AVE, which should be greater than the variances shared between the constructs. After checking the results, we found that except for interactivity against several constructs, all other constructs have adequate discriminant validity. Therefore, in examining the psychometrics properties of each indicator there is no evidence of discriminant validity between interactivity and most of other factors. As it is required when developing a measurement instrument, great emphasis should be addressed to discriminant validity, which means all factors of a multidimensional scale should have distinct measures, and consequently assuring the unidimensionality of each factor. As a result, we test a five factor measurement model after excluding interactivity factor from further analysis.

[2] For the six factor measurement model, standardized loadings, Cronbach’s alpha, composite reliability, average variance extracted, and correlations of the measures will be available on request.

**Assessing the five factor first-order measurement model**

In assessing the respecified five factor first-order measurement model we ran CFA not only to test the overall fit but also to test the validity of the measures. As shown in Table 1.2, the results supported convergent validity for all measures: all estimated factor loadings of the items are above the threshold of 0.5 and were all significant ($p < 0.001$) exceeding the statistical significance level accepted in this study. Standardized residuals suggest no modification: all residuals are bellow 2.5 suggesting no major problems with items covariances discrepancy. Except, the highest residual between De3 and Tra2 (3.67) suggests De3 is suspect (beyond its low standardized loading), but to adhere to the three item indicator rule it was remained in the model.

The overall model fit was satisfactory: chi-square (213,18) with 121 degrees of freedom, p=.000, CMIN/DF was 1.76, which is less than the maximum of 3, and the CFI, the GFI, and the RMSEA were satisfactory (0.975, 0.93 and 0.051, respectively). Using the 90% confidence interval we conclude the true value of RMSEA is between .039 and .062 (even the upper bound is lower than the threshold of 0.08) which is acceptable. Both the CFI and the RMSEA exceed the GOF guidelines proposed by Hu and Bentler (1999) for a model of this complexity and effective sample size. Both the .05 and .01 Hoelter's (1983) Critical N values for our hypothesized model were > 200 (206 and 224, respectively) which leads us to conclude that the size of our sample (N = 298) was satisfactory according to Hoelter's benchmark that the CN should exceed 200.

Given that, we have developed a new scale to measure the online shopping experience, it is appropriate to examine construct validity – specifically in terms of convergent, discriminant, and nomological validities. As Table 1.2 shows, all the items loaded highly (above the threshold of 0.5) on the factors to which they were assigned is itself a test of convergent validity of the scale. We assess construct validity examining convergent, discriminant and nomological validity. The value of Cronbach's alpha of the constructs exceeded the normally accepted 0.7 threshold. The minimum reliability (CR) of these measures was over the threshold of 0.7. In addition, the AVE across the constructs exceeded 0.5 as we demonstrate in Table 1.2, which provides evidence of reliable measures.

Table 1.2 Psychometric properties for the first-order and nomological constructs

| Measured items | Factor loading $\lambda_\iota$ | CR | AVE | Cronbach's α |
|---|---|---|---|---|
| *Webstore* | | 0.87 | 0.62 | 0.88 |
| Web1 | $0.83^{***}$ | | | |
| Web2 | $0.84^{***}$ | | | |
| Web3 | $0.73^{***}$ | | | |
| Web4 | $0.75^{***}$ | | | |
| *Transaction* | | 0.82 | 0.54 | 0.84 |
| Tra1 | $0.82^{***}$ | | | |
| Tra2 | $0.70^{***}$ | | | |
| Tra3 | $0.71^{***}$ | | | |
| Tra5 | $0.70^{***}$ | | | |
| *Customer Support* | | 0.88 | 0.65 | 0.89 |
| Cs1 | $0.92^{***}$ | | | |
| Cs2 | $0.83^{***}$ | | | |
| Cs3 | $0.71^{***}$ | | | |
| Cs4 | $0.74^{***}$ | | | |
| *Product value* | | 0.80 | 0.58 | 0.85 |
| Pv1 | $0.71^{***}$ | | | |
| Pv2 | $0.80^{***}$ | | | |
| Pv3 | $0.76^{***}$ | | | |
| *Delivery & Returns* | | 0.86 | 0.68 | 0.83 |
| De3 | $0.51^{***}$ | | | |
| De4 | $0.92^{***}$ | | | |
| De5 | $0.96^{***}$ | | | |
| Nomological constructs [a)] | | | | |
| *e-Satisfaction* | | 0.96 | 0.85 | 0.96 |
| Sat1 | $0.85^{***}$ | | | |
| Sat2 | $0.93^{***}$ | | | |
| Sat3 | $0.95^{***}$ | | | |
| Sat4 | $0.95^{***}$ | | | |
| *Recommendation Intention* | | 0.90 | 0.69 | 0.91 |
| Rec2 | $0.69^{***}$ | | | |
| Rec3 | $0.96^{***}$ | | | |
| Rec4 | $0.86^{***}$ | | | |
| Rec5 | $0.79^{***}$ | | | |

Notes: *** $p < 0.001$
CR: Composite reliability ≥ 0.7; AVE: Average variance extracted ≥ 0.5; α ≥ 0.7. All items are listed in Appendix B.
[a)] Given that these dimensions have more than three items each, hence CR from separate confirmatory factor analysis would be meaningful rather than Cronbach's α alone.

As shows Table 1.3, the discriminant validity of the research instrument was assessed by checking that the square root of the average variance extracted for each of the constructs, along the diagonal, was greater than the correlation shared between the different constructs in the off diagonal (Fornell and Larcker, 1981). After examining the results we found that all five first-order constructs have adequate discriminant validity indicating that the constructs of interest are unidimensional and have distinctive measures.

Table 1.3 Intercorrelations, average variance extracted, means and standard deviation of the first-order constructs

| **Construct** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| 1. Webstore | **0.79** | | | | |
| 2. Transaction | 0.71 | **0.73** | | | |
| 3. Customer Support | 0.63 | 0.67 | **0.81** | | |
| 4. Product Value | 0.67 | 0.71 | 0.66 | **0.76** | |
| 5. Delivery & Returns | 0.69 | 0.68 | 0.77 | 0.63 | **0.82** |
| (Items) Mean | 3.65 | 4.21 | 3.45 | 3.58 | 3.75 |
| Scale Mean | 14.62 | 16.82 | 13.82 | 10.73 | 11.24 |
| Standard Deviation | 3.52 | 2.82 | 3.59 | 2.98 | 2.56 |

Notes: Square root of average variance extracted on the diagonal; correlation estimates below the diagonal. Means are reported but not analyzed.

From the examination of correlations, in Table 1.3, we observe the first-order constructs are highly correlated and in particular, delivery and returns factor is highly correlated with customer support (0.77) and transaction with product value (0.71) just to point the highest values. This could explain why there is so much common variance to make a higher-order factor structure appropriate.

### 1.4.2 Assessing the second-order factor structure

We assess nomological validity to test the plausibility of the second-order factor. Nomological validity is the ability of a new measure to perform as expected in a network of known causal relations and well-established measures (Hair et al., 2006; Bagozzi and Yi, 1988; Bagozzi, 1980). One cannot have confidence in a measure if it does not behave in a reasonable fashion in relation to other theoretically accepted constructs. In the case of e-shopping experience factor, a relevant demonstration of nomological validity would be the extent to which the construct do actually predict e-satisfaction or intention to recommend the site in ways that are consistent with current knowledge and expectations based on prior research.

One way to test the ability of e-shopping experience to predict consumer behavioral outcomes would be to regress the first-order constructs on e-satisfaction and intention to recommend the site. However, since some of the constructs are highly correlated, multicollinearity would be a problem with a regression analysis of this kind. The multicollinearity problem can be side-stepped by a second-order factor analysis in advance of examining the structural relations between the second-order factor and nomological constructs (Hair et al., 2006). Following, we test the alternative higher-order factor structure in order to determine the plausibility of second-order model of both six and five factor structure, just for comparison purposes. The six factor model, although not perfect, since the interactivity factor has not shown adequate discriminant validity, however the level of fit seems sufficient to proceed with an assessment of the second-order model (Bagozzi et al., 1991).

**Testing alternative higher-order factor structure**

The first step in assessing the proposed higher-order factor structure was the test for six dimensions as indicators of second-order construct e-SEI. A confirmatory factor analysis of this model showed an acceptable fit, both at the first-order level ($\chi2$=397.5, with df=189, CFI=.95, RMSEA=.061), and at the second-order level ($\chi2$=432.4, with df=198, CFI=.95, RMSEA=.063) as demonstrated on Table 1.4. When comparing the different order models, the second-order model, as shown in Table 4, it performs as well on indices that reflect parsimony PCFI=.81 (.78) and RMSEA=.06 (.06) and shows nomological validity in predicting e-satisfaction both at first-order $R^2$=.83 as the second-order $R^2$=.76. However, the second-order factor e-SEI does not explains the theoretically related outcomes e-satisfaction and intention to recommend the site better than does the combined set of the first-order factors because the first-order factor model explains covariance among latent constructs better than a higher-order representation of the same data. Hair and colleagues (2006) they cautioned that, first-order model will always fit better in absolute terms because it uses more paths to capture the same amount of covariance. In contrast, the second-order model is more parsimonious, as it uses fewer degrees of freedom (p.817).

Then, the last test of the proposed higher-order factor structure was the test for the five factor structure. As it shows Table 1.4, confirmatory factor analysis of this model reveals a good fit both at the first-order level ($\chi2$=213.2, df=121, CFI=.97 and RMSEA=.05) and at the second-order level ($\chi2$=230.4, df=126, CFI=.97 and RMSEA=.05) demonstrating that first-order factor model explains covariance among latent constructs as well than a higher-order representation of the same data.

Table 1.4 Testing alternative higher-order models

| **Model description** | $\chi2$ | **df** | **CFI** | **RMSEA** | **PCFI** | $R^2$ e-Sat Reci | $\Delta\chi2$ |
|---|---|---|---|---|---|---|---|
| 6 factor first-order model | 397,5 | 189 | .954 | .061 [.053; .069] | .781 | .83 .68 | _ |
| 6 factor second-order model | 432,4 | 198 | .948 | .063 [.055; .071] | .813 | .76 .59 | _ |
| 5 factor first-order model | 213,2 | 121 | .975 | .051 [.039; .062] | .771 | .82 .67 | p < .01 |
| 5 factor second-order model | 230,4 | 126 | .972 | .053 [.042; .064] | .800 | .79 .63 | p < .01 |

Though, the comparison between a first-and second-order measurement model is generally nested: the empirical comparison using a $\Delta\chi2$ statistic is not as useful as it is when comparing measurement models of the same order. We use the $\chi2$ difference statistics to test the difference between the two models. We compute a $\chi2_D$ separately for each level order model between the six and five factor structures, and results are following reported: the first-order models $\chi2_{D1}$ (68) = 397,5 – 213,2 = 184,3 > $\chi^2$ (68); p=.01, and the second-order models $\chi2_{D2}$ (72) = 432,4 – 230,4 = 202,0 > $\chi^2$ (72); p= .01 shows that the larger values of both $\chi^2_{D1}$ and $\chi^2_{D2}$ statistics lead to the rejection of the hypothesis of equal fit between the two higher-order models, which means that the improvement in overall fit due to model trimming is statistically significant at the .01 level. In addition to the examination of the $\chi2_D$ between the second-order models as the definitive test, and following Cheung and Rensvold's (2002) guidelines, we also might look at the differences in the $\Delta$CFI > .01 for the practical significance of improvement in overall model fit. Then, when comparing the second-order measurement models of different factor structure, the five-factor second-order model is supported to the extent that shows better fit (CFI=.972), exhibits more parsimony (RMSEA=.05) and greater nomological validity ($R^2$=.79 and .63) (beyond the adequate discriminant validity) than the six-factor second-order model (CFI=.948; RMSEA=.06; $R^2$=.76 and .59).

The increase in CFI of the five-factor second-order model is just that .02, and the RMSEA drops .01, when compared to the fit of six-factor second-order model. This provides additional evidence that the model trimming has not worsened overall fit, and even more confidence in the five-factor second-order model.

Taken together these results, the five-factor second-order model is supported to the extent that it shows adequate nomological validity: the second-order factor e-SEI explains the theoretically related outcomes, such as e-satisfaction and recommendation intention as well than does the combined set of the first-order factors. Thus, evidence in favor of the second-order model representation is provided, as a primary validation criterion becomes how well a higher-order factor explains the theoretically related constructs (Hair et al., 2006; Bagozzi and Heatherton, 1994) . Therefore, the higher-order structure is strongly supported, suggesting that the five-factor model of e-SEI (see Figure 1.2) is valid. Besides, as we prior mentioned the higher-factor could be interpreted as common method bias. Given the second-order factor explains theoretical constructs as expected this result provides evidence that the chance of e-SEI could be interpreted as common measurement bias is lower. Taken together these results we propose the five-factor structure as more acceptable to measure e-SEI at a higher-order level, and therefore is included in further analysis.

### 1.4.3 Cross-validation for testing scale invariance

Even though our proposed five-factor structure shows a good fit to the data, we recognize that the results could be specific to this particular sample. Therefore, a second confirmatory factor analysis using the same measurement instrument was conducted using multi-group analysis to validate our findings (Byrne, 2010). We classified respondents as being either e-experienced customers or e-novice customers regarding online shopping experience. We defined e-experienced customers as those with 5 or more years and e-novice with fewer than 5 years of online shopping experience. On the basis of responses to our survey question about the length of online shopping experience (see Table 1.1) we classified 140 e-experienced participants (47%) and 158 (53%) as e-novice from the effective full sample (n=298). We use the sub-samples of customers as a procedure to test scale invariance (Byrne, 2010; Hair et al., 2006). In seeking evidence of multi-group equivalence, we are interested in finding if the items comprising the measurement instrument operate equivalently across the different groups of customers (e.g., e-shopping experience). In other words, we test if the measurement model is group-invariant. The results of this analysis are presented in Table 1.5.

First, we estimate the unconstraint model sometimes referred as the totally free multi-group model (TF) because the same parameters ($\lambda$, $\Phi$, $\theta_{\delta}$) are estimated freely in each group (separately) which means, with no equality constraints. Results related to this first multi-group model, testing for configural invariance or factor structure equivalence, reveal the $\chi2$ value to be 365,22 with 242 degrees of freedom. The CFI and RMSEA values, as expected, are .97 and .041, respectively. From this information, we can conclude that the hypothesized multi-group model of e-SEI structure is satisfactory well fitting across novice and highly e-experienced consumers. Thus at least, minimal evidence of cross-validation or configural invariance is presented.

Table 1.5 Cross-validation statistics for e-SEI scale dimensions

| **Model Description** | **$\chi2$** | **df** | **CFI** | **RMSEA** | **$\Delta\chi2$** | **$\Delta$ *df*** | **p** | **Comments** |
|---|---|---|---|---|---|---|---|---|
| Unconstraint (TF) model | 365.22 | 242 | .97 | .041 | – | – | | Configural invariance |
| Factor Loading Equivalence | 378.09 | 255 | .97 | .040 | 12.87 | 13 | p ≈ . 458 | Invariance |
| Structural Covariance Equivalence | 398.52 | 270 | .97 | .040 | 20.43 | 15 | p ≈ . 156 | Invariance |
| Error Variance Equivalence | 434.54 | 292 | .96 | .040 | 36.02 | 22 | p ≈ . 030 | No invariance |

Having established good fit for the configural model we now proceed in testing for the invariance of factor measurement and covariance structure across the two groups of e-consumers. We test for the equivalence of factor loadings (i.e. the factor loadings are constraint to be equal in each group). The results (see Table 1.5), as expected, reveal the fit of this model to be consistent with that of the configural model (CFI = .97; RMSEA

= .040). The $\chi2$ difference and CFI difference tests reported for the configural model ($\Delta\chi2$ (13) = 12.869, $p\approx 0.458$ and $\Delta$CFI < .01) provides evidence of factor loading invariance and even greater evidence of partial cross-validation is present.

When we test for factor loading plus interfactor covariance equivalence the model results reveals good fit: both the CFI and the RMSEA remain unchangeable, and $\Delta\chi2$ (15)= 20.429, $p\approx 0.156$, provide statistical evidence that the added constraints improve model fit. As before the $\Delta\chi2$ is not significant; hence the added constraints have not worsened fit and even more evidence of cross-validation is present.

Lastly, when tested for factor loading, interfactor covariance and error variance equivalence, it adds the constraint that the error variance associated with each residual is equal between groups (Byrne, 2010; Jöreskog, 1971). The model results ($\Delta\chi2$ (22) = 36.017 is statistically significant at a probability value < .05) suggest that the added constraints provide no evidence of tight or full cross-validation. On the other hand, the RMSEA and CFI values are quite similar for each model, which contends that the measurement model is completely invariant as the $\Delta$CFI value is not greater than the .01 cutoff point proposed by Cheung and Rensvold (2002)[3]. Presented with these divergent findings, it seems reasonable to assume that tight cross-validation is considered more imposing than is necessary (MacCallum et al., 1994). Historically, the Jöreskog (1971) tradition of invariance testing held that the equality of error variances and their covariances should also be tested. However, it is now widely accepted that this parameterization is considered to be an excessively stringent test of multi-group invariance. Thus, testing this model is relatively uncommon and represents an overly restrictive test of the data (Byrne, 2010). Given that, it seems reasonable to assume that partial cross-validation, as represented by a test of a factor loading plus structural covariance equivalence should provide adequate evidence of cross-validation (Byrne, 2010; Hair et al., 2006). Therefore, having determined evidence of invariance when all

[3] Over the past decade or so, applied researchers have argued that from a practical perspective, the $\chi2$ difference test represents an excessively stringent test of invariance and particularly in light of the fact that SEM models at best are only approximations of reality (MacCallum et al., 1994; Cudeck and Browne, 1983). Consistent with this perspective, Cheung and Rensvold (2002) reasoned that it may be more reasonable to base invariance decisions on a difference in CFI ($\Delta$CFI) rather than on $\chi2$ values. Thus, based on a rigorous Monte Carlo study of several goodness-of-fit indices, Cheung and Rensvold proposed that evidence of noninvariance be based on a difference in CFI values exhibiting a probability < 0.01. Although, this more recent and practical approach to testing for invariance has not been granted the official SEM stamp of approval to date, its use is increasingly reported in the literature, largely because it makes a lot of practical sense to do so (Byrne, 2010).

factor loadings and structural covariance are held equal across groups, we conclude that our data shown adequate cross-validation. As a result, the measurement instrument which comprises the focal five dimensions could be used to assess online shopping experiences of both e-novice and more e-experienced online consumers.

### 1.4.4 Reliability and validity of second-order factor e-SEI

Following good measurement practices, we assess reliability and validity of the second-order factor e-SEI. Construct validity is demonstrated by plausible correlations of the second-order construct with the first-order indicators, while convergent validity could be suggested by an AVE for the second-order construct that is greater than .5 (Ping, 2004; Bagozzi et al., 1991). Following Ping's (2004) guidelines, we compute CR and AVE using the error variances ($\zeta$'s) and loadings ($\beta$'s) of the first-order constructs on the second-order construct in a second-order measurement model in place of $\lambda$'s and Var($\varepsilon$)'s. The values of CR = .92 and AVE = .68 are greater than the recommended values suggesting higher reliabilities and convergent validity for the second-order construct. The loadings of the first-order latent variables on the second-order factor are all positive and statistically significant at $\alpha = 0.001$ and exceed the recommended value 0.7 permitting to justify the importance of each dimension to create the second order factor (Hair et al., 2006; Ping, 2004). The results demonstrate (see Table 1.6) that the second-order factor e-shopping experience is highly correlated with the five individual first-order dimensions ranging from 0.88 to 0.79. These high loadings indicate that the importance and contribution of each dimension to the overall index of online shopping experience is almost identical. What this means is that e-consumers evaluate online shopping experience according the proposed five basic dimensions, and in addition, they view overall online shopping experience as a higher-order factor in the consumer's mind. The high construct reliability suggests that online shopping experience analysis could be appropriately conducted at the dimension as well the overall level. In addition, the overall fit indices (CFI =0.97 and RMSEA=0.05 exceeding the acceptable values) indicate that the second-order model is appropriate to measure overall e-shopping experience. Regarding these empirical results there is evidence of theoretical support in the sense that the five first-order factors are the dimensions and indicators of one single higher-order factor e-SEI.

### 1.4.5 Online shopping experience composite index

The measures of e-shopping experience index (e-SEI) can be combined and then weighted to form a composite measure, because they are almost evenly distributed among the five dimensions and no single factor is compellingly or strongly dominant. Moreover, the high correlations of e-SEI second-order factor with the five individual first-order dimensions indicate that the equal importance and contribution of each dimension are suitable to form an overall composite index (Dabholkar et al., 1996). Developing the e-SEI to obtain for each customer an overall score of their online shopping experiences is more easily interpreted when evaluating the shopping site surveyed. From the second-order confirmatory factor analysis we compute the factor scores weights for the second-order factor e-SEI. The e-SEI can also be computed in terms of each factor averaged items. However, the use of the second-factor scores weights to compute the composite index is a more reliable method, as accounts for measurement error. Thus, the overall scale index may be free of measurement error, and consequently will give more predictive accuracy. When computed the e-SEI mean scores, standard deviation and variance were 4.8, 0.94 and 0.89, respectively (as reported on Table 1.3, the means and standard deviations for each individual factor were relatively high). The global score for e-SEI was 99.9 (transformed to a 0- to 100-point scale to facilitate index comparisons), which is above to the average customer satisfaction index for the online retail industry in the USA in 2011[4] (ACSI score = 81) and above to the top ranking company Amazon (ACSI score = 86).

### 1.4.6 Assessing the higher-order factor in a structural model

Having established confidence in our five-factor second-order measurement model, the last test of the proposed higher-order factor structure is to assess the nomological validity of the e-SEI. To determine the nomological validity of e-SEI we use the two dependent constructs e-satisfaction and site recommendation intention. To assess the reliability of their measures, we conduct a separate CFA to calculate the CR and AVE. As we showed in Table 1.2 the CR is 0.96 for e-satisfaction and 0.90 for intention to

[4] The ACSI score for the online retailing industry can be obtained at: http://www.theacsi.org/index.php

recommend the site, and AVE equals to 0.85 and 0.69 respectively, largely exceeding the recommended values which provide evidence of reliable measures. Moreover, the AVE exceeds the squared correlation between the two constructs (0.57), which supports discriminant validity.

To assess the nomological validity of the second-order construct model we embedded the e-SEI in a nomological network with the two dependent constructs: e-satisfaction and intention to recommend the site, as shows Figure 1.2. We assessed the structural model by checking the goodness-of-fit indexes and putting more emphasis on the magnitude of effect size, direction and statistical significance of estimates of the structural weights. There are some reasons why the results of statistical tests may be more relevant in assessing the main effects of structural model. Fit indices fail to assess more detailed effect size magnitudes and signs, which means that statistical tests may be more relevant to assess the predictive validity of the model more accurately (Cohen, 1988). In Table 1.6, we report the path estimates, the standard errors, confidence intervals and statistical significance level of each individual parameter.

Table 1.6 Assessing the higher-order model of online shopping experience and testing the hypotheses for the structural model

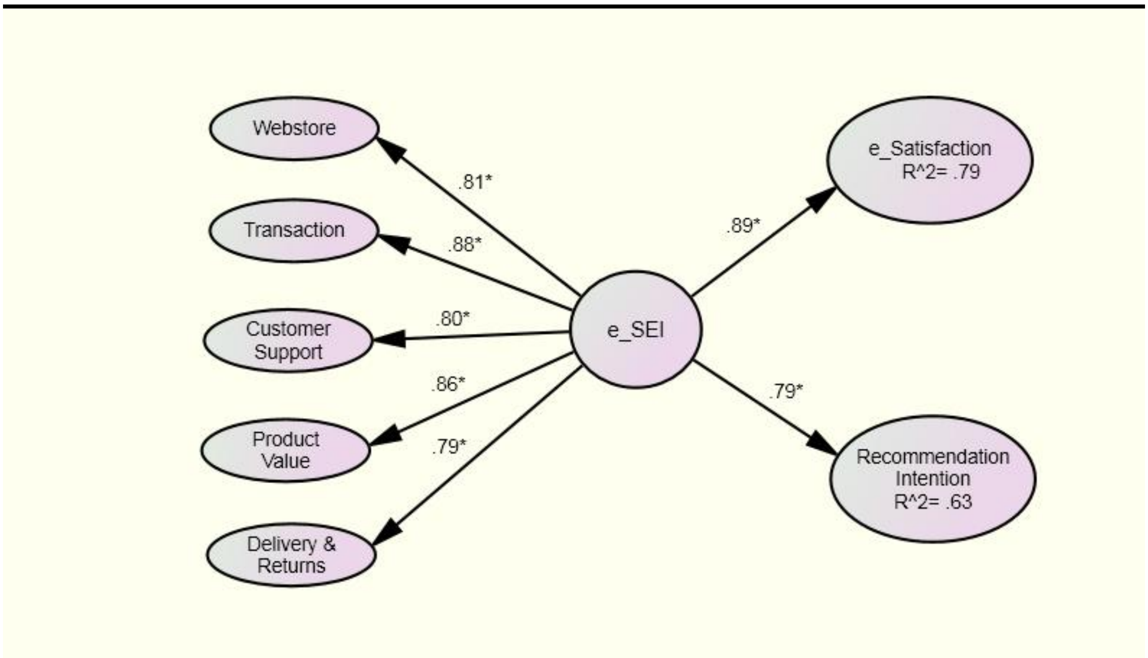
| **First-order factors** | **Second-order factor** e-Shopping experience | |
|---|---|---|
| | Standardized direct effects | S. E. |
| Webstore | 0.81* [0.75, 0.87][a] | (.037)[b] |
| Transaction | 0.88* [0.83, 0.93] | (.031) |
| Customer support | 0.80* [0.74, 0.85] | (.036) |
| Product value | 0.86* [0.79, 0.91] | (.037) |
| Delivery & returns | 0.79* [0.73, 0.84] | (.035) |
| | **Nomological constructs** | |
| | e-Satisfaction | Recommendation intention |
| e-Shopping experience | $H_1$: 0.89* [0.85, 0.92][a] (.022)[b] | $H_2$: 0.79* [0.73, 0.86][a] (.038)[b] |
| $R^2$ | 0.79 | 0.63 |
| CFI=0.965; RMSEA=0.052 [0.044; 0.059]; $\chi2(286) = 512.907$ | | |

* p < 0.001.
[a] The lower and upper boundaries of bootstrap 95% confidence intervals for standardized direct effects.
[b] Standard error of standardized direct effects.

To obtain the standard errors and confidence intervals for the standardized direct effects we used the bootstrap method (Efron and Tibshirani, 1993), which seems to be more appropriate for AMOS than Sobel's (1982) large sample test.

We find support to $H_1$ and $H_2$. As demonstrated in Table 1.6, e-SEI factor predicts significantly each nomological construct: we find a significant and a strong positive impact of e-SEI on e-satisfaction ($H_1$: $\beta$ = 0.89 [0.85, 0.92], p< .001) and on site recommendation intention ($H_2$: $\beta$ = 0.79 [0.71, 0.86], p< .001). Based on recommendations by Cohen (1988) about effect size interpretations of correlations in the social sciences, these standardized path coefficients can be classified as large ($\geq$ .50). Although not formally hypothesized, we also find a positive relationship between e-satisfaction and site recommendation intention ($\beta$ = 0.26 [-0.041, 0.516], p <.05). Thought the path estimate is significant this is a large interval, and more problematic the lower bound is negative. This path was included in the model and analyzed next in order to eventually test this meaningful theoretical relationship.

Figure 1.2 Estimated structural e-shopping experience index model




Note: Standardized path estimates; significance level *p < 0.001.
Each factor's measurement indicators ($x_i$, $y_i$), error terms ($\delta_i$, $\varepsilon_i$) for the manifest variables and the disturbance terms ($\zeta_i$) are omitted in the figure to simplify the representation of the model.

From this result we infer that higher-order factor e-SEI explains more variance on site recommendation intention than overall e-satisfaction. The variance explained by the model in terms of $R^2$ is 0.79 for e-satisfaction and 0.63 for intention to recommend the site. According to the effect sizes defined for $R^2$ by Cohen (1988) these effects can be classified as large ($f^2 > 0.35$). A test of the power of the study has been strongly recommended in order to establish confidence in the predictive validity of a measure. The power (1- β) of a test is defined as the probability of rejecting a false $H_0$; power constitutes the complement to type II error. As a convention for behavioural research, a value of 0.80 is used for power (Cohen, 1992, 1988). We use Cohen's method (1988) to test power analysis of the study: for a significance level of .05 (two-tailed) and sample size n=298 we find power to be greater than .995, highly above the recommended high value (.80). These results strongly provide support for the nomological validity of e-SEI in predicting e-satisfaction and recommendation intention constructs. Moreover, the $R^2$ values of e-satisfaction and intention to recommend the site are quite similar to the results of e-CSI study[5] (Hsu, 2008), which provides consistency to our data.

## 1.5 Conclusion

This study proposes and validates an e-shopping experience index, which is suited for studying e-retail business that offers a variety of goods, (such as books, music, hardware and software, electronic and entertainment) to gather benchmark data regarding current levels of e-retail performance as well as to conduct periodic "checks" to measure performance improvement. Our proposed measurement instrument is a first step towards integrating a multidimensional reflective higher-order measurement model to propose an index for the online retail context.

First, at dimension level the first-order model could serve as a diagnostic tool that will allow online retailers to determine e-business areas that are weak and in need of improvement. One way to do this is by testing the five basic dimensions, if e-retailers

[5] The $R^2$ values for overall customer satisfaction and customer loyalty are 0.73 and 0.69, respectively in the e-CSI study (see Hsu, 2008).

are greatly concerned about the additional information on each dimension, obtained by further partitioning the variance explained.

Secondly, by proposing e-shopping experience as a second-order factor, e-retailers can capture the extent to which the basic dimensions represent overall e-shopping experience. Another way to use the instrument as a diagnostic tool is by computing at overall level an index for e-retail. The index scores obtained represent a uniform and comparable system of measurement that allows for systematic benchmarking over time and across e-business.

Analysis of data at these different levels would allow evaluations of overall e-shopping experience and at dimension level of e-shopping experience would permit e-managers to identify problem areas within their online stores in order to concentrate resources on improving particular aspects of e-business.

This study also confirms that overall e-shopping experience determines customer e-satisfaction and intention to recommend the site. Unlike prior research, we conclude the overall satisfaction is not the key factor to predict customer behavioral intentions. Past studies have typically used single-item measures of overall satisfaction where it is possible that customers could focus on certain aspects of the e-service or products in their minds while responding to these questions. Consequently, these measures may not accurately reflect their overall e-shopping experience.

The second-order factor model with reflective indicators to form a composite index has implications for practitioners as well as academics. Practitioners are often interested in determining overall customer perceptions or satisfaction about service or products they sell, as well as specific dimensions. Although no researcher can claim to definitively capture customer perceptions of overall e-shopping experience, we believe that we came closer to capturing these overall evaluations because the second-order factor extracts the underlying commonality among dimensions. If the respondents have put thought into answering all the questions, then in addition to obtaining their evaluations of the dimensions, the second order factor captures the common variance among these dimensions, reflecting the respondents’ overall assessment of their online shopping experience. It should be noted that sample respondents have considerable e-purchase experience not only from the surveyed site. So, as online shopping experience increases individual evaluations become more accurate and e-SEI dimensions become more important to reflect the overall online shopping experience.

This study also reveals another important finding. The measurement instrument at dimension level is suitable to measure both more e-experienced and e-novice customers. For e-managers this finding offers important contributions to the actions they can take. For example, they could benchmark ratings from more e-experienced, sophisticated and demanding customers on newly acquired customers. At dimension level diagnosis, this model also allows the online retailer to understand the specific factors that significantly influence overall customer e-satisfaction and intention to recommend the site to other people by reading the causal relationships in the e-SEI model. The results suggest that e-SEI may be more important to capture the influence of other factors at transaction and post-transaction stages (e.g. online transaction, product value) in determining customer satisfaction. To deliver superior service and products, an online business must first understand how customers perceive and evaluate their e-shopping experience at dimension level. The e-SEI model can be used to determine the specific areas in which the online retailers' improvement can have a significant impact, including the performance of customer support, the correctness of order fulfillment, the attractiveness of the Web site, convenient product returns, and on-time delivery. That is, the online retailer must answer customers' complaints and queries properly, process orders accurately, offer a good variety of products at competitive prices, deliver products on time, and improve the appearance and usability of the site.

The results also suggest the influence of e-SEI may be important on transaction, customer support, and delivery and returns. These findings are in line with other research. Wolfinbarger and Gilly (2003) suggest that the first opportunity to cement customers to an online brand comes when they have a problem with the order and customer loyalty increases substantially when online vendors are willing and able to solve a situation quickly. Moreover, our findings have important implications for the online retailer's decisions when outsourcing third-party logistics companies to pick, pack and deliver or return a product. Customer ratings on these specific items could serve to assess the outsourced functions and gather data regarding current levels of performance of third-party firms.

Lastly, the predictive power of the e-SEI as a diagnostic tool, to check future customer behavior, i.e. to predict retention or to warn about customer defection is of major relevance for managers due to the highly competitive and non-contractual e-retail context. We believe that customer satisfaction and intention to recommend the site are even more important in the online context, because e-tail sites provide platforms for consumers to post their reviews about online retailers. More and more customers will read these reviews before they make a purchase. One customer's negative experience with the e-retailer can be disseminated among many potential consumers, which is not the case in traditional shopping environments. Moreover, recommendation intention is of major relevance in e-business. Nowadays, more and more sites provide direct links to social networks facilitating site recommendation by online shoppers. In these interconnected days, this has enormous potential for new product diffusion and potential market attraction for e-business.

**Limitations and future research**

One limitation of this study is that the findings are based on a one-site sampling scheme, which limits their generalizability. However, notwithstanding this limitation this study provides important theoretical and practical contributions. Our limitations also suggest directions for future research. In future, surveying diverse samples and conducting a cross-sites study may develop a validated and a more generalizable scale. It will help to confirm if the scale is equivalent across-sites; if Internet shopping dimensions are equivalently important to customer satisfaction across-sites and if e-SEI dimensions equivalently affect relevant consequential behavioral variables across-sites selling different consumer goods (e.g. site heterogeneity / product heterogeneity). Besides, Internet technology is a fast changing environment. Hence, the e-SEI should not be regarded as a final measure, but as a starting point towards a better measure. We suggest a few directions for further research. First, further testing for discriminant validity needs to occur by examining effective measures of site-customer interactivity. Another way to deal with the problem of unidimensionality and discriminant validity is the index construction with formative indicators, (Diamantopoulos and Winklhofer, 2001) as an alternative to scale development in future research.

Moreover, concerning the advances of web 2.0 the interactivity construct calls for radically net-enhanced measures. The increasing number of companies that offer on-site interactive tools providing consumers with a convenient and inexpensive way to personalize or co-create products, or to interact with other community members, bring to light this future research avenue. Moreover, we believe that strategically designing more sophisticated and customer-made interactive tools will create customer value and will retain customers for a webstore.

## Appendix A - Review of e-service quality scales

| Study | Dependent Variables | Scale Dimensions | Comment |
|---|---|---|---|
| Yoo and Donthu (2001)<br><br>SiteQual<br><br>"*Internet Shopping Quality*" | Attitude<br>Overall Loyalty<br>Purchase intention<br>Site Equity<br>Site revisit intention<br>Site toward site | *Site-related factors:*<br>Ease of use<br>Aesthetic design,<br>Processing speed<br>Security<br>*Vendor-related factors:*<br>Competitive value<br>Clarity of ordering<br>Corporate and brand equity<br>Product uniqueness<br>Product quality assurance | Site-related factors (9 items) showed construct reliability, nomological validity and good fit indices of measurement model. Vendor-related factors were excluded from the analysis due to missing data problems with the use of student samples. |
| Francis and White (2002)<br><br>PirQual<br>"*Perceived Internet Retail Quality Model*" | Behavioral Intentions | *Self-service Properties:*<br>Web store functionality<br>Product attribute description<br>*Ownership Properties:*<br>Ownership conditions<br>Delivered products<br>*Relationship Properties:*<br>Customer service<br>Security | Measures only test face or content validity. Construct validity requirements were not assessed. |
| Wolfinbarger and Gilly (2003)<br><br>*EtailQ* | Web site Quality<br>Satisfaction<br>Loyalty intentions<br>Attitude toward site | Website design,<br>Fulfillment/ reliability<br>Privacy/ security<br>Customer service | Measures show strong construct validity. Website design and customer service dimensions demonstrate higher positive effects on satisfaction, quality and loyalty. |
| Parasuraman, Zeithaml and Malhotra (2005)<br><br>*e-S-Qual*<br>*e-RecS-Qual* | E-Service Quality<br>Perceived Value<br>Loyalty Intentions | *E-S-Qual:*<br>Efficiency<br>Fulfillment<br>System Availability<br>Privacy<br>*E-RecS-Qual:*<br>Responsiveness<br>Compensation<br>Contact | E-S-Qual measures show good construct validity (convergent, discriminant and nomological). E-RecS-Qual measures were not validated due to missing data problems with sample inexperience related to e.tail recovery service. |
| Bressolles et al. (2007)<br><br>*NetQual* | Customer Satisfaction<br><br>Buying<br>Impulse (moderator) | Ease of use<br>Information<br>Design<br>Reliability<br>Security / Privacy<br>Interactivity/Personalization | The study use previously validated NetQual measures (Bressolles, 2006) also demonstrating good construct validity. |
| Loiacono et al. (2007)<br><br>*WebQual ™* | Reuse Intention | *Usefulness*:*<br>Informational fit-to-task<br>Tailored information<br>On-line completeness<br>Relative advantage<br>*Ease of Use*:*<br>Ease of understanding<br>Intuitive operations<br>*Trust**<br>*Response time**<br>*Entertainment**<br>Visual appeal<br>Innovativeness<br>Emotional appeal<br>Consistent image | The study identifies 11 constructs showing good construct validity. Emotional appeal was excluded from the analysis.<br>Scale measures are more suitable to assess website attributes (interface design) than service quality.<br>Customer service was excluded from the analysis due to methodological reasons: students sample are less experienced with online shopping and buying only a few categories of products<br>*2nd order factor analysis predicting website reuse. |

## Appendix A - Review of e-service quality scales (cont.)

| Study | Dependent Variables | Scale Dimensions | Comment |
|---|---|---|---|
| Hsu (2008)<br><br>*e-CSI Model* | Complaints<br>Loyalty | E-Service Quality (E-SQ):<br>Information relevance/value<br>Up-to-date information<br>On-time delivery<br>Correctness of order fulfilment<br>Web connection speed<br>Product returns process<br>Customer service performance<br>Logical layout of product list<br>Search facilities<br>Use of personal information<br>Confidentiality of customer information<br>Attractiveness of the Website<br>Website professional appearance | E-SQ, trust and perceived value, are important in determining customer satisfaction index (e-CSI) and customer satisfaction in predicting customer loyalty.<br>E-SQ and perceived value measures does not discriminate the constructs, and except e-SQ (using 13 formative indicators), all constructs use two or less reflexive indicators. |

# Appendix B - Research constructs and measures

| Construct | Initial Full Measured Items [a)] | Source |
|---|---|---|
| *Webstore* | | Hsu, 2008; Zhu and Kraemer, 2002 |
| | Wb1 -This website has logical layout of product list. | |
| | Wb2 - This website has adequate search facilities | |
| | Wb3 - I can easily find what I need at this site | |
| | Wb4 - The website provides in-depth and up-to-date product/service information. | |
| | Wb5 - The website offers reliable information provided by other customers about product reviews | New |
| *Transaction* | | Hsu, 2008; Wolfinbarger & Gilly, 2003 |
| | Tr1 - It is easy and quick to complete a transaction at this website. | |
| | Tr2 - I feel safe in my transactions with this website | |
| | Tr3 - The company assures the confidentiality of customer information. | |
| | Tr4 - This web store has convenient payment methods | |
| | Tr5 - I can track the order progress at this web store. | New |
| *Customer Support* | | Wolfinbarger & Gilly, 2003; Parasuraman et al., 2005 |
| | Cs1 - The website provides assistance to respond to customer needs, questions or problems with the products/services it is selling. | |
| | Cs2 - Inquiries are answered promptly to customers. | |
| | Cs3 - This site has customer service representative available online. | |
| | Cs4 - The website offers the ability to speak to a live person if there is a problem. | |
| *Product Value* | | Mathwick et al. 2001; Chen et al., 2010 |
| | Pv1- This website has unique products that I cannot find elsewhere. | |
| | Pv2 - The prices of the product(s) I purchased from this webstore provide a good economic value. | |
| | Pv3 - Products have competitive prices at this online store. | New |
| | Pv4 -The online store provides a wide range of products. | New |
| | Pv5 - Purchased product features match my expectations. | New |
| *Delivery and Returns* | | Hsu, 2008; Parasuraman et al., 2005 |
| | De1 - The webstore correctly delivers the product that I ordered. | |
| | De2 - The delivery time is convenient. | |
| | De3 - The shipping and handling charge is reasonable. | |
| | De4 - The webstore provides me convenient options to return a product. | |
| | De5 - This webstore offers a meaningful guarantee to return a product. | |
| *Interactivity* | | |
| | In1 - The interaction level at this website enables me to choose product features to fit my personal preferences. | New |
| | In2 - At this site I can access to personalized accounts or private messages | |
| | In3 - The level of interaction at this site is about right. | |
| | In4 - The website offers an online community where I can share product information and shopping experiences with other customers. | |
| *e-Satisfaction* | | Tsai and Huang, 2007 |
| | Sat1 - In general, the products/services of this online store meet my expectations. | |
| | Sat2 - Overall, this is a good online store to do business with. | |
| | Sat3 - My choice to purchase from this online store was a wise one. | |
| | Sat4 - In general, I am satisfied with the services or products this online store provides. | |
| *Site Recommendation Intention* [b)] | | Kim and Son, 2009 Yang and Peterson, 2004 |
| | Rec1 - I will recommend the website to anyone who seeks my advice. | |
| | Rec2 - I would post positive messages about the website on some Internet message board. | |
| | Rec3 - I will refer my acquaintances this is a good online store to do business with. | |
| | Rec4 - I will invite friends and relatives to do business with this website. | |
| | Rec5 - I will refer product novelty and promotions that website send me that match my friends' needs. | New |

a) Items measured on a five-point Likert scale ranging from (1) Strongly disagree to (5) Strongly agree
b) Items measured on a five-point Likert scale ranging from (1) Very unlikely to (5) Very likely.

# Chapter 2

## A dual mechanism of customer retention in the context of online commerce

The ability to retain and lock in customers in the face of competition is a major concern for online businesses, especially those in which customers have lower switching costs. Although researchers and practitioners in the field of e-commerce are now paying more attention to online customer post-adoption behavior, the focus previously was on the drivers of technology adoption and use. In this paper, we drew on information systems and consumer behavior literature to formulate a conceptual framework that considered two mechanisms, commitment-based and constraint-based drivers of online customer retention. We develop and implement an approach for measuring the determinants and magnitude of customer's switching costs and repurchase behavioral intentions. Furthermore, the potential interrelationships between these drivers were explored, examining how firm-and individual-specific investment factors affect switching costs and retention. We then empirically test our hypotheses using data obtained from a large online retailing store selling different goods. The results strongly support most of the hypotheses. The findings indicate that while the importance of personalization benefits is equally significant across the two mechanisms, the search costs influence switching costs and loyalty rewards influence repurchase intentions for online stores. We also find important customers' characteristic, such as loyalty card holder is associated with increased repurchase intentions and increased perceived loyalty reward benefits. Theoretical and managerial implications of the findings are discussed.

***Keywords***: online store; customer retention; switching costs; search costs; personalization; loyalty rewards, and repurchase intention.

## 2.1 Introduction

The ability to retain and lock in customers in the face of competition is a major concern for online businesses. Especially, due to the intense competition and consumers' lower switching costs in the electronic markets (Brynjolfsson and Smith, 2000; Shapiro and Varian, 1998; Bakos, 1997). Sustained online purchases through consumers' patronage at the post-adoption stage are known as a key to the survival of an online retail provider. Although a firm's survival depends on repeated purchases, is also influenced by a variety of other behavioral outcomes that include, but are not limited to, willingness to repurchase, and switching costs that lead to inattentiveness to alternatives. Unsurprisingly, online firms are eager to effectively manage individuals' post-consumption experiences with their products and services (Kim and Son, 2009; Benbasat and DeSanctis, 2001).

The information system (IS) literature explains various adoption behaviors, especially related to individuals' acceptance and use of Internet technology (Davis, 1989). Accordingly, prior IS research has been focusing on technical features of online services (e.g. Internet applications and website characteristics) when examining customer retention or switching behavior towards an online provider (Tsai et al., 2006; Chen and Hitt, 2002). However, Internet technical features do not fully explain consumers' retention behavior within an ongoing relationship with an online retailer. In view of that, the IS literature has little relevance for those who seek to understand online consumer retention at post-adoption stages. As with IS research, research on e-consumer behavior suggests that post-consumption behaviors are the key to a firm's survival in the highly competitive marketplace (Reichheld and Schefter, 2000). Repeated purchases which drive sustained online store sales, is one such behavioral outcome, but the literature also suggests that others, such as switching costs are critical, especially in the online environment.

Taking advantage of technology features, online business are increasingly investing in strategic customer retention plans. First of all, personalized recommendation systems, based on collaborative filtering may increase repeated purchase intention on the Internet. Typically firms use low prices, high quality or good service as strategies to retain customers. But there are other ways. Amazon.com gives out free coffee mugs, tshirts, upgraded shipping, and other bonuses. They offer customized services based on the shopping history of their customers that would be difficult for competitors to imitate. If all interaction with a customer is via a Web site (browser), it is easy to capture that information and offer rewards to customers based on their purchase history or referral behavior. Secondly, online retailers currently offer loyalty rewards (e.g. points, credit, discounts) encouraging customers to make repeated purchases from their websites. Consequently, another strategic firm-investment which was expected to become more widespread in Internet retail is the frequent-purchaser program. As a fast growing medium, online retailing represents a highly expandable channel category that is quickly displacing traditional channels. Thus, loyalty programs offered in this new channel make it even more appealing to consumers, and encourage them to buy more from this channel rather than from traditional stores.

Recently, the IS literature suggests that post-adoption behaviors are driven not only by perceived benefits offered by firms, but also by customer-specific investments or constraints that tend to “lock-in” customers towards a specific retail provider, which in turn increases the perception of switching costs (Kim and Son, 2009; Chen and Hitt, 2002; Karahanna et al., 1999). Switching costs by definition represent a constraint on a buyer’s exploration of new vendors. Specifically, in a technology-intensive environment, such as electronic commerce, constraints tend to grow with intensive use: e.g. personalization features, registration of personal data, customer profiles, e-mail messages, intensive search and information overload provided by search engines and shopbots are time-consuming actions. Although shopbots and other search engines provide easy access to a huge amount of information in a few seconds, it takes time and effort to evaluate and compare this information overload. Those who invest in using them end up with a lower price, but at the cost of a more elaborate search (Smith, 2002; Greenwald and Kephart, 1999).

Literature maintains that switching online providers often involves search costs, learning costs, personalization costs (Kim and Son, 2009; Balabanis et al., 2006; Chen and Hitt, 2002) . These costs merely arise from technological constraints imposed by website interaction. Customers in a constraint situation realize that they have to continue with the current provider, and that actively looking for alternatives makes no sense. Despite, the evidence that switching costs have a significant impact on repeat choice behavior (Heide and Weiss, 1995), there is little solid empirical research on switching costs which reflects the wide range of customers' investments which limits customers' switching behavior. As Shapiro and Varian (1988) point out: "You just cannot compete effectively in the information economy unless you know how to identify, measure, and understand switching costs and map strategy accordingly" (p. 133). This is even more relevant, especially in the non-contractual online retail environment, where it has been claimed consumers have lower switching costs and zero search costs (Brynjolfsson and Smith, 2000; Varian, 2000; Bakos, 1997). However, they are not deeply explored in the e-consumer behavior research.

In an attempt to extend e-commerce post-consumption research this study develops and tests a model that explains customer maintenance towards a current provider in the context of online retail. Drawing on a dual model of relationship maintenance in consumer behavior research (Kim and Son, 2009; Tsai et al., 2006; Bendapudi and Berry, 1997) we propose a conceptual framework to study and explain online customer retention drivers.

In particular our dual model of e-customer retention builds on two key mechanisms: (1) the consumer's commitment to the firm as generated by the prospect of long-term mutual benefits to maintain an ongoing relation (Srinivasan et al., 2002; Oliver, 1999), and (2) the constraint that makes it difficult for the customer to switch to an alternative provider (Lam et al., 2004; Burnham et al., 2003; Jones et al., 2002, 2000). The former is driven by firm-specific investments such as personalized recommendation systems and loyalty rewards to provide customer benefits to maintain an ongoing relation with the online provider are likely to influence positively repurchase intentions. The search costs and personalization representing the constraint mechanism are likely to impact positively consumer perceptions of online switching costs. Taken as a whole, the constraint-based mechanism is essentially seen in the Internet technology (IT) context as a technology-based constraint given by the customer-specific investments. However, the commitment-based mechanism is not exclusively specific to Internet business, but to other firm-specific investments.

More specifically, the dual model of online customer retention proposed in this study is designed to address the following interrelated issues.

First, few in the e-commerce research area have examined online consumer behavior from these two perspectives. One of the goals of the present study is to identify the commitment and constraint factors that are operative specifically in the context of online retail, and test that both mechanisms are important to explain online customer retention.

Second, although personalization (e.g. customization) has been shown to influence online switching costs, little is known about whether the same factor determines both constraint and commitment. This study is intended to carefully examine whether personalization is simultaneously an important measure of the effectiveness of both mechanisms.

Third, to the best of our knowledge no studies have taken into account search costs and loyalty reward variables in order to explain constraint and commitment outcomes, respectively. Besides, both variables have been relatively ignored in consumer retention research in the Internet retail context. Therefore, this study is intended to examine whether the constraint and commitment outcomes have different antecedents.

Finally, this study examines the potentially differential effects on constraint and commitment of different antecedents on different customers' characteristics.

In essence our proposed model provides a theoretical account of how the commitment- and constraint-based mechanisms differ in their antecedent and outcome variables. The findings of this study are expected to shed light on online consumer behavior literature, providing empirical evidence on how the two contrasting mechanisms simultaneously, yet differentially, shape the nature of ongoing relations in the context of online B2C retail.

The study results also provide contributions to management. Online firms could analyze trade-offs between investments in positive switching costs and other retention programs. Hence, we are convinced that switching costs remain a useful measurement construct, especially for online business in a highly competitive and non-contractual context where customers have lower switching costs. As a result, the cost of monitoring and managing customers' switching costs is central to online firms' sustainability. It becomes a marketing axiom that it is from four to six times less costly to retain old customers than to develop new ones, so managers should give top priority to creating strategies that build and maintain customer loyalty (Reichheld and Schefter, 2000).

The organization of this paper is as follows: The next section reviews relevant literature in the information systems and consumer behavior areas. Subsequently, the section 2.3 develops a structural model of online consumer retention and proposes relevant research hypotheses. The research methodology is described in the section 2.4. We specifically chose to examine actual customers of a leading online retailer to collect data. The online retail industry is one of the most rapidly growing sectors of the digital B2C economy according to Boston Consulting Group; hence it seems timely and relevant to assess the validity of the theoretical framework in an online retail context. The section 2.5 presents the results of data analysis and the research hypotheses. This paper concludes with a discussion of research findings, the limitations of this study, and the opportunities for further research.

## 2.2 Theoretical background

Literature on e-consumer behavior posits the existence of two mechanisms of customer retention: first customer commitment, the desire-based cognitions are the determinants to maintain an ongoing relationship with an online provider. The rationale behind this mechanism is that (1) a customer considers the current value of the relationship (e.g. perceived benefits) as a cue from which to infer the future value, and (2) the consumer is likely to favor a long-term relationship with the provider in anticipation of future value (Parasuraman and Zinkhan, 2002; Oliver, 1999) .

Second, customer constraints, the constraint-based cognitions, entail a consumer’s cognitive effort (i.e. post-adoption rationalization) driven by potential losses when considering switching from an incumbent online provider. Switching costs, in the context of an ongoing relationship with an online provider, involve Internet technology constraints because all the interaction with the provider is via a website. Basically, prior IS and e-commerce (EC) research have been focusing on technical features of online services (e.g. Internet applications and website characteristics) when examining customers’ switching behavior towards an online provider (Kim and Son, 2009; Tsai et al., 2006; Chen and Hitt, 2002).

In particular, the new stream of research shows that Internet post-adoption behaviors are mainly driven by the perceived fit between the Internet application and the user's needs, which require continued interactions (Bhattacherjee, 2001; Karahanna et al., 1999). Prior research found perceived usefulness and ease of use the major drivers of Technology Adoption Model (Davis, 1989), nevertheless they are very restrictive in predicting post-adoption behaviors. Trust and value are obviously key determinants of customer retention, especially towards an online retailer (Gefen et al., 2008; Gefen et al., 2003). Moreover, the constructs are over-researched and are very restraining in their contribution to guide managerial strategic investments into customer retention.

Considering that post-adoption behaviors can be framed within the larger context of individuals' reactions to an Internet retail provider, the efficacy of traditional IS models in predicting post-adoption behaviors is limited (Kim and Son, 2009; Jasperson et al., 2005). According to Jasperson et al. (2005) rational task-technology fit models fall short of explaining post-adoption behaviors because the traditional models ignore a user's history of interacting with the Internet application. Probably this limitation of traditional models may simply reflect that Internet technologies had not yet matured at the time, a question that can be explored in future research. Let us take an example of an online retailer that offers IT enabled personalization capability to customers. In today's digital environments customers' purchase history can be tracked in order to adapt customized product offers. For example, Amazon.com offer customized services based on the shopping history of their customers (e.g. customer profile) that would be difficult for competitors to imitate. Initially, online consumers may perceive the availability of personalization as a potential benefit. Yet it takes time to build a personal profile, and such a profile is not easily transferable to another website. Thus, the use of a personalization feature could result in customer service-specific investments that later create "lock-in" (Gilmore and Pine, 2002). Moreover, although many customers actively take advantage of the personalization feature and develop ongoing relationships with the online retail provider, not every customer would want to invest the time that such a personalization feature require or to give private information to be profiled online (Awad and Krishnan, 2006). Thus, for a better understanding of post-consumption behaviors that foster customer retention, more attention should be paid to such customer-service-specific investments as personal profiles and the extent of time and effort that vary widely over time with a customer's history of using a specific Internet application.

The preceding discussion indicates that online consumers may choose to continue to use the same retail provider because either the product or service are deemed to offer value (i.e., perceived benefits), or because they simply feel locked in (i.e., customer-specific investments). This implies that at least two contrasting forces - i.e. constraint-based and commitment-based - are in play in determining the customer-firm relationship and shaping post-consumption retention behaviors. Likewise, a number of studies in other disciplines have shown that these two motivational factors characterize a variety of relationships (Bendapudi and Berry, 1997; Dunham et al., 1994).

Social exchange theory provides a theoretical outline for the analysis of long-standing relationships driven by these two different factors. According to social exchange theory, people are believed to engage in ongoing relationships "either because they genuinely want to or because they believe that they have no option" (Wulf and Odekerken-Schröder, 2001), p.86)). Specifically, within this conceptual framework, two different types of retention, namely commitment and constraint, characterize relationship maintenance (Bendapudi and Berry, 1997); whereas commitment-based relationship maintenance is based on attitudinal commitment resulting from "genuine appreciation for the relationship" (p. 20), constraint-based relationship maintenance centers on locked-in "economic, social, or psychological" investments (p. 18). This theory has been shown to be useful in analyzing long-term relationships such as personal relationships (Stanley and Markman, 1992), employee-firm relationships (Dunham et al., 1994), and customer-firm relationships (Bendapudi and Berry, 1997). Clarification of the complex nature of online customer behavior requires an understanding of the subtle implications/nuances that the customer-firm relationship may entail. Accordingly, social exchange theory, along with its notions of commitment and constraint, is likely to offer a theoretical basis for explaining online consumer behavior with regard to enduring business-to-consumer relationships.

In the consumer behavior literature, a customer's commitment to a service is often examined through loyalty. Loyalty refers to the individual's deeply held affective commitment toward the service (Oliver, 1999). This type of dedication commitment occurs in anticipation of long-term benefits from maintaining an ongoing relationship with the partner. In general, people expect that a provider who delivers value at present will continue to perform consistently in the future. Thus, the formation of loyalty is initially based on individuals' current perceptions of the benefits of maintaining a relationship with the incumbent provider (i.e. perceived benefits). However, the perceived benefits, which focus on the transactional value of the product and/or service or the loyalty rewards for repeated purchases, may foster ongoing customer-firm relationships. Many online retailers are currently offering customers' loyalty rewards (e.g. credits, points, bonus, etc.) as benefits or incentives for customer maintenance with the provider. Consequently, it is such a commitment that eventually leads to behavioral outcomes, such as repeated purchases oriented toward long-term benefits for both parties involved (Lam et al., 2004; Yang and Peterson, 2004).

Customer loyalty is widely known as an essential component for the survival of a firm in an offline setting. Yet loyalty is regarded as an even more prominent factor in the profitability of online businesses. This is because, recommendations and support from loyal customers can be spread faster across the Internet than in face-to-face media (Reichheld and Schefter, 2000). An increasing body of research consistently shows that repurchase behavior, or dedication commitment outcome, is an important predictor of customer retention in online service settings (Kim and Son, 2009; Tsai and Huang, 2007; Balabanis et al., 2006; Chen and Hitt, 2002; Srinivasan et al., 2002).

In marketing literature, customer constraint behaviors towards a current provider are often examined through switching costs. Switching costs refer to the extent to which a customer feels dependent on a provider because of economic, social, or psychological investments that would become useless in other alternative providers (Burnham et al., 2003; Jones et al., 2002). A number of studies in the digital economy literature provide evidence that online switching costs are mainly influenced by technological interface (Brynjolfsson and Smith, 2000; Shapiro and Varian, 1998; Bakos, 1997). The literature maintains that switching online providers often involves search costs, learning costs, and personalization costs. These costs are merely the result of technological constraints imposed by website interaction. As mentioned earlier, many online retailers are currently offering customers product information in a highly personalized form. However, personal data (e.g., e-mail messages, customized information) that are accumulated as a result of one's ongoing relationship with the provider cannot be easily transferred to other webstores (e.g. online registering, customer profiles). Moreover, customers incur search costs when they decide to choose an alternative online provider, which entails searching and comparing information about competitive online retailers (e.g prices and product characteristics, shipping and delivery or return conditions). For example, shopbots and other search engines (such as Yahoo shopping, Google, Bizrate, MySimon, Priceline) query dozens and dozens of sites and report back price, availability and shipping charges in a few seconds. On a recent query the total price for a particular book varied from $25.08 to $42.84! However, these infomediaries provide easy access to a huge amount of information in a few seconds and it takes time and effort to compare this vast information. Probably this is truer for routinely buying products (e.g. commodities). Given these this search cost paradox, several researchers have investigated the economics of shopbots and find that those who invest in using them end up with a lower price, but at the cost of a more elaborate search (Smith, 2002; Greenwald and Kephart, 1999).

In such a case, where the overall costs of switching to another online provider are relatively high, the customer may need to stick with the current service not because of commitment but because of constraints. Switching costs are known to represent such a constraint-based commitment, which ultimately leads to behavioral outcomes that are performed reluctantly just to avoid the termination of a relationship with the incumbent provider (Lam et al., 2004; Burnham et al., 2003; Jones et al., 2000). Indeed, much research empirically shows that switching costs regulate consumers' post-consumption or post-adoption reactions to online providers both in (non)contractual settings (Kim and Son, 2009; Tsai and Huang, 2007; Balabanis et al., 2006; Chen and Hitt, 2002). Thus, the concept of switching costs, which represents a constraint-based mechanism of customer retention, is considered a key to understanding relationship maintenance in online B-to-C settings.

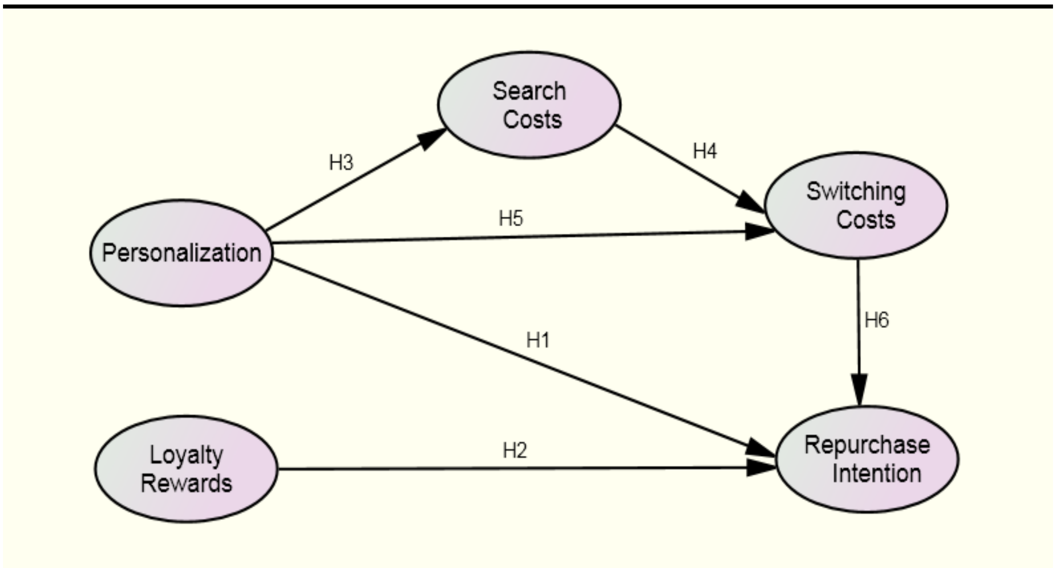
In summary, the IS literature suggest that customers' response towards an incumbent online provider (i.e. maintaining an ongoing relationship with an online provider) are driven not only by perceived benefits of customer incentives, but also by customer-specific investments. In addition, the marketing literature points out that commitment and constraint behaviors determine the nature of relationship maintenance. It should be noted that whereas perceived benefits appear to be the driving force of commitment

(Oliver, 1999), customer-specific investments are considered the major source of constraint (Kim and Son, 2009; Shin and Kim, 2008). Thus, the IS and marketing perspectives seem to complement each other nicely to offer a better explanation of online customer retention phenomenon.

## 2.3 Conceptual model and hypotheses

A model of a dual mechanism is proposed in this study for examination of online consumer retention behavior in the context of an ongoing relationship with an online retailer. Figure 2.1 depicts the proposed model. It focuses on three key antecedents of customer retention (search costs, personalization and loyalty rewards) and two outcomes of customer retention: customers switching costs perceptions (e.g. the constraint-based mechanism) and repurchase intention (e.g. the commitment-based mechanism). The major purpose of this dual model of customer retention is to demonstrate that the intervening antecedents and outcomes variables are quite different in both constraint and commitment-based mechanisms. This section provides a theoretical rationale for the two mechanisms and proposes research hypotheses.

Figure 2.1 Hypothesized model




Notes: For the sake of simplicity each factor’s measurement indicators and error terms are not included in the figure.

### 2.3.1 Commitment-based mechanism

**Repurchase intention**

The commitment-based mechanism centers on the concept of repurchase behavioral intention which is an important customer retention and loyalty outcome (Tsai and Huang, 2007; Oliver, 1999). Repurchase intention refers to the degree to which a customer thinks he or she will return and rely upon the provider. According to Bendapudi and Berry (1997), repeated use is a dedication-based, as opposed to constraint-based, behavioral outcome. Repeated use tends to raise the investments specific to the customer-firm relationship, and thus it will eventually lead to a stronger tie between the customer and the firm. Thus, a loyal customer who is dedicated to establishing a long-term relationship with the firm (i.e., true commitment) is willing to visit the webstore more frequently, makes greater relationship-specific investments, and establishes a stronger relational bond with the firm.

According to the dual model proposed in this study, perceived benefits of personalization and loyalty rewards serve as the basis for the formation of repurchase intentions. The rationale behind this proposition is that (1) a customer considers the current value of a relationship with the retailer (e.g. perceived benefits of personalization and loyalty rewards) as a cue from which to infer the future value of the transaction relation (e.g. ongoing benefits), and consequently the customer is likely to favor a long-term relationship with the provider in anticipation of future value.

Through this process the consumer intends to engage in repeated purchases from the online provider that currently offers some benefits; that is, personalized product offers and promotions that match customer needs, and loyalty rewards, which correspond to current value, will have positive effects on repurchase intentions, which is the customer's attitudinal attachment to the provider. A basic premise of this reasoning is that consumers will have positive behavioral intentions toward a retailer, vis-à-vis other alternative providers, if they have had some rewarding purchase experiences.

Accordingly, Oliver's (1999) conceptual framework, loyalty - which indicates a favorable attitude toward maintaining a long-term relationship with the provider - results from cognitive perceptions about the current value of using the provider. Overall, it is reasonable to expect that online customers tend to be repeat consumers because they believe their ongoing interactions with the online provider will be beneficial in the long run, even if this is not the case at the moment.

**Loyalty rewards**

There is a general agreement that retailers are often torn between the need to stimulate customer retention and well established promotional techniques, which encourage customers to make repeated purchases, preventing customers from switching between different shops and brands. Loyalty reward schemes are often based on classical promotional techniques, with delayed or immediate rewards (e.g. gifts, price reductions, credit points) which encourage consumers to purchase more often, and remain loyal to the store (Meyer-Waarden, 2007; Lewis, 2004).

We define loyalty rewards as the long-term-oriented programs that allow consumers to accumulate some form of program currency, which can be redeemed later for free rewards. For example, an airline’s frequent-flier program represents a typical loyalty program. A number of studies show that long-term loyalty programs that offer consumers delayed rewards, rather than one-shot reward promotion, are more likely to produce sustained customer loyalty or revenue potential for a firm whereas one-shot promotional features do not (Leenheer and Bijmolt, 2008; Liu, 2007; Keh and Lee, 2006; Lewis, 2004; Yi and Hoseong, 2003; Zhang et al., 2000).

In line with prior research, we believe that loyalty programs are designed to create a future orientation towards the current provider and increase sales over the long run. Because the nature of loyalty rewards is quite misleading, we introduce here some discussion on the theme. The literature refers to loyalty rewards as artificial switching costs deliberately built up by firms to lock-in customers. The nature of artificial switching costs is well-examined in the literature and we refer readers to Burnham and colleagues’ (2003) work for more detailed information on the topic. In fact, artificial costs related to contractual or initiation fees are designed by firms to create switching barriers not to lose subscribers by increasing hidden costs and subscriber lock-in (Shin and Kim, 2008; Zauberman, 2003). Basically, these nontransferable investments customers have already incurred are sunk costs. But online retail is typically free from contractual or initiation fees to the consumers. This being so, in a highly competitive non-contractual online retail environment, it is common for firms give customers frequent purchase rewards.

Taking a forward looking value approach, we argue that loyalty programs, instead of creating switching costs, are designed to give customers positive future gains if they remain with an incumbent provider, without the significant burden or constraint of switching cost (e.g. contractual hidden costs that lead to customer lock-in). Unlike switching costs resulting from artificial costs, loyalty programs relate entirely to firms' positive actions, such as rewarding customers for repeated use (Varian, 2000). In our view customers represent the best asset of a firm and should be rewarded for their value. Thus, in our conceptualization loyalty rewards are different from artificial switching costs and are created to retain customers, increasing spending and gaining customer insights (Nunes and Drèze, 2006).

As mentioned earlier, repurchase intention is considered one of the most important loyalty outcomes (Kim and Son, 2009; Tsai and Huang, 2007; Srinivasan et al., 2002) which represents the commitment-based mechanism. Such commitment is influenced by customers' perceived benefits of loyalty rewards, which leads to repurchase intention and consequently leads to mutual benefits between a customer and a preferred vendor.

**Personalization**

It is generally known in IS research that the personalization factor, in essence, captures the perceived value of using an IT application concerning e-commerce usefulness. We define personalization as "personalized recommendations on products or services to customers matching their profiles based on a purchase history and feedback data".

In some e-commerce environments intelligent agent-based systems provide personalized recommendations on products or services to customers (e.g. collaborative filtering) using explicit ratings on items from users' explicit feedback data, in order to increase recommendation accuracy (Lee et al., 2008). For example, Amazon.com offers customized services based on the shopping history of their customers (e.g. customer profile) that would be difficult for competitors to imitate. We believe that customized services related to personalized product offer and service alert that match the customer profile (e.g. bundling, promotions, new product related, birthday card offer) might increase customers´ benefits in maintaining a relationship with an online provider.

However, this requires a history of customer interactions. Thus, we suggest one way for online firms to retain customers for repeated purchases is to provide personalized recommendations based on retrieved optimal product information that really interests the customers.

In several studies in the domain of IS research have found that effective recommender systems, providing personalized recommendations, base their operation on past user ratings over a collection of items, for instance books, CDs, etc., and the customer's current preferences obtained from the iterative system-customer interactions (Symeonidis et al., 2008; Lee et al., 2002). Furthermore, several researchers found in the context of online B-to-C that "customization-based" is a major determinant of e-repurchase intentions and potentially impacts e-loyalty (Tsai and Huang, 2007; Srinivasan et al., 2002).

In line with prior research, we suggest that customers will perceive the benefits of personalized recommendation features as a cue for the potential value to maintain an ongoing relationship with the online provider. The foregoing discussion implies that in an online retail context, perceived value of personalization and loyalty rewards are expected to positively influence online repeated purchase intention. Taken together, we propose the following hypotheses:

H1: The extent of perceived benefits of personalization performed by an online retailer will be positively related to repurchase intention.

H2: The extent of perceived benefits of loyalty rewards offered by an online retailer will be positively related to repurchase intention.

### 2.3.2 Constraint-based mechanism

**Switching costs**

The constraint-based mechanism focuses on the concept of switching costs, which reflects the full number of sacrifices that customers associate with the process of switching from one provider to another (Burnham et al., 2003). Switching costs are conceptualized as a cognitive-level construct in this study, which entails a consumer's cognitive effort of a post-consumption rationalization driven by potential costs when considering switching from an incumbent provider. Accordingly, a number of studies refer switching costs to a constraint response when customers face switching to another provider, because of their perceptions about the investments devoted to a certain provider that are not easily transferable to other providers (Kim and Son, 2009; Balabanis et al., 2006; Lam et al., 2004; Jones et al., 2000).

In the economics literature the concept of cost "is the value of sacrificed opportunities and is based on the concept of opportunity cost" (Besanko and Braeutigam, 2005). Because costs are not necessarily synonymous with monetary outlays (expenditures), economists distinguish between explicit costs (which involve a direct monetary outlay) and implicit costs (which do not involve outlays of cash).

Existing theory on switching costs[6] posits that switching costs may perceive impediments ranging from search costs, transaction costs, learning costs, customer habit, emotional costs and cognitive effort, linked to financial, set up, relationship loss costs on the part of the buyer (Burnham et al., 2003; Jones et al., 2002; Fornell, 1992; Klemperer, 1987). More specifically, switching online services may include impediments ranging from search costs, evaluation costs, transaction costs, learning costs, personalization costs, and artificial costs (Chen and Hitt, 2002; Jones et al., 2002). Transaction and learning costs are considered not relevant as website design and online transaction features are becoming standard among competing websites. In this sense, the investment in effort and time incurred in learning to use the website and how to use the service may not be relevant to customers' switching costs. Unlike, artificial switching costs which are created deliberately by service providers to lock-in customers (e.g. initial fees), loyalty rewards are clearly not customer investments. As we discussed earlier, loyalty rewards provided by online retailers result entirely from firms-specific-investments to keep current customers in the relationship.

Thus, we consider the two types of customer-specific investments to contribute to the formation of online switching costs: (1) personalization which represents the effort required for customers to put personalized information on the website, and (2) search costs which occur when customers search and evaluate new alternative providers.

[6] For more detailed discussion on switching costs, Burnham, Frels and Mahajan (2003) offer an excellent study of switching costs typology.

**Personalization**

Personalization was earlier conceptualized as customer perceived-benefits that relate to one's history of interacting with an online retailer over time, but also involves customer-specific investments. In this sense, personalization relates to investments in personalized information (e.g. explicit information) provided to the online retailer which is expected to affect switching costs. Personalization relates to initial setup costs and ongoing usage costs. Specifically, if the provider knows the customer well through the personal profile accumulated in the website, the provider is likely to serve the customer better than competitors will. Thus, they incur ongoing usage costs if they leave the provider**.** The customer will recognize that he or she will have to go to the trouble once again of setting up the complex personal data necessary to receive the same level of optimal product information that matches the customer profile, from a new provider. Accordingly, the customer's investment in providing personal information to the incumbent online provider is not necessarily transferrable to other provider. As such, the customer - who took the time and effort to upload the information, following procedures, and features of the service (e.g., the amount of information to provide, how to get personalized information from the website, email messages, etc.) - tends to consider the costs of switching as rather high. In addition, "personalized recommendation service" based on customers' profiles as early related to firm-investments, individuals could take no effort to develop, but lose a lot of benefits when they switch providers. Through this process the consumers consider the loss of non-transferable benefits they incur when switching provider that currently offers some benefits, which corresponds to potential future value of maintaining an ongoing relationship. Thus they must allocate irrecoverable resources to develop a relationship with a new e-retailer (Kim and Son, 2009; Tsai and Huang, 2007).

In line with this reasoning, recent empirical studies find that online switching costs are mainly driven by: service customization from an online retail store (Tsai and Huang, 2007; Tsai et al., 2006); the time and effort spent to actively customize information into the websites required by the use of personalization feature of Web Portal (Kim and Son, 2009), or defining a personal profile and registering on the website takes time and effort (Balabanis et al., 2006). Drawing on the well-recognized economics literature (Klemperer, 1987) those investments are basically "sunk costs", but people tend to expect that a similar amount of time and effort will be required to switch to another online retailer (Jones et al., 2002).

**Search costs**

Search costs are related to customer specific-investment incurred in searching for information about the incumbent online provider and are associated with switching costs (Lam et al., 2004; Burnham et al., 2003; Jones et al., 2002). Accordingly, the customer incurs search costs to actively search and evaluate information about competitive online retailers and to discover the prices and characteristics of products (Bakos, 1997). Moreover, it was predicted that great price differences on the Internet potentially increase consumers' search costs (Brynjolfsson and Smith, 2000). Despite the fact that Web-based price comparison agents have been generally viewed as beneficial to consumers, this is not totally obvious (Smith, 2002). In line with this reasoning, we suggest that Internet consumers should invest time and effort to systematically compare a great amount of information, especially for routinely buying commodity products. Likewise, the customer who took the time and effort to search for information about alternative online providers (e.g. to assess and compare information, etc) is likely to realize that switching costs will be high, because the effort and time required to assess the information overload will be huge, even if it is easy to obtain the information. Thus the searching effort required to assess competitive alternative providers for products routinely buying is believed to positively influence overall switching costs. Several studies indeed show that switching costs tend to reduce the number of alternatives (Heide and Weiss, 1995) and decrease the propensity to search for alternatives (Zauberman, 2003). Thus we hypothesize that as search costs increase, online customers are more likely to decrease their propensity to search for alternatives, which will positively influence switching costs. Therefore, we propose that searching for and evaluating competitive online providers will be one of the major sources of the formation of online switching costs.

Moreover, the customer who undertook personalization investment will perceive higher search costs. More specifically, we mean the cost for one additional search will be high in the presence of personalization costs and consequently both potentially strengthen the influence of switching costs. Our view seems to be in line with IS research. In previous studies collaborative filtering was found to be a successful recommendation technique that confronts the "information overload" problem (Symeonidis et al., 2008). Hence, personalized recommender systems are a strategic resource to increase customers' costs when searching for an alternative retailer. Therefore, personalization investments will decrease customers' propensity to search and switch from their current provider.

It therefore seems reasonable to argue that in the context of online retail, such customer-specific investments as the extent of their personalization and the extent of their search costs will be the basis for the formation of constraint behavior, or switching costs. Thus, we propose that personalization and search costs will be the major sources of the formation of switching costs towards an online retailer. Moreover, search costs will mediate the relationship between personalization and switching costs.

Taken together we hypothesize the following:

H3: The extent of perceived personalization will be positively related to search costs.

H4: The extent of perceived search costs will be positively related to switching costs.

H5: The extent of perceived personalization will have a direct effect on switching costs (a), and will be mediated by search costs (b).

The proposed model in Figure 2.1 shows that overall switching costs influence repurchase intentions. Switching costs, by definition, are potential costs that could result from terminating the existing relationship and establishing a new one. Thus we propose that customers in a constraint manner and feeling "locked" in tend to engage in ongoing purchase behavior. Repurchase intention, as earlier conceptualized as a commitment-behavior, defines a buyer's overall intention to return and rely upon the provider. According to Oliver (1999), repurchase intention is one of the outcome measures of the loyalty concept (e.g. attitudinal loyalty) as loyalty manifests itself in a variety of behaviors: repeated purchases (e.g. behavioral loyalty) and commitment (e.g. attitudinal loyalty) and both measures are important.

Consistent with this line of reasoning, the literature maintains that switching costs are strongly related to repurchase intentions. Several conceptual and empirical studies have posited switching costs or barriers as a key determinant of repurchase intentions (Balabanis et al., 2006; Tsai et al., 2006; Yang and Peterson, 2004; Jones et al., 2002). These switching barriers are intended to lock-in customers, to decrease their propensity to search and switch after an initial investment, which is determined both by a preference to minimize immediate costs and by an inability to anticipate the impact of future switching costs (Shin and Kim, 2008; Zauberman, 2003). Interestingly, some evidence indicates that in addition to perceived benefits, switching costs would positively influence the formation of repurchase behavioral intentions — suggesting a spillover effect of the constraint-based mechanism on the commitment-based mechanism (Kim and Son, 2009; Tsai and Huang, 2007; Dick and Basu, 1994). Bendapudi and Berry (1997) specifically mentioned self-justification as a psychological process underlying such a spillover effect. In particular, this line of reasoning posits that customers who are locked in tend to convince themselves that they committed the resources because they like the provider. It goes on to predict that as long as their provider is not opportunistic, customers will keep reinforcing their "post-commitment rationalization", believing that the nontransferable investments already incurred actually represent their commitment to the provider. Consistent with this reasoning, Dick and Basu (1994) argue that switching costs will positively influence customer loyalty. Specifically, in the context of online retail several studies showed that e-loyalty was a function of switching costs (Balabanis et al., 2006; Tsai et al., 2006; Srinivasan et al., 2002). In addition, Srinivasan et al., (2002) maintain that along with satisfaction, switching costs will ultimately influence loyalty. Accordingly, we expect that through the self-justification process, switching costs will have a positive impact on repurchase intention in the context of online retail. Therefore we propose the following:

H6: The extent of switching costs will be positively related to repurchase intention.

### 2.3.3 Moderating influence of loyalty card holder

From a managerial standpoint, it is important to consider what consumer characteristics accentuate the commitment-and constraint-based mechanisms. We consider one consumer characteristic, the loyalty card holder, as businesses are extensively using it to retain customers. We distinguish between two groups, those who own and those who do not own a customer card from the e-retailer. The perceptions that affect switching costs and lead to repurchase for the consumers owning a loyalty card may not be the same as those of consumers who do not agree to a loyalty program. Only by understanding the magnitude variation of these switching costs could firms measure trade-offs between investments in loyalty and retention programs and other types of investments such as advanced personalized services. The following hypothesis summarizes this discussion regarding the moderating roles of the consumer loyalty card holder in our proposed conceptual model:

H7: Loyalty rewards, switching costs and repurchase intentions are greater for loyalty card holder consumers than for consumers without loyalty cards.

## 2.4 Method

### 2.4.1 Research setting

We use an online survey to assess the drivers and outcomes of customer commitment and switching costs perceptions of real consumers from a leading online retailer (Fnac Online), selling different products directly on its website. We choose the online retailer as a specific empirical setting for this study for two main reasons: first e-retailers selling books, computers, software, music and technological products are among the most widely used online retailers. Given that our model was specifically developed to test switching costs perceptions in customers' mind which requires past use of e-shopping experiences.  Thus the online retailer is considered and appropriate setting in which to test it. Second, online retailers are increasingly using personalized features (e.g using collaborative filtering features to send customers tailored product promotions e.mail messages matching their specific interests and needs) and offering loyalty rewards for repeated purchases (e.g. credit points, coupons). These marketing activities of e-retailer made it possible for us to examine customer specific benefits (i.e. personalization and loyalty rewards), which have been studied far less in the information system domain and e-commerce settings. Taken together, the e-retailer appears to offer a desirable empirical environment for testing the efficacy of the model. Consequently, we attempt to test our model with data collected from actual consumers of one largest online retailer.

### 2.4.2 Data collection

We first developed an initial version of the questionnaire to tap into the proposed model. Whenever possible, previously tested questions were used. Then we asked several domain experts (including three e-commerce managers and five academic researchers) to review the preliminary questionnaire. Their feedback recommended that we redefine the wording of a few items for the sake of redundancy. Accordingly, we corrected some redundancy between items from search costs and switching costs constructs. Later we used 15 subjects among online consumers, doctoral students and faculties who are familiar with the issue of e-commerce to conduct a pilot test of the modified version of the online survey. The comments of these subjects were used to further refine the clarity of instructions and questions in the questionnaire. Finally, a field study using an online survey was conducted to collect the data necessary for testing the causal model and the hypotheses. We considered the population of interest to be composed of adult consumers of online retailer. Then the actual customers of the online retailer were used to collect a sample of respondents. The online retailer was asked to post on its website's homepage an invitation to customers participate in the survey and included a link to a Web-based questionnaire.

The online survey ran for eight weeks from June 2011 and we were able to collect a total of 577 responses. Incomplete questionnaires were eliminated. This resulted in a total of 308 valid questionnaires yielding an effective response rate of 53.4 percent[7]. After deleting cases with ambiguous values and outliers we obtained a usable sample of 300 online customers. The vast majority was aged between 25-39 years old, 62 percent were male, and 69 percent hold a higher degree of education. We found that 48 percent had Internet shopping experience for more than 5 years, and about half of respondents spent more than 5 hours a day on the Internet. By duration of customer relationship, 14 percent had a relation with the respective e-retailer for at least one year, 49.7 percent had a relation between one and three years, and 30.5 percent had a relation for more than three years. By frequency of purchases, 49 percent made purchases 3 to 4 times a year, and 76.9 percent hold the retailer loyalty card. Full results of the respondents' characteristics are summarized in the Appendix C.

[7] To ensure that only current consumers from the online retailer are included in the sample, we instructed non-consumers to stop the survey at the beginning and close their browsers. Because of this, the effective response rate was 53.4 percent reported here.

### 2.4.3 Measures

Scale measures used in this study were adapted mainly from existing scales that previous research has shown to be reliable and valid. In those cases in which appropriate measures were not available in the literature, we attempted to develop new ones. The specific items included in this study are shown in the Appendix D. Unless otherwise noted, the anchors for all items were 1= strongly disagree to 5= strongly agree.

To investigate search costs, we used a multi-item scale measure consisting of five items; four of them were adapted from Burnham et al. (2003) and Srinivasan et al. (2002) “modification” scale (i.e. questions were reworded to fit our online retailer context) and we developed one new item (i.e., “It is tough to compare systematically prices changes and product characteristics of competing e-retailers”).

The personalization scale measure included five items; three of them were adapted from Kim and Son (2009) and Tsai and Huang (2007). Because the concept of personalization has often been used in the context of e-service (i.e. website portal features), we took special care in developing additional measures covering e-retailing specific personalization features. We developed two new items based on the definition of the construct and adapted from Tsai and Huang (2007) “modification” scale: “The advertisements and promotions that online store provides are tailored to my situation” and “This online store makes me feel a unique customer”.

The loyalty rewards measure consisted of four items; two of them were operationalized based on “modification” scale measures of “artificial costs” in Burnham et al. (2003), and Tsai et al. (2006); the other two measures were newly developed: “It takes time and effort to accumulate benefits such as points, credits as a reward for being a loyal customer of this online store” and “Comparing to alternatives the rewards type that I received from this e-retailer for being a loyal customer provides me value”. We develop the measure of switching costs by referring to the existing scales. We drew especially upon the items used by Burnham et al. (2003), Kim and Son (2009) and Tsai and Huang (2007) to develop our five items that were used to capture the concept of switching costs. Repurchase intention was measured by four items adapted from Tsai et al. (2006) and Burnham et al. (2003). Special care was made to measure behavioral intention: first avoiding to be confused with loyalty concept because loyalty (e.g. affection related) has often been confused with its behavioral outcomes such as repurchase intention and word-of-mouse, we took care to capture only behavioral intentions. Secondly, special effort was taken to measure repurchase intention regarding the extent of continued repurchase, rather than using the use/non-use decision. The anchors for the items were 1= very unlikely to 5= very likely. Finally, a single item-scale was used to measure each of the demographic variables: age, genre, Internet shopping experience, purchase frequency, Internet usage, customer relationship length, online search patterns and loyalty card holder.

## 2.5 Data analysis and results

### 2.5.1 Measurement model

To assess the psychometric properties of the measures, we performed a confirmatory factor analysis (CFA) using AMOS (version 19). We evaluated model fit through multiple fit criteria, each of which represents a different aspect of the model. In particular, five fit indices examined in this study were the comparative fit index (CFI), the normed fit index (NFI), the root mean square error of approximation (RMSEA), the goodness-of-fit index (GFI), and the adjusted goodness of fit (AGFI). For each index, an acceptable level of fit is indicated as follows: CFI > 0.95; NFI > 0.95; RMSEA < 0.06; GFI > 0.90, and AGFI >0.80 (Gefen et al., 2000; Hu and Bentler, 1999). The measurement model included 5 factors with their final 16 corresponding indicators as listed in the Appendix D. Items deletion from the initial set of measures was determined by improvements on reliability and consistency (Ping, 2004, p. 132). As a result, the final itemization of measures was a trade off among consistency, unidimensionality, reliability, average variance extracted, and content or face validity. We ran the measurement model, and the results indicated that the model fit the data satisfactorily in terms of all the fit indices considered in this study: $\chi2(90) = 178.58$, $p < 0.001$, CMIN=1.984; CFI = 0.98, NFI = 0.96, RMSEA = 0.057, GFI = 0.93, AGFI = 0.90. Table 2.1 shows, based on our measurement model, the means, standard deviations, Cronbach’s alpha, construct reliability (CR), average variance extracted (AVE), and correlations of the measures.

To further ensure the psychometric properties of the measures, we examined the validity and reliability of the scales (Bagozzi and Yi, 1988; Fornell and Larcker, 1981). First, convergent validity is established if the factor loading of an item is 0.60 or more (Fornell and Larcker, 1981). We found from the CFA output that loadings ranged from 0.68 to 0.97, (see the Appendix D) indicating that the convergent validity of the scale measures was acceptable. Second, discriminant validity is shown if the square root of the AVE of a measure is larger than its correlation coefficients with the other measures (Fornell and Larcker, 1981). We found, as Table 2.1 shows, that each of the scales met the criterion mentioned previously; except for loyalty rewards against personalization (i.e. AVE equals its correlation) all other constructs have adequate discriminant validity. In testing for further evidence of discriminant validity among loyalty rewards and personalization, we compare a model in which the constructs of interest correlate freely, with one in which they are perfectly correlated (Bagozzi and Yi, 1990). This comparison yielded a $\Delta\chi2$ value that was statistically significant ($\chi2$ [1] = 13.827, $p < .001$), thereby suggesting only modest evidence of discriminant validity.

Table 2.1 Properties of measurement scales

| | Mean | SD | Alpha | CR | AVE | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1. SC | 8.90 | 3.44 | 0.91 | 0.91 | 0.78 | **0.88** | | | | |
| 2. PER | 9.13 | 2.78 | 0.85 | 0.80 | 0.58 | 0.39 | **0.76** | | | |
| 3. LOR | 9.90 | 2.89 | 0.77 | 0.79 | 0.56 | 0.31 | 0.75 | **0.75** | | |
| 4. SWC | 7.77 | 3.52 | 0.92 | 0.93 | 0.81 | 0.75 | 0.58 | 0.45 | **0.90** | |
| 5. REPI | 15.04 | 4.10 | 0.93 | 0.93 | 0.77 | 0.35 | 0.72 | 0.71 | 0.49 | **0.87** |

Notes: N= 300. Means are reported but not analyzed. SD = standard deviation; CR = composite reliability ≥ 0.7; AVE = average variance extracted ≥ 0.5. Value on the diagonal is the square root of AVE; Value below the diagonal is correlation. SC= search costs; PER= personalization; LOR= Loyalty rewards; SWC = switching costs; REPI = repurchase intention.

In addition, to convergent and discriminant validity, we also examined the reliability of the scales. Three types of reliability indices examined in this study were Cronbach's alpha, composite reliability, and average variance extracted. Acceptable levels of Cronbach's alpha, composite reliability, and average variance extracted are said to be 0.70, 0.70, and 0.50 or higher, respectively (Bearden et al., 1993; Bagozzi and Yi, 1988;

Fornell and Larcker, 1981). As showed in Table 2.1, the reliabilities of the scale measures (i.e., Cronbach's alpha ≥ 0.77, composite reliability ≥ 0.79, and average variance extracted ≥ 0.56) are all above the recommended values. Although not perfect, the level of model fit, validity, and reliability of measures seems to be very acceptable for subsequent tests of the structural model and the research hypotheses.

### 2.5.2 Test of research model and hypotheses

We used a structural equation modeling (SEM) technique via AMOS (version 19) to test the proposed model. In the structural model, the two antecedent factors (i.e. personalization and loyalty rewards) were specified as exogenous variables, whereas the three outcome variables (i.e. search costs, switching costs and repurchase intention) were treated as endogenous variables.

The results of data analysis showed that the proposed theoretical model satisfied the recommended criteria for all fit indices considered in this study, which suggests that the model fit the data reasonably well: $\chi 2$ (92) = 178.73, $p < 0.001$, CMIN=1.94, CFI = 0.98, NFI = 0.96, RMSEA = 0.056, GFI = 0.93, AGFI = 0.90. We also found that the proposed model explained a significant amount of variation in the endogenous variables: switching costs explain 67 percent, repurchase intentions 59 percent and search costs 15 percent. Taken together, our model was deemed to be a reasonable representation of individuals' reactions to an online retailer. Figure 2.2 shows the unstandardized regression estimates and the significance level of the relationships between the research variables. For the sake of brevity, the measured indicators and their corresponding paths and errors have been left off the diagram. Table 2.2 presents the full results of the SEM analysis, including the structural path regression estimates, standard errors, statistical significance and explained variances.

When examining the hypothesized relationships proposed to characterize the commitment-based mechanism the results strongly supported most of the hypotheses, except one. Specifically, the results showed that personalization and loyalty rewards were found to have a significant effect on repurchase intention (H1 and H2 supported). The effect of switching costs on repurchase intention was not statistically significant (H6 not supported). This finding seems to suggest that the commitment-and constraint-based mechanisms operate quite independently only being connected through the intervening personalization variable.

The hypothesized relationships proposed to characterize individuals' response to online switching costs, as a constraint-based retention mechanism, also received empirical support and the results strongly supported all the hypotheses. In particular, both perceived online search costs and personalization had significant positive effects on switching costs (H4 and H5$_a$ supported). In addition, we found that personalization significantly affected search costs (H3 supported) and indirectly affect switching costs through the mediation effect of search costs (H5$_b$ supported). Taken as a whole, the vast majority of the research hypotheses proposed in this study were empirically supported.

Table 2.2 Structural equation model results

| **Commitment-based Mechanism** | Regression Estimates | | | Statistics | | |
|---|---|---|---|---|---|---|
| | Unstandardized | SE | Standardized | CR | p-value | Decision |
| Direct Effects: | | | | | | |
| PER → REPI | 0.540* | 0.171 | 0.350 | 3.151 | 0.002 | $H_1$ supported |
| LOY → REPI | 0.475** | 0.122 | 0.390 | 3.886 | < 0.001 | $H_2$ supported |
| SWC → REPI | 0.120 | 0.073 | 0.129 | 1.635 | 0.102 | $H_6$ not supported |
| **$R^2$** | 0.59 | | | | | |
| **Constraint-based Mechanism** | | | | | | |
| Direct Effects: | | | | | | |
| PER → SC | 0.648** | 0.109 | 0.391 | 5.957 | < 0.001 | $H_3$ supported |
| SC → SWC | 0.620** | 0.045 | 0.622 | 13.832 | < 0.001 | $H_4$ supported |
| PER → SWC | 0.566** | 0.083 | 0.342 | 6.841 | < 0.001 | $H_{5a}$ supported |
| Indirect Effect: | | | | | | |
| PER → SWC | 0.402* | 0.085 | 0.243 (.154, .337)[a] | - | 0.007 | $H_{5b}$ supported |
| **$R^2$** | 0.67 | | | | | |

*p < 0.01; **p < 0.001 (two-tailed).

Notes:

SE= standard error. CR= critical ratio [a]Confidence interval bias-corrected at 95% confidence level for bootstrap distributions is defined using the values that mark the upper and lower 2.5% of each distribution. SC = search costs; PER = personalization; LOR= Loyalty rewards; SWC = switching costs; REPI = repurchase intention.

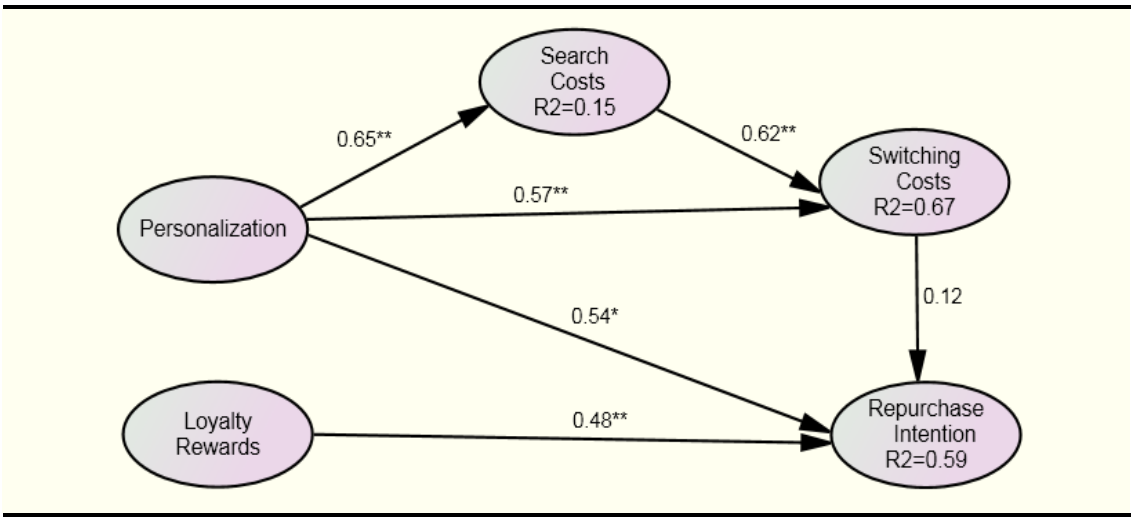
As shown in the lower panel of Table 2.2, a significant relationship exists between personalization and search costs ($\gamma = 0.65$, $p<0.001$), personalization between switching costs ($\gamma = 0.57$, $p< 0.001$), and search costs between switching costs ($\beta= 0.62$, $p<0.001$). In addition, the results indicate that the mediation mechanism was significant: personalization was found to have a significant indirect effect on switching costs ($\beta= 0.40$, $p< 0.01$) mediated by search costs. Hence, personalization indirect effect occur when the utility of perceived benefits (say, personalized product offers matching customers profiles) increases customers search costs and indirectly switching costs. As expected, these relationships support the constraint-based mechanism. This result is consistent with IT literature which posits that online personalized features based on collaborative filtering will impose customers the perception that the cost of an additional search will increase the cost for searching for alternatives.

The results also support the commitment-based mechanism. As we expected, and shown on the top panel of Table 2.2, we found that both personalization factor ($\gamma = 0.54$, $p< 0.01$) and loyalty rewards ($\gamma = 0.47$, $p< 0.001$) have a positive effect on repurchase intention. These results indicated that, although perceived benefits of loyalty rewards play an important role in determining customer's commitment-based outcomes through ongoing repurchased intentions, perceived benefits such as personalization also have a strong effect on the outcome. What we found here suggests that loyalty rewards, when added to personalization benefits may foster repurchase outcomes. Therefore, personalization benefits may increase repurchase intention when associated to loyalty reward benefits. The results also showed that the effect of switching costs on repurchase intention was not statistically significant. We speculate that switching costs are less to retain customers in a constraint manner. This result, however unexpected is somewhat consistent with consumer behavior theory previously discussed, in which online switching costs in a non-contractual setting are less to lock-in customers and compelling them to engage in ongoing repeated purchases. Also, this result shows evidence that the constraint and commitment-based mechanisms are quite completely independent.

Overall we can infer from the model results that personalization acts as an intramechanism between the constraint- and commitment-based mechanisms. The direct effects of personalization are complementary and affect positively both mechanisms.

Taken as a whole the constraint-based outcome switching costs are essentially seen in the IT context as a technology-based constraint given by the customer-specific investments. While the commitment-based outcome repurchase intention is not only specific to IT business but related to firm-specific investments.

Figure 2.2 Estimated model




Notes: Unstandardized path estimates of the model; significant paths $**p < 0.001$, $*p < 0.01$.

### 2.5.3 Assessing rival models

One important criterion of a model's success is its performance compared with that of rival models in which, the examination of the relationships for which no hypothesis was theorized increase the internal validity of the findings (Bagozzi, 1980). Our proposed model is based on an elaborate framework that specifies the constraint- and commitment-based mechanisms operate quite independently. To examine this proposition we perform a *post hoc* analysis testing the relationships for which no hypothesis was theorized (Hair et al., 2006). For example, our model allows no direct path from loyalty rewards to switching costs[8]. To examine this proposition we

[8] As early discussed, switching costs literature relates loyalty rewards to artificial switching costs.

controlled for the overflow relationships across the mechanisms. A non-parsimonious model would allow direct paths from the exogenous constructs directly to both endogenous constructs. We included the following direct paths (which are not allowed in our proposed model): from loyalty rewards to search costs and to switching costs.

We compared our hypothesized model with the rival model using the following criteria: overall fit and statistical test of model's fit differences, percentage of the model's statistically significant parameters, theoretical interpretation of the paths, and explained variance of the endogenous constructs.

The overall fit for the rival model was about equal to that of our proposed model ($\chi2$ [90] = 178.578, $p < .001$, CMIN=1.98, CFI = .98, NFI = .96, RMSEA= .057, GFI= .93). When investigated the structural relationships among the focal constructs on both mechanisms, the results indicated that the added relationships were generally insignificant, as expected. The results showed that the effects of loyalty rewards on search costs ($\gamma = .058$, s.e.= .148, $p > .05$) and on switching costs ($\gamma = -.007$, s.e.= .102, $p > .05$ ) were not statistically significant. We speculate that the loyalty reward losses are less than the cost to search and switch to an alternative online retailer. More problematic, the results showed that loyalty rewards have a negative effect on switching costs. This result is not consistent with positive correlation, shown on Table 2.1, which may indicate a suppressor effect, and is contrary with theory. Likewise, the proposed model we found the effects of other hypothesized relationships remain unchangeable. This result provides additional evidence of the path estimates stability when other stressors are controlled. In our proposed model 5 out of 6 (83.3%) of the paths were significant, whereas only 5 out of 8 (62.5%) of the paths were significant in the rival model. Finally, as expected the explained variances for all exogenous constructs were about equal to that of our proposed model: search costs ($R^2 = .15$), switching costs ($R^2 = .67$) and repurchase intention ($R^2 = .59$). The added paths have not provided a better overall fit. The $\Delta\chi2 = 0.156$ with 2 degrees of freedom, was not significant ($p > .05$), which mean the proposed model does not have a significantly worse fit and is more parsimonious than the rival model.

Thus, through a process of elimination of specious paths will increase the internal validity of the findings (Bagozzi, 1980). On the base of these findings, we acknowledge that this comparison provided added confidence to the independence of both constraint-and commitment-based mechanisms in our conceptual model. Our model assumes that only personalization interplays between the mechanisms.

**Rival mediation model**

We asses another rival model that is more parsimonious and reflects current conventional wisdom about the mediated effect of switching costs on behavioral outcome. A rival mediation model would hypothesize direct paths from the antecedents, such as personalization, search costs and loyalty rewards to switching costs, and therefore assuming the relationship of the variables to repurchase intention outcome is fully mediated by switching costs. Such a model imposes relatively little nomological structure on the constructs.

The overall fit for the rival mediation model was lower to that of our proposed model ($\chi2$ [94] = 257.64, $p < .001$, CMIN = 2.80, CFI = .957, NFI = .935, RMSEA = .078, GFI= .91) and is accompanied by reduced nomological validity. The explained variances for the endogenous constructs, except for switching costs ($R^2_{rival} = .65$ versus $R^2_{proposed} = .67$) were much lower in the rival model for repurchase intentions ($R^2_{rival} = .14$ versus $R^2_{proposed} = .59$). All the paths estimates in the rival model were statistically significant: personalization ($\gamma = .35$, $p< .001$), search costs ($\gamma = .46$, $p< .001$) and loyalty rewards, although weaker, ($\gamma = .18$, $p< .05$) were shown to have positive significant effects on switching costs. More problematic, the results showed that switching costs have a strong positive effect ($\beta= .80$, $p< .001$) on repurchase intention which is contrary to our proposed model results. This result may indicate a spurious causal relationship, when other stressors are not controlled (Shrout and Bolger, 2002). When comparing the proposed and the rival mediation models' overall fit, the ΔCFI (.02) and the ΔRMSEA (.02) at the two decimals places is more than the cutoff point .01 (Hair et al., 2006; Cheung and Rensvold, 2002). The $\Delta\chi2 = 78.903$ with two degrees of freedom, $p< .01$ was significantly large, which means our hypothesized model shows an overall better fit to data. Taken together these findings our proposed model out-performs both rival models[9]. Models comparison and testing models fit differences are summarized in Table 2.3.

[9] Detailed results for the rival models are available on request.

Table 2.3 Comparing and testing models fit differences

| Models | $\chi 2$ | DF | CFI | RMSEA | NFI | $\Delta\chi 2$ | $\Delta$ CFI | $\Delta$ RMSEA |
|---|---|---|---|---|---|---|---|---|
| CFA/ Methods: | | | | | | | | |
| ML | 178.58 | 90 | .98 | .057 | .96 | _ | _ | _ |
| GLS | 156.38 | 90 | .86 | .050 | .74 | _ | _ | _ |
| ADF | 206.64 | 90 | .86 | .066 | .78 | _ | _ | _ |
| SEM: | | | | | | | | |
| Proposed Model | 178.73 | 92 | .98 | .056 | .96 | _ | _ | _ |
| Rival Model | 178.58 | 90 | .98 | .057 | .96 | $p \approx .924$ | .00 | .01 |
| Rival Mediation M. | 257.64 | 94 | .96 | .078 | .94 | $p < .05$ | .02 | .02 |

ML = Maximum Likelihood; GLS = General Least Squares; ADF = Asymptotic Distribution Free.

### Assessing the mediation mechanism of switching costs

We also assess the mediation effect to test the interplay of personalization across both constraint-and commitment-based mechanisms. Because relationships are not always clear, we evaluate the plausibility of mediation mechanism (Shrout and Bolger, 2002). Mediation is said to occur when a causal effect of some variable X on an outcome Y is explained by some intervening variable M (Baron and Kenny, 1986). When mediation occurs the $c'$ path (i.e. the estimate of indirect effect of X on Y is the product of sample estimates of $a$ and $b$) is smaller than the $c$ path (i.e. the total effect of X on Y) due to a meditated or nonzero indirect effect $a \times b$. When the indirect effect does not equal the total effect $c$ but is smaller and of the same sign, we say the effect of X on Y is partially mediated by M. In this case, the path $c'$ is a value other than zero. Following Baron and Kenny's (1986) guidelines for assessing mediation, we present in Appendix E the full results of the four steps of regression analyses. The results of mediation analysis show the maximum likelihood and general least squares estimates (and the standard errors) of the parameters of direct and indirect effects, and the Bootstrap[10] 95% of percentile and bias-corrected confidence intervals (Efron and Tibshirani, 1993; Bollen and Stine,

[10] The estimate of indirect effect (the product of the sample estimates of a and b) is subject to estimation error. The bootstrap procedure was implemented, using options in AMOS, to generate standard errors for standardized estimates. The regression effects were estimated using maximum likelihood method and 100% of the bootstrap samples converged. In a groundbreaking article, Bollen and Stine (1990) showed that bootstrap methodology could be very useful in studying the sampling variability of estimates of indirect effects in mediation models, as an alternative method to Sobel's (1982) large sample test.

1990). The difference between ML estimation and GLS estimation is slight in some cases, which provides evidence of the relative performance of the two estimation methods according to the population discrepancy (Arbuckle, 2010). According to Arbuckle, ML is the best estimation method, and in all cases, is the method with the lowest mean discrepancy. Subsequently, we rely on the ML standardized estimates.

As the Appendix E shows, the results clearly demonstrate (steps 1 to 3) that there are significant bivariate direct effects between personalization and both mediator variables search costs and switching costs, and outcome variable repurchase intention that may be mediated (Kenny et al., 1998). The bootstrap estimates at 95% confidence intervals (bias-corrected and percentile method) are nonzero for all direct effects. When testing for the direct path between personalization and repurchase intention when mediators are controlled (step 4), bootstrap standardized estimates at 95% confidence intervals show that total effect of personalization factor on repurchase intention is .612 ($p < .001$) of direct effect, and .096 (not significant) of indirect effect mediated by both search costs and switching costs. As shown, the lower bound of 95% bias corrected confidence interval of the ML indirect effect estimate includes zero. This is a bias-corrected bootstrap[11] confidence interval that produces more accurate confidence intervals that adjusts for possible bias with small samples (see Efron and Tibshirani, 1993, p. 178). In this case, data are consistent with large direct effects and no indirect effect, which means the relationship between personalization and repurchase intention is consistent with no mediation effect (neither partial mediation) affected by competing causes. Therefore, the results provide evidence that personalization factor and repurchase intention are connected directly, not indirectly. The size of the indirect effect is trivial relative to the strength of the direct effect. Adding it to the direct effect leaves it virtually unchanged. On the base of these findings, we acknowledge that this mediation analysis provided further confidence to the personalization factor inter-relationship between both constraint- and commitment-based mechanisms in our conceptual model.

---

[11] The computational details of the bias-correction adjustment are beyond the scope of this study, but, in brief, take into account skewness of the bootstrap distribution and the estimated change in the standard error of the parameter as a function of the presumed parameter value. The bias-correction adjustment is not a closed-form equation but rather an algorithm that makes use of resampling. Efron and Tibshirani (1993) provided the details as well as evidence of the improved accuracy of the adjustment. The algorithm is implemented in the AMOS statistical software system (Arbuckle, 2010).

### 2.5.4 Moderating influence of loyalty card holder

We conducted a mean structure difference using multiple sample analyses (Jöreskog and Sörbom, 2001) for the loyalty card holder/ no loyalty card holder subsamples to test our hypothesis regarding the role of moderating variable. On the basis of responses to our survey question about having a loyalty card (see Appendix C) we classified 231 costumers (77 %) having a loyalty card from the company and 69 costumers (23%) having not a loyalty card from the company, from our effective sample (n=300). In $H_7$, we posited that the loyalty rewards, switching costs and repurchase intentions would be greater for loyalty card holder than for no loyalty card holder customer subsamples. To test this hypothesis, we conducted a structured means analysis in AMOS 19, using the following model of means structures (Jöreskog and Sörbom, 2001):

$$x(g) = \tau x + \Pi x \xi(g) + \delta(g) ,$$

where, g refers to the respective subsample, x(g) is a vector of input variables, $\tau x$ is a vector of constant intercept terms, $\Pi x$ is a matrix of coefficients of the regression of x on $\xi$, $\xi$ is a vector of latent independent variables, $\delta$ is a vector of measurement errors in x, and the means of the $\xi(g)$ equal $\kappa(g)$.

We intend to test for differences in the latent means of factors for each group. This requirement imposes the restriction that the factor intercepts for one group to be fixed to zero[12]; this group then operates as a reference group against which latent means for the other group are compared (Byrne, 2010). In the present case it was decided to use the "No loyalty card holder" subsample as the reference group (i.e., the latent means were fixed to a value of 0.0) and, thus, moved on to removing the mean constraints for the Loyalty card holder subsample and replacing them with a label that allows these parameters to be freely estimated for the "Loyalty card holder" subsample. Accordingly, for the moderating variable, we set the $\kappa$No loyalty card equal to zero to define the origin and units of measurement of the $\xi$ factors; then, we computed $\kappa$Yes loyalty card and determined whether the differences in the factor means between the groups were significantly different from each other. Table 2.4 provides the results.

[12] Because it is not possible to estimate, simultaneously, the mean of each factor for both groups, the latent means for one group must be constrained to zero (Byrne, 2010).

Table 2.4 Test of factor mean differences between customer subsamples

| | Customer Subsamples | | |
|---|---|---|---|
| **Construct** | **No Loyalty Card Holder Subsample Factor Mean** (κNo) | **Loyalty Card Holder Subsample Factor Mean** (κYes) | **CR , p-Value** |
| Loyalty rewards | 0 | .65 | 4.34, $p < .001$ |
| Repurchase intention | 0 | .49 | 2.89, $p < .01$ |
| Switching costs | 0 | .05 | .30, not significant |

Table 2.4 shows that when loyalty card holder group is compared with no loyalty card holder group, the factor means for loyalty rewards and repurchase intention constructs are significantly higher for loyalty card holder group of consumers, as we hypothesized. However, factor mean of switching costs is not significantly different for the two subsamples. On the whole, these results support $H_7$.

## 2.6 Conclusion

The major objective of this study was to examine the commitment- and constraint-based mechanisms that describe consumer retention phenomena in the context of online retail. Our findings, based on actual customers of an online store, are highly consistent with the dual model proposed in this study. Specifically, we found that in the commitment-based mechanism, personalization and loyalty rewards influence repurchase intentions. In the constraint-based mechanism, meanwhile, personalization influences search costs, and both are found to affect switching costs.

The findings of this study provide strong support for our dual model, which posits that the commitment- and constraint-based mechanisms simultaneously, yet differentially, determine customers' reactions to the online retail provider at the post-consumption stages, and potentially will keep customers in the long run. The two mechanisms exhibit highly discernible patterns, but they are not completely independent of each other; this is because personalization relationships across the mechanisms - e.g. inter-mechanism relationships - are positive and significant (except the relationship between switching costs and repurchase intentions).

Overall, this research contributes to IT and e-consumer behavior research by offering a conceptual framework that helps to shed light on the complex nature of customer retention behavior in characterizing a long-term and non-contractual relationship between customers and firms, in the context of e-commerce.

### Theoretical implications

The construct of personalization has often been treated in IS research in the context of online services related to switching costs (Tsai and Huang, 2007; Tsai et al., 2006) (Balabanis et al., 2006). In research, personalization is generally regarded as an Internet technology (IT) characteristic that affects website usability and eventually the commitment-based mechanism (Agarwal and Venkatesh, 2002). But personalization related to perceived benefits is insufficient to explain switching costs. Interestingly, our study shows that personalization not only affects commitment (i.e., repurchase intentions) but also constraints (i.e., switching costs). We found that personalization (e.g. intermechanism relationship) affects both commitment and constraint-based retention mechanisms. The two perspectives are complementary and do not contradict each other but there remains a scarcity of published research that combines both. This finding has important implications for research, because a significant amount of work has shown the relevance of perceived benefits of personalization in explaining online consumer behavior (Kim and Son, 2009; Devaraj et al., 2002). As far as we know, no studies in either marketing or electronic commerce have shown that personalization exerts its effects on both commitment-and constraint-based mechanisms.

Taken together the present study fills a gap by revealing the limitations of the simplistic view of the online customers' constraints approach and shedding light on the powerful effects that personalization and loyalty rewards, as firm-specific investments, have on online consumer behavior. We attempt to extend an extant view of Internet technology usage to a more integrative theory of value-oriented approach. Our model integrates a variety of behavioral antecedents; while some of them are often examined in the IT literature, others are rarely mentioned despite their significance to online retailers (e.g. loyalty rewards). Much post-adoption IT research takes a restrictive view that perceived benefits, such as perceived usefulness and satisfaction, serve as the main drivers of individuals' reactions to online providers. However, we found that perceived benefits, such as loyalty rewards, affect the commitment-based mechanism but exert no effect on the constraint-based mechanism. This finding also has important implications for e-consumer behavior research because a significant amount of work has shown the influence of loyalty programs, related to artificial costs, in explaining online switching costs. Our study contributes to relevant knowledge to the Internet technology and e-commerce literature showing the complex nature of online consumer behavior. More important, our study demonstrates the "search cost paradox" in the online context. A large body of research in the IS field posits that the dramatically reduced search costs on the Internet will impact negatively switching costs (Bakos, 1997). Meanwhile, our study found that switching costs are mainly driven by online search costs, specifically the time and effort spent in systematically comparing the information overload (e.g. products and price information) even it is easy to get. To the best of our knowledge, no studies in either e-consumer behavior or information systems have shown that online search costs, as customer-specific investments, exert their effects on constraint-based response.

Our study shows that switching costs have no significant impact on repurchase intentions, and no relationship exists between switching costs and loyalty rewards. In the IT discipline, loyalty and switching costs have often been examined simultaneously. Moreover, the relationship between the key concepts in past research was moderated by customer satisfaction, examining asymmetric switching costs under different satisfaction levels. A number of studies have found satisfaction and switching costs to be relevant antecedents of customer retention. Our treatment of the relationship was not sophisticated and did not reflect the notion that the affective-level construct (e.g. satisfaction) may influence commitment.

These findings imply that our dual mechanism model, which draws on social exchange theory with emphasis on commitment and constraint response, is superior to existing models in clarifying seemingly complex post-consumption customer retention phenomena, in the online environment. In this sense, this study contributes to the literature by theoretically highlighting the duality of consumers' reactions and empirically demonstrating that the repurchase intention representing commitment, and switching costs representing constraints, are both customer retention driving forces in the online B-to-C domain. In addition, our study provides an innovative contribution, by empirically demonstrating that customers are willing to repeat purchase, not in a constraint manner, when perceived benefits to maintain an ongoing customer-firm relationship are taken into account.

In summary, although an increasing number of IT studies have explored online consumer behavior (e.g., online shopping, online brokers, Web portals), considerable effort has gone into this stream of research without realization of the importance of the two different mechanisms underlying online consumer behavior. To address this void we attempt to extend an extant view of Internet technology usage to a more integrative theory of customer behavior. Thus we have made an important step toward a better understanding of a dual model of online customer retention at the post-consumption stage by empirically testing the hypotheses using actual and experienced online consumers. We hope that our study will help to incorporate empirical findings into a coherent body of knowledge in the online consumer stream of research.

**Managerial implications**

Overall this study shows that personalization acts as an intermechanism between the constraint- and commitment-based mechanisms, suggesting the important role such investments play in regulating individuals' post-consumption reactions to online retailers. An important implication of this finding for online business practices is that online retailers have incentives to promote customers' personalized interactions with the webstore because these interactions will ultimately increase customers' non-transferable benefits they receive from the incumbent retailer. For exemple e.Bay proposes product offers based on very particular personal customer information, such as birthday, children, and special occasions.

Another important finding of this study is that online customers who perceive greater personalization feature benefits are more sensitive to information search costs and are also the customers less willing to switch from the current online provider. For online managers this finding also has important implications. For example, online retailers need to actively encourage customers to customize their products, in terms of adapting product features or build them in from zero. Such firm-investments in sophisticated personalization tools (e.g. providing space on the website for co-creation, co-design, intelligent agents tracking customers' searching needs) will create customer value and enhance the retention process to a specific e-retail site.

Firms today use information about customers to improve service and to design personalized offerings. To do this successfully, however, firms must collect consumer information. As such, online managers should encourage customers to provide personal information so that the product recommendation can be tailored to customers' needs and desires. Those personalization efforts are non-transferable customers-specific investments when they switch to another provider. Therefore the amount of private information provided by customers will decrease the need for additional search for other alternatives and will keep them with the current provider. Through such investments of their time and effort, customers will become more dependent on the providers (i.e., higher constraint), and at the same time, they become more dedicated to the provider i.e. higher commitment.

A major implication of the dual model for managers is that a clear understanding of the intermechanism and intramechanism relationships is a key to effective customer retention management. For example, our findings suggest that it is important for online firms to enhance repurchase behavior by offering a variety of valuable customer benefits because loyalty rewards will affect both short-term firm performance by an immediate increase of sales, and long-term success by offering ongoing delayed loyalty reward incentives. Another important implication, from the *post hoc* analysis in this study, is that loyalty rewards do not provide a distinctive factor to retain customers in a constraint manner. The plausible explanation for this finding is that when all companies have loyalty programs, the market is characterized by an absence of change of the competitive situation. This finding has important implications for managers regarding actions they can take. Online firms could analyze trade-offs between investments in loyalty and retention programs in the long-term, for example, testing customers' reactions to different loyalty reward programs.

We found that switching costs do not have a relationship with commitment-based outcome; a management tactic to inflate switching costs appears to be more effective in boosting customer’s perceived benefits of personalization features. In contrast to other studies that found loyalty to be especially volatile when influenced by switching costs, our finding implies that customer loyalty (e.g. repurchase behavior) will be rather stable when powerful new competitors enter the market. To managers this finding may suggests that online business should carefully exploit “positive” switching costs, especially in a highly competitive and non-contractual context. For example, there are some problems associated with switching costs when relying on barriers to exit, such as lock-in contracts because: (1) perceived switching costs can impede customer acquisition; and (2) may be neutralized or eliminated by external forces (Fornell, 1992). In line with this reasoning, Burnham et al. (2003) highlight the importance of firms having lower procedural switching costs in order to facilitate new customer acquisition. It has become an economic axiom that lower switching costs force competition for initial subscribers and liberate second period subscribers from a particular aftermarket (Varian, 2000). Thus, switching costs must be managed carefully, reducing them for potential new customers and increasing them in ways that add value for existing consumers. Therefore, to effectively manage and build customer retention, online retailers should be aware of the importance of a constraint-oriented strategy that can complement the widely recognized commitment-oriented strategy.

**Limitations and further research**

In our view, a potential limitation of this study relates to the possibility of ignoring salient factors of customer retention. For example, we do not explicitly include the concept of trust, value or satisfaction in our model. The rationale for this is that the effect of trust and value are among the most relevant factors of customer retention in the online context. However, the effects of trust and value on behavioral outcomes are well examined in the IT literature and known to be fully mediated by satisfaction. It is our assumption that any bias resulting from the omission of trust and value would be minimal, at least in this particular study, whereas participants are existing customers with considerable relationship duration with the online retailer. Nevertheless, it is still possible that value can exert its influence on customer behavior over and above extended perceived benefits, in other contexts.

In the e-consumer behavior discipline, a number of studies have found satisfaction and switching costs to be relevant antecedents of customer commitment. Moreover, the relationship between the key concepts in past research was moderated by customer satisfaction. Our treatment of the relationship was not sophisticated and did not reflect the notion that the affective-level construct (e.g. satisfaction) may influence commitments. Thus, it is important for further research to investigate the asymmetric effects of switching costs under different satisfaction levels, on customer behavioral outcomes. Thus, our findings should be carefully interpreted with these potential problems in mind.

Another limitation of this study is that it focuses on the extent of personalization benefits as a whole without paying much attention to the specific features that could be personalized by customers. Although the examination into personalization at a global level is meaningful in the context of our study, it is also important to examine at a micro level how personalization features are used, the intervening variables, and the outcome of such personalization. We encourage researchers to perform a feature-level analysis to gain better insights into managerial strategic actions that could affect customer retention at a post-consumption stage.

Meanwhile, we found from our study that online customers who perceive greater personalization feature benefits are more sensitive to information search costs, and are also the customers least willing to switch from the current online provider. This result poses a dilemma for firms investing in personalization; as the customers who value their time and effort for information searching are also less likely to participate in personalization investments, namely consumer willingness to provide information for online personalization. Another important issue for online managers is to anticipate which customers are willing to be profiled online. As Awad and Krishnan (2006) found customers who value information privacy are also less likely to share information for online personalization. Thus, in order to manage this dilemma it is important for further research to investigate the effectiveness of personalization features that address the needs of (1) consumers who are more willing to partake in personalization (e.g. explicit data feedback) and (2) the privacy sensitive minority of consumers who are unwilling to participate in personalization (e.g. using implicit automated data) to retrieve optimal products based on the customers' current preferences.

A major theme of this study is that post-consumption retention phenomena are driven by the commitment and constraint mechanism. Although essential, however, the two mechanisms are insufficient to offer a complete picture of post-consumption retention behavior. Therefore it is important for further research to incorporate additional antecedents into the dual model. For example, switching cost is continuously evolving – shedding some features, moving into new areas, developing new strategies. Thus, as technology is a fast changing environment, online switching cost drivers stands in need of further developments of theoretical, conceptual and empirical kinds. Two areas are of major importance: addressing online community building, from the perspective of consumers' retention based on peer interactions and shared information. Another important area is co-creation, concerning personalized and co-created products, made available by sophisticated web interactive tools, allowing customers to configure and design their own products and making available their own accounts on the website. Our conceptual framework is flexible enough to accommodate such additional constructs and still offers insights into their relationship with other variables. More credibility can be given to our model if the newly added variables behave in a nomological network as the model implies. We hope that in this manner further research can extend the conceptual framework proposed in this study.

Finally, the data in this study were collected from a single webstore, rather than from multiple webstores, which implies that our findings here should be viewed with this potential limitation in mind. However, some of the remarkable findings in this study are that all things being equal, experienced, skillful and highly educated customers tend to react quite differently in a constraint manner to online firm strategies. In fact other studies found that heavy Internet users felt less constrained to the incumbent provider than occasional Internet users (Kim and Son, 2009) and, Burnham et al. (2003) found evidence that domain expertise has a negative relationship with switching costs. Thus, further research is certainly required for a better understanding of the roles that skills, e-experience or social status play in regulating switching costs and behavioral outcomes across various online retail contexts.

## Appendix C - Characteristics of the respondents

| Variable | Category | Frequency | Percent (%) |
|---|---|---|---|
| Gender | Male | 192 | 62,3 |
| | Female | 116 | 37,7 |
| Age | 18 below | 10 | 3,2 |
| | 18-24 | 70 | 22,7 |
| | 25-29 | 80 | 22,0 |
| | 30-39 | 101 | 32,8 |
| | 40-49 | 39 | 12,7 |
| | 50 above | 8 | 2,6 |
| Education level | Middle school or less | 13 | 4,2 |
| | High school or equivalent | 80 | 26,0 |
| | College graduate | 115 | 37,3 |
| | Post-graduation | 34 | 11,0 |
| | Master's/ Doctoral degree | 66 | 21,4 |
| Occupation | Scientific and intellectual professionals | 70 | 22,7 |
| | Business managers | 41 | 13,3 |
| | Technicians | 49 | 15,9 |
| | Free-lancers and entrepreneurs | 18 | 5,8 |
| | Service personnel (white-color) | 40 | 13,0 |
| | Student | 66 | 21,4 |
| | Other | 24 | 7,7 |
| Online shopping experience /use | 1 year or less | 43 | 14,0 |
| | Between 2 – 4 years | 117 | 38,0 |
| | Between 5 – 9 years | 110 | 35,7 |
| | 10 years or more | 38 | 12,3 |
| Customer relationship length with online retailer | 1 year or less | 115 | 37,3 |
| | Between 2 – 4 years | 126 | 41,0 |
| | 5 years or more | 67 | 21,7 |
| Purchase Frequency from online store | Once a week, or less | 16 | 5,2 |
| | Monthly | 73 | 23,7 |
| | 3 – 4 times a year | 152 | 49,4 |
| | Once a year | 40 | 13,0 |
| | Less frequent | 27 | 8,8 |
| Search behavior [a] | Online: | | |
| | Google or other search engines | 103 | 33,4 |
| | Online networks or communities | 12 | 3,9 |
| | Other Website links | 5 | 1,6 |
| | Offline: | | |
| | Physical store | 133 | 43,2 |
| | Family and friends | 18 | 5,8 |
| | Advertising | 15 | 4,9 |
| | Other | 22 | 7,1 |
| Loyalty card holder | Yes | 237 | 76,9 |
| | No | 71 | 23,1 |

a Multiple answer question (frequencies of responses could exceed 100%).
n= 308.

## Appendix D - Summary of measures

| Construct (α [a]) | Measures [b] (Item Loading [c]) | Source |
|---|---|---|
| **Search Costs (0.91)** | | |
| | Sea1 - Comparing the benefits of this e-retailer with the benefits of other e-retailers takes too much time and effort, even when I have the information. ( 0.75*) | Burnham et al. 2003; Srinivasan et al. 2002 |
| | Sea2 - It is hard to explore many competing websites in order to find an alternative to this site. ( 0.94*) | |
| | Sea3 - It is tough to compare systematically prices changes and product characteristics of competing e-retailers. (0.94 *) | New |
| | *Sea - I hate spending time finding a new internet store.* [e] | Balabanis et al. 2006 |
| | *Sea - It takes time and effort to conduct an extensive search before making a purchase at this website.* [e] | |
| **Personalization (0.85)** | | |
| | Per1- The website sends me purchases recommendations that match my needs. (0.70*) | Kim & Son, 2009; Tsai & Huang, 2007 |
| | Per2 - The advertisements and promotions that website provides are tailored to my situation. (0.71*) | |
| | Per3 - This online store makes me feel a unique customer. (0.87*) | New |
| | *Per - I spent a lot of time and effort to put personal information at the website site.* [e] | |
| | *Per - I hate re-registering to another internet store.* [e] | Balabanis et al. 2006 |
| **Loyalty Rewards (0.77)** | | |
| | Lo1 - Switching to a new online store would mean losing points, credits, and so on that I have accumulated with this online provider. (0.68*) | Burnham et al. 2003; Tsai et al., 2006 |
| | Lo2 - I expect that in the future, I will use the award points that I accumulate for being a loyal customer. (0.72*) | |
| | Lo3 - Comparing to alternatives the rewards type that this e-retailer offers me for being a loyal customer provides me value. (0.84*) | New |
| | *Lo – It takes time and effort to accumulate benefits such as points, credits or rewards.* [e] | |
| **Switching Costs (0.92)** | | |
| | Sw1- If I switch to another online store, I will waste a lot of time and effort that I have already made in this website. (0.91*) | Kim & Son, 2009; Tsai and Huang, 2007 |
| | Sw2 - Switching to a new website would involve some hassle, time and effort. (0.97*) | |
| | Sw3 - I would feel uncertain if I had to choose a new online store. (0.82*) | Burnham et al. 2003 |
| | *Sw - I will lose benefits of being a loyal customer if I leave this online store.* [e] | |
| | *Sw - Overall, I would lose a lot if I switch to another online store.* [e] | |
| **Repurchase intention (0.93)** [d] | | |
| | Rep1- I will consider this online store as my first choice for online shopping. (0.91*) | Tsai et al., 2006; Burnham et al. 2003; |
| | Rep2 - I will do more business with this online store in the near future. (0.90*) | |
| | Rep3 - If I was to repurchase again, I would choose this website. (0.89*) | |
| | Rep4 - I intend to interact with this online store sometime in the near future. (0.80*) | |

* $p < .001$.

[a] α Cronbach's alpha; CR: Composite reliability.

[b] Unless indicated otherwise, we obtained responses using five-point Likert scales, anchored by 1="strongly disagree" and 5 = "strongly agree."

[c] We report standardized item loadings.

[d] We obtained responses using five-point Likert scale anchored by 1= "very unlikely" and 5 = "very likely".

[e] Deleted items to improve reliability, consistency and unidimensionality of the construct's measures.

# Appendix E - Mediation analysis and bootstrap results

| | | | Regression Estimates | | | Bootstrap 95% CI Method | |
|---|---|---|---|---|---|---|---|
| Step | Effect | Method | Unstandardized | SE | Standardized | Percentile | Bias-Corrected |
| 1 | PER → REPI | ML | 1.054** | 0.101 | 0.722 | (0.640, 0.792) | (0.637,0.788) |
| | | GLS | 1.058** | 0.103 | 0.723 | (0.648, 0.798) | (0.621, 0.788) |
| 2a | PER → SWC | ML | 0.998** | 0.116 | 0.553 | (0.409, 0.664) | (0.409, 0.663) |
| | | GLS | 1.107** | 0.132 | 0.602 | (0.465, 0.703) | (0.458, 0.701) |
| 2b | PER → SC | ML | 0.666** | 0.114 | 0.352 | (0.190, 0.486) | (0.190, 0.489) |
| | | GLS | 0.664** | 0.116 | 0.359 | (0.197, 0.508) | (0.192, 0.508) |
| 2c | SC → SWC | ML | 0.758** | 0.045 | 0.753 | (0.679, 0.819) | (0.668, 0.813) |
| | | GLS | 0.760** | 0.045 | 0.754 | (0.682, 0.827) | (0.645, 0.808) |
| 3 | SWC → REPI | ML | 0.681** | 0.067 | 0.737 | (0.606, 0.863) | (0.606, 0.865) |
| | | GLS | 0.769** | 0.072 | 0.834 | (0.732, 0.943) | (0.731, 0.942) |
| 4 | PER → REPI | ML | 0.925** | 0.128 | 0.612 | (0.440, 0.757) | (0.433, 0.755) |
| | | GLS | 0.839** | 0.144 | 0.541 | (0.344, 0.736) | (0.344, 0.737) |
| | PER → REPI (Indirect) | ML | 0.145 | 0.087 | 0.096 | (-0.017, 0.211) | (-0.025, 0.205) |
| | | GLS | 0.250* | 0.130 | 0.081 | (0.005, 0.322) | (-0.006, 0.313) |

**p < 0.001; *p < 0.01.
SE= standard error. CI = confidence interval. Percentile 95% CIs for bootstrap distributions are defined using the values that mark the upper and lower 2.5% of each distribution.
ML = Maximum likelihood, GLS= general least squares.
SC = search costs; PER = personalization; SWC = switching costs; REPI = repurchase intention.

# Chapter 3

# Virtual recommendation diffusion and online co-shopping influence: the role of network externalities

In this paper we develop and estimate a conceptual model of how different aspects of customer's motivations to recommend a site impact their intentions, behaviors and influence regarding co-shopping. We describe how different individuals' motivations, such as voluntary collaboration and incentive seeking lead to greater recommendation intention, and behavioral consequences, which in turn affect the influence of co-shopping within a network of connections. We examine the moderating effect of customers' network size and test the hypotheses by estimating a structural equation model with online survey data from a sample of online consumers of a leading retailing website.

The study empirically verifies that the existence of direct network externalities (i.e. the value of customers' incentives to recommend a site or product increases when the customers' social network expands) may be crucial for the overall welfare of both online retailers and customers. This study provides an empirical contribution to the networked customer theory by demonstrating that: 1) "match dyads" in social networks of connections provide valuable high-quality information that will improve the match between the product and the potential customer and, 2) bridging online social connections function as a proxy for information about the potential market that is difficult and expensive to access and attract. The paper concludes with a consideration of the implications of predictions for managerial practice.

***Keywords***: voluntary collaboration; incentives; co-shopping influence; online customer recommendation diffusion; network externalities.

## 3.1 Introduction

Marketers are becoming more and more interested in building and facilitating online brand communities and there are undoubtedly many reasons in this interest. In these interconnected days, social networks are an interesting phenomenon, which are gaining business and researchers' attention due to their potential for market information and attraction (Van Den Bulte and Wuyts, 2007). Researchers point out that a virtual community is a valuable business medium for web vendors in terms of disseminating information and retaining customers (Wu et al., 2010). Consumers share information about products. Some brand aficionados even band together in vibrant brand communities (Bagozzi and Dholakia, 2006). The virtual collaboration of customers is therefore an emerging reality as organizations embrace new e-business processes to take advantage of electronic communication technologies. In such turbulent times, with marketing pressure for more efficient targeting of resources, marketers are rediscovering the importance of social contagion, facilitating brand communities and social network sites to access the customers' "voice" (Ho and Dempsey, 2010). Many factors underlie this interest including the ability of brand communities or social networks to influence members' perceptions and actions, often through frequent social interaction, to rapidly disseminate information, to learn consumers' evaluations about new offerings, to speed up market product novelty and so forth and to maximize opportunities to engage and collaborate with highly loyal customers. One way to create linkages to external resources, as a proxy to market attraction (e.g. customer referrals), is through personal electronic communication networks. In the present-day competitive and often hostile marketing environment, many researchers believe social multiplication of marketing efforts gained from social networks is both cost effective and powerful (Cole, 2007; Balasubramanian and Mahajan, 2001; Varian, 2000). Hence, for business, there are different reasons why networks matter. Among the most relevant, theory posits that social network externalities potentially impact firm value, and are crucial for firms' market share and profitability, especially for consumer goods where competition is higher (Van den Bulte and Stremersch, 2004).The existence of network externalities strongly impacts the success of electronic commerce: when more consumers join the network, a product's value increases, due to scale effect even for marginal products (Varian, 2000). Moreover, social network externalities potentially impact firm value: with the help of increasing online interactions among customers firms' efforts and investments in attracting new customers will be reduced e.g. advertising, promotions, and market data gathering (Balasubramanian and Mahajan, 2001). Electronic networks create enormous potential for interaction that would be impossible or too costly through traditional media. In such interconnected times, individuals and consumers have increasing power of information diffusion and influential behavior in social networks. Networks will erode the effectiveness of traditional marketing for branding efforts, connecting brand and retailers to consumers, as a link to a potential market that is difficult and expensive to attract. Thus, the role of the networked customer, as a "new media", represents a great challenge for e-marketing investment in customer alliances, both for new product recommendation and for attraction of new customers. Nowadays, many e-marketeers believe that the facilitation of recommendation tools on their websites is both cost effective and influential. At the same time, e-marketeers embarking on such initiatives want to better understand how networked customers create value for their online business. However, these marketing activities of e-retailers have been studied far less in the information system (IS) domain and e-commerce (EC) setting.

For managers, the million dollar questions are: Which consumer is most relevant for which social contagion driver? Which customer has the highest potential for recommendation diffusion and contagion? What motivations drive consumer to share and spread market information? How does network structure affect individuals' behavior? What kind of social networks are relevant for the different types of marketing decisions? Besides, for firms there is a lot of interest in increasing market share by targeting and making marketing alliances with those most likely to influence others and with the best-connected customers.

This study provides an empirical and theoretical contribution to networked consumer research, which marketers should take into consideration when deciding which actions to take. This raises several issues. A salient issue is how to measure and evaluate which online customer is influential and has the highest potential to increase recommendation diffusion. To accomplish this it is important to understand the motivations which drive networked consumers to spread market/product information, to give product recommendation, how prevalent is it, how they get product recommendation acceptance, and which customers influence their peers to purchase existing products together (i.e. co-shopping influence), and the conditions that accentuate this influence. Another issue is to provide evidence about the moderating effect of social network structure on the impact of virtual recommendation behavior, on co-shopping influence feedback, and its impact on ongoing motivational behaviors. Although this issue is relevant for understanding the leverage of online network externalities, we are not aware of any rigorous quantitative evidence.

The purpose of our research is to develop and estimate a conceptual model to explicate the motivations and consequences of virtual recommendation diffusion and co-shopping influence regarding online networked consumers. We describe how the customer's intrinsic and extrinsic motivations precede and contribute to his or her intention to recommend the site/product. We also describe how recommendation intention leads to positive behavioral outcome and ultimately leads to co-shopping influence. Moreover, we consider the different interplay among co-shopping influence and customer´s intrinsic and extrinsic motivations. We examine the moderating effect of customers' network size among the set of relationships between the constructs.

We test our hypotheses by estimating a structural equation model with survey data from a sample of online customers from a leading retailing website. We also develop and validate new scales to measure some constructs in the model, such as voluntary collaboration, co-shopping influence, incentive seeking and site recommendation intention, which may be useful to conduct further survey-based online consumer research.

This paper is organized as follows. In the next section, by reviewing the literature, we develop the theoretical framework and the research hypotheses. The section 3.3 describes the research method, measures and sample characteristics. The results of model analysis are presented in the section 3.4. We provide discussion and conclusions of the results in section 3.5. Finally, we present future research topics based on the study limitations.

## 3.2 Theoretical framework and hypotheses

Our conceptual framework explains the motivations and consequences of virtual recommendation diffusion and co-shopping influence amongst online networked consumers. The framework draws on recent marketing studies of social networks (Van Den Bulte and Wuyts, 2007), social exchanges (Hars and Qu, 2002), and group-based consumer interactions (Bagozzi and Dholakia, 2006; Dholakia et al., 2004), and it adds to these ideas by explicitly including the effect of network externalities (Katz and Shapiro, 1985) and the conditions that accentuate network influence (Van Den Bulte and Wuyts, 2007; Watts, 1999; Granovetter, 1982).

### 3.2.1 Co-shopping influence

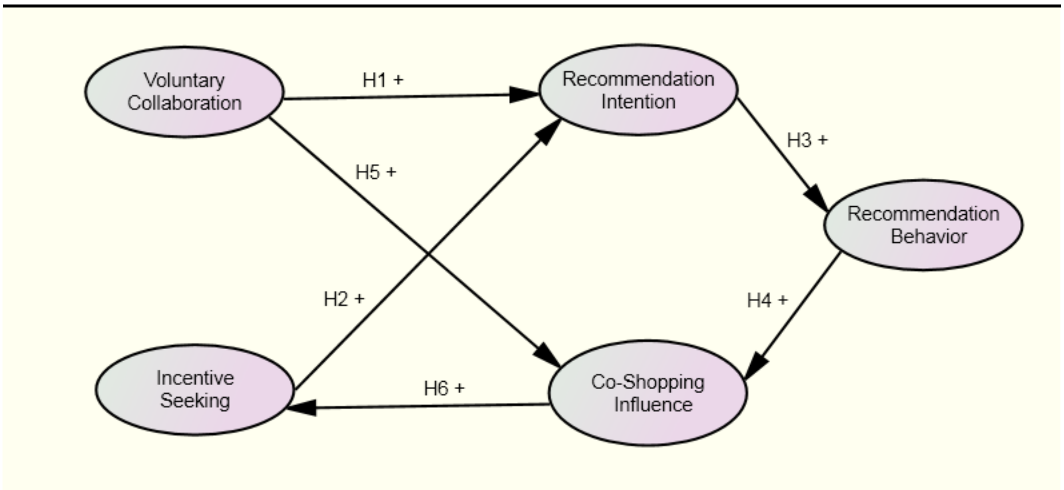
We begin by considering the strength of co-shopping influence on networked consumer behavior. In our framework, "co-shopping influence" is a key construct and is defined as the response of matched recommendations concerning joint consumption action amongst network peers, to purchase existing products together. In our conceptualization, co-shopping influence refers to a feedback mechanism which occurs in the reciprocal interactions of network peers, as a response to the influence of "better matched" recommendations in joint consumption action. We note here that such joint action may not necessarily be contemporaneous; members can perform their respective parts at different times. In literature, individuals' motivations and desires to participate in the virtual community are described as "we-intentions" which are defined as a commitment of an individual to engage in joint action, and involves an implicit or explicit agreement between the participants to engage in that joint action (Dholakia et al., 2004, p.247). More recently, research has referred to the "co-shopping" phenomenon related to the motivations and benefits of the group-based consumption behavior of virtual communities, e.g. "Let's buy this product together to get bigger discounts" (Chan and Li, 2010); and the fact there is more likelihood of teenagers shopping with friends, related to peer influence and enjoyment of shopping with pals (Mangleburg et al., 2004).

Regarding the feedback component of co-shopping, within our framework "co-shopping influence" refers to the positive feedback of the influence of matched recommendations regarding joint purchase action, which is supported by network social interactions and dyadic reciprocating behaviors. This view is also informed by recent brand community research which indicates that reciprocity in virtual community interactions enhances members' co-shopping intentions (Chan and Li, 2010). Moreover, the increasing online social interactions provide the structural route for reciprocating behaviors (Ho and Dempsey, 2010), and previous interactions not only increase the level of trust in virtual community members, but also enhance relationship commitment and member stickiness (Wu et al., 2010).

Regarding the influence component of co-shopping, by extending better match theory (Simon and Warner, 1992) in our framework, co-shopping influence means the "we influence" of better matched recommendations on the network of peers' co-shopping decisions. In our view, social bonds and strong ties in networks of connections enhance the likelihood of "better matched" recommendations, based on individuals' similarities, shared needs and previous awareness of consumption behavior tendencies, which in turn are more likely to positively influence co-shopping. From our perspective, co-shopping influence offers a useful way to examine the effectiveness of customers' recommendation behavior. We emphasize this relationship by positioning the conceptualization of co-shopping influence as involving a triadic consumer-brand-consumer relationship. Moreover, from a managerial standpoint it helps to identify which customer is influential, thus providing an indication for recruitment of potential new customers with matched needs. To the best of our knowledge, this study is a first attempt to develop and investigate the co-shopping influence construct in networked customer behavior.

As shown in Figure 3.1, the model depicts behavioral intention regarding site recommendation as a consequence of individual motivations, such as voluntary collaboration and incentive seeking influence site recommendation intention which leads to recommendation behavior. These consequences lead to a positive outcome, co-shopping influence, which in turn, has the strength to directly affect incentive seeking, representing the reciprocity mechanism to persuade ongoing behaviors. These relationships influence various network-and consumer-related behaviors of managerial relevance. Next, we develop the model in detail.

Figure 3.1 Hypothesized model




Notes: In the interest of space, each factor's measurement indicators, error terms and moderator hypotheses are not included in this figure.

### 3.2.2 Consumer motivations regarding behavioral consequences

In our framework, individual's motivations are posited to have a positive influence on site recommendation intention. There exist some unobserved individual characteristics that lead to higher recommendation level. This assumption is consistent with sociological and psychological theories which posit that what drives people to share market information is a combination of individual intrinsic and extrinsic motivations. We discuss here two individual dimensions that prior research indicates may be relevant to explain product/site recommendation diffusion in social networks of connections: "voluntary collaboration" and "incentive seeking".

#### Voluntary Collaboration

First, consider the customers' reasons to give free and voluntary market information and personal recommendations. In our model "voluntary collaboration" means whatever induces people to engage in spontaneous sharing behavior to give free and voluntary market or product recommendation into the network of connections. The construct receives theoretical support both from previous research on market helping behavior (Price et al., 1995), group-based consumer interactions (Wasko and Faraj, 2005; Dholakia et al., 2004; Hars and Qu, 2002), and altruism literature, on arousal of peer-to-peer "match dyad" empathy and reciprocity. Chang and Chuang (2011) found that altruism, identification, reciprocity, and shared language had a significant and positive effect on knowledge sharing in a virtual community.

Prior research provides evidence that what drives consumers to engage in voluntary collaboration for sharing resources, offering personal opinions and giving free and voluntary market information, answering questions, influencing peers, helping them to make good purchase decisions, and even validating their past decisions and behaviors is concerned with individuals' altruistic characteristics (Ho and Dempsey, 2010; Hars and Qu, 2002). Price et al. (1995) define "helping market behavior" as acts performed by consumers in the marketplace that benefit others in their purchases and consumption decisions. As researchers note in their netnography study, online social connections initiate helping behaviors and feelings of moral obligation to help, which sustain commitments to the community (Nelson and Otnes, 2005). Virtual community research acknowledges that social bonds, linking-values and members' commitment to the community all lead participants to behave in an altruistic manner. For example, Hars and Qu (2002) measure altruism as "I don't care about money", "Recognition from others is my greatest reward", "Community members should help each other out", or "I deeply enjoy helping others - even if I have to make sacrifices" to explain motivations to engage in virtual collaboration in open source online communities.

Thus, in our model voluntary collaboration means that the consumer agrees to give free and voluntary product recommendation and advice, sharing market information, offering personal opinions and answering others' questions helping them to make good purchase decisions. Therefore, voluntary collaboration results from the overlaps that members perceive between their own unique self-motivation and their group-based identity. Moreover, group collaboration is viewed as congruent to, and as an expression of personal values (Bagozzi and Dholakia, 2006; Dholakia et al., 2004). The construct is also consistent with the notion of "match dyads" as formulated in the social exchange and network literature (Van Den Bulte and Wuyts, 2007; Coleman, 1990). Thus, we hypothesize the following:

$H_1$: Greater voluntary collaboration leads to greater site recommendation intention.

**Incentive Seeking**

Secondly, we consider “incentive seeking” as a motivational dimension which relates to external rewards or monetary incentives that consumers receive from a company to give referrals. The emergence of the incentive motive suggests that consumers use online brand communities to obtain rewards and incentives in exchange for their community participation. For example, in certain cases, brand communities and retailing sites tend to provide monetary and nonmonetary incentives, such as sales promotions, community events, contests, sweepstakes, and coupons as rewards for member’s participation and recommendation diffusion. This suggests that consumers are already aware of the fact that a number of e-retailers offer a variety of promotions and future rewards and that their main incentive for joining such communities’ activities may therefore be the incentives offered. Evidence of this belief is provided by some empirical studies that find monetary compensations and future rewards (e.g. “I receive some form of explicit compensation, salary, contract for participating in the project”, “Participating in the project makes me more marketable”) are more significant predictors of community contribution than intrinsic or altruistic motivations (Sung et al., 2010; Hars and Qu, 2002). An explanation for this behavioral motivation is that a surprisingly large number of participants were paid for their open-source efforts, which in some way poisoned the voluntary collaboration engagement. These findings suggest that these monetary incentives play a significant role in motivating consumers who are less altruistic and less motivated to process and share market information for free in large networks. Therefore, we hypothesize the following:

$H_2$: Stronger incentive seeking leads to stronger site recommendation intention.

### 3.2.3 Recommendation behavior and co-shopping influence

We consider how the ways in which recommendation intention, behavior and co-shopping influence interplay. First, we consider the impact of site recommendation behavior on co-shopping influence. We suggest that consumers who actively provide recommendation diffusion are more likely to receive higher levels of feedback from their acquaintances related to co-shopping influence. The rationale behind this premise is that consumers seek the advice of others to solve consumption-related problems, and therefore, they forward online content giving opinions and suggestions about purchase opportunities (Ho and Dempsey, 2010).

Researchers also show that a consumer tends to rely more on recommendations and product experiences of other people, when considering online choices (Senecal and Nantel, 2004). In line with the literature, we suggest that the internet shopper, like e-market mavens (Price et al., 1995), has the knowledge of the best sites to shop and of product novelty or promotions to recommend to their acquaintances and network peers with similar consumption needs. Meanwhile, network members reciprocate the support they receive from those valuable matched resources. Research provides evidence that social interaction, including reciprocating behaviors, reflects processes of receiving and giving various resources (Chan and Li, 2010). The helper who provides resources, such as information or social support, receives reciprocal expressions of gratitude, and admiration or recognition from the person(s) helped. Moreover, reciprocity as a collective behavior pertains to the value dimension of reciprocity, a generalized moral norm that states people should reciprocate by repaying those who provide direct help (Hars and Qu, 2002). In this context, resource exchange theory (Foa, 1971) posits that individuals share information as a valuable resource, and that social systems facilitate the exchange of various types of resources by matching available resources with needs.

Customers' recommendation intention should also have an impact on the consumer's related behavior. In particular, we expect that the customers' intention to recommend the site has a positive impact on true behavior, because a key marker of a customer who is truly committed to the company is ongoing recommendations providing referral to the brand. Thus, consistent with attitude-theoretic formulations of goal-directed behavior (Eagly and Chaiken, 1993; Ajzen, 1991), we expect that higher levels of site recommendation intention lead to corresponding behaviors. This path is stated formally as a hypothesis, despite the fact that it has been well documented in the literature, but it is included in our model for the sake of completeness. We measured recommendation behavior as the number of times customers have recommended the site, in the last three months. Taken together we hypothesized the following:

$H_3$: Higher levels of recommendation intention lead to stronger behavioral recommendation.

$H_4$: Higher levels of recommendation behavior lead to stronger co-shopping influence.

### 3.2.4 Voluntary collaboration and co-shopping influence

In our model voluntary collaboration is posited to have an impact on co-shopping influence. We suggest that voluntary collaboration, experienced as altruistic behavior which represents the self-instigated motivations by customers to freely recommend the site or product, will have a positive impact on co-shopping influence. In our view, the positive and self-instigated (i.e. intrinsic) motivations which drive customers to freely recommend the brand/site should lead to positive rewards. Here, rewards mean the expressions of gratitude and recognition that the customer referral receives from peers. Therefore, consumers who expend additional voluntary collaboration effort, in an altruistic manner, are likely to receive reciprocating behaviors giving feedback and recognizing the value of the received recommendation.

Our perspective is supported by prior research on networks and social exchange theory. For example, in prior research on networks of collaboration (e.g. open source software) it was found when there is a strong norm of reciprocity in the group, individuals trust that their effort to contribute knowledge will be reciprocated by peer recognition, thereby rewarding individual efforts as future returns to maintain ongoing contributions (Wasko and Faraj, 2005; Hars and Qu, 2002). Accordingly, social exchange theory (Blau, 1964) sustains that all interactions which are exchanges of rewards and the valuation of rewards vary because people reflect their own preferences, e.g. which arise from the feeling of being rewarded just by being in a relationship. Moreover, when there are strong and close ties in the network, individuals that engage in voluntary recommendation are more likely to influence other members´ decisions in matched needs. This is because the social influence mechanism is based on trusted and unbiased information from one’s peers (Childers and Rao, 1992). Therefore, we propose the following:

$H_5$: Stronger voluntary collaboration leads to stronger co-shopping influence.

### 3.2.5 Co-shopping influence and incentive seeking

Co-shopping influence suggests that when network peers reciprocate giving feedback and recognizing the value of the received recommendation, the referrer should be eager to repeat behaviors that lead to such positive “rewards” or incentives. Rewarding individual efforts as future returns to maintain ongoing contributions, therefore ultimately leads to continuing recommendations. Moreover, feedback always has a positive effect in that it indicates to consumers who make referrals that people are using their recommendations (Wasko and Faraj, 2005; Hars and Qu, 2002). Thus, individuals who receive rewards or incentives to recommend the site/product, adding to positive feedback about their recommendations, are probably more motivated to engage in ongoing recommendations. Hence, in line with social exchange theory (Blau, 1964) co-shopping influence refers to a self-reinforcing mechanism for it encourages the referral to expend additional effort related to ongoing recommendations. Broadly speaking, we suggest the role of reciprocating behavior as a response to co-shopping influence 1) is a substantiation of “better matched” recommendations and 2) a self-reinforcing mechanism ensuring ongoing recommendations in the presence of incentives. Therefore, incentive seeking, which represents the utility aspects of the rewards to recommend the site, is likely to be experienced positively when customers receive positive feedback about co-shopping influence.

For example, in some cases online retailers offer such (non)monetary incentives on the basis of referral effectiveness, which means new customers’ first purchases. From a marketing standpoint, by rewarding individual efforts to ensure ongoing recommendations, managers can not only generate positive word-of-mouth among consumers, which in turn can reinforce the consumer–brand relationship, but can also drive customers to engage in more purchase-related behaviors and co-shopping influence. In line with recent research (Sung et al., 2010), these possibilities imply that such monetary incentives may play a significant role in motivating consumers to engage in ongoing recommendations within the network on a regular basis. This view is also consistent with social exchange theory, in the sense that "incentive seeking" helps to explain when members choose to participate and contribute, in a manner that maximizes their total social-interaction utility. Hence, we suggest when network peers reciprocate, giving positive feedback about the influence of received recommendation about joining consumption action, members are likely to be eager to repeat behaviors that lead to such utility rewards, and they should have higher levels of behavioral intentions as a result. Therefore, we propose:

$H_6$: Stronger co-shopping influence leads to stronger incentive seeking.

### 3.2.6 The network externalities: moderator effect of network size

The relevant literature discusses the effects of network externalities (Tirole, 1988; Katz and Shapiro, 1986, 1985). The term *network effects* refers to the phenomenon in which the value of a product to one user increases as more users adopt the product (Katz and Shapiro, 1985). This characteristic, commonly referred to as "the more, the merrier", changes short-term performance objectives for the firm, the dynamics of market competition for market attraction (Lee and O'Connor, 2003), and gives rise to demand-side economies of scale, or economies of mass adoption (Katz and Shapiro, 1986) . In a network effects context the principle behind e-commerce success is to maximize the installed base rapidly rather than skimming marginal profits (Shapiro and Varian, 1998). There are several possible sources of these positive network effects: direct and indirect effects that give rise to consumption externalities. In all of these cases, the utility that a given user derives from the good depends upon the number of other users who are in the same "network" (Katz and Shapiro, 1985).

In this study, by extending the theory of network externalities we focus on only one of these elements: network effects considered by the scope or size of the network that gives rise to the consumption externalities. More specifically, our focus is on the consumers' expectations about the future installed base and the resulting benefits of "the more, the merrier" phenomenon which plays a critical role in their product recommendation decisions. The term direct network externalities, our focus here, refers to the fact that the value of a consumer's recommendation of a site or a product increases as the corresponding site or product's network expands (Katz and Shapiro, 1985). Due to the data limitation, the existing empirical studies on direct network externalities are scarce. In a recent study, researchers found that a large network is crucial for the success of hedonic goods, especially if the readers have more confidence in search attributes than in experience attributes evaluations (Yang and Mai, 2010). This finding suggests that network dimension is crucial to generate the externalities effects of recommendation diffusion. From a managerial standpoint, it is important to consider which characteristics of the consumer's network accentuate recommendation diffusion and co-shopping influence among its members. We consider one network characteristic: its size (as defined by membership count). This characteristic is managerially significant in the sense that it provides specific guidance to managers regarding actions they can take (e.g., spreading market information, determining who is influential and has social contagion power).

Thus, we consider the size of the customer network. In larger social networks (defined in our empirical study as those with 50 or more active members), members are more likely to identify with the community as a whole than with specific people in it (Dholakia et al., 2004). In addition, Van Den Bulte and Wuyts (2007) state that because of their large exposure on the network, innovative and e-leading "hubs" (e.g. highly connected individuals in a network) speed up the information diffusion process, and follower "hubs" increase the market size. Like a "broker", they have an important position in knowledge access and transfer to the network. "The strength of weak ties" (Granovetter, 1982, 1973) one of the most famous paradox theories, involving social networks, provides the following explanation: people we know only casually (weak ties) are less likely to know each other (lower closure) and are likely to have new information to offer, than people we know intimately and see often (strong ties) who share the same limited information (closure) are less able to offer new information (redundancy). Granovetter's (1982) argument is really not about the strength of ties but about the fact that "bridging weak ties" are of special value to individuals. The significance of weak ties is that they provide people with access to information and resources beyond their closed social circles. On the other hand, strong ties have greater motivation to be of assistance and are typically more available. As a consequence, weak ties suffer from a low-motivation problem which will not lead to an information advantage if that information is closely guarded, and in some cases, even in the search for “cheap” information (Bian, 1997).

In line with prior research, we suggest that larger customer networks are far more likely to be bridges of weak ties, and thus provide enormous potential for consumer recommendation diffusion. Furthermore, as we suggested earlier, the monetary incentives play a significant role in motivating less altruistic and less motivated consumers in large networks to process and share market information for free. In our view, the seeking of incentives will overcome the low-motivation problem of weak ties in large networks. Our rationale is also in line with network externalities theory (Katz and Shapiro, 1985), in which the smaller network will reduce members’ initial willingness to recommend the product/site even with the payment of incentives.

Therefore, if this fundamental assumption concerning direct network externalities holds, a larger network will offer higher utility for any customer (a) getting incentives to recommend the product/site, and (b) obtaining feedback of co-shopping influence, which maximizes the utility rewards that lead to repeated recommendation behavior. In other words, in large networks, as a “reward” for maintaining ongoing recommendations, co-shopping influence increases the effectiveness of incentives provided to recommend the site/product. Therefore, we suggest the interplay between the behavioral intentions behind consumer recommendation - incentive seeking and co-shopping influence - is greater in large social networks.

*Dyadic effects***.** On the other hand, we also believe that individuals belonging to small social networks have closer ties and social bonds than those belonging to larger networks (Van Den Bulte and Wuyts, 2007; Watts, 1999). Indeed, previous research provides evidence that smaller networks (those with fewer than 50 members “everybody knows everybody else”) are characterized by strong relational ties, rather than weak ties which result in stronger and multifaceted interpersonal relationships between consumers, social influence and sharing behavior. For example, “I am willing to share personal information and experiences with close friends, not with anonymous people” (Algesheimer et al., 2005). Likewise, in small networks individuals have strong feelings of social identity, shared history, similar needs, shared interests and consumption tendencies e.g. "other network members and I have close friendship ties and share the same objectives and interests" (Bagozzi and Dholakia, 2006; Dholakia et al., 2004).

In our framework, we also suggest the strong effect of social bonds in close networks encourages individuals to interact reciprocally, which also encourages resource sharing, voluntary collaboration, and cooperation, which are critical for the likelihood of recommendation diffusion and co-shopping influence. In line with this rationale, Chan and Li (2010) find that the strength of social bonds that consumers establish in the community positively influences the consumers' reciprocating behaviors, which in turn stimulate co-shopping intentions. Hence, this finding gives support to our rationale, since these dyadic network-based interactions, which are reciprocal rather than generalized, provide the structural route for virtual recommendation diffusion and feedback from co-shopping influence.

Furthermore, voluntary collaboration results from the overlap that members perceive between their own unique self-motivation and their group-based identity. It is also consistent with the notion of "match dyads" as formulated in the social exchange and network literature, which states that the "small worlds" are structured on close social bonds, and "match dyads" are more exposed to social contagion. Networks of this kind have received little attention, yet they appear to have enormous potential for sharing valuable information and social influence (Watts, 1999). More recent research (Friedkin, 2011) finds that small world contact networks are structures with startlingly efficient process performance which is premised on the existence of shortcuts, they are a potential structural basis of reliable flows of information, influence and material, rather like a simple model of disease transmission. Likewise, Katona and colleagues (2011) find that the average influential power of individuals decreases with the total number of their contacts in the network.

In line with previous research and "better match" theory we suggest that social bonds and strong ties in a close network of connections enhance the likelihood of "better matched" recommendations, based on peers' similarities, shared needs and previous awareness of consumption behavior tendencies, which in turn are more likely to positively influence co-shopping. The following hypotheses summarize this discussion regarding the moderating role of the consumer's social network effects, in our proposed conceptual model:

$H_7$: The positive impacts of incentive seeking on site recommendation intention, of co-shopping influence on incentive seeking and, of site recommendation intention on behavioral recommendation are stronger for members of large online social networks than for members of small social networks.

$H_8$: The positive impacts of voluntary collaboration on site recommendation intention, on co-shopping influence, and recommendation behavior on co-shopping influence are stronger for members of small online social networks than for members of large social networks.

## 3.3 Method

### 3.3.1 Development of measures

For several constructs in our framework we derived measures from existing scales or studies in the literature (as we described previously), adapting them to suit the context of our study. For co-shopping influence, voluntary collaboration and incentive seeking, we developed new scales. Briefly, we used the following procedure that the literature on marketing scales measures advocates (Churchill, 1979). We conducted in-depth interviews with three online managers of three leading website retailers to better understand how these experts perceived and described the constructs. We generated an initial set of items from this exploratory research. Next, to enhance the constructs' face validity, we asked other experts to evaluate this initial item set. We provided construct definitions and asked the experts to evaluate each item with respect to wording, fit with construct, completeness, and uniqueness. We rephrased improperly worded items and deleted those that did not fit the construct definition.

In the final step, 20 doctoral students and academics who are familiar with the issue of e-commerce and who belonged to one or more online communities participated in a quantitative pretest of the modified items. They responded to the items, described their understanding of each one, provided an explanation for their responses, and indicated any problems they encountered while responding to the online questionnaire. We made several minor changes in wording based on this feedback and finalized the items to be used for the main study (all items measures are provided in Appendix F). We note that some of our items for voluntary collaboration are similar in content to Bagozzi and Dolakia's (2006) altruistic behavior scale.

### 3.3.2 Online survey participants

Finally, a field study using an online survey was conducted to collect the data necessary for testing the causal model and the hypotheses. We considered the population of interest to be composed of real consumers of a leading online retailer, and also who were member of an online social network. We chose the online retailer as a specific empirical setting for this study for two main reasons: first, e-retailers selling books, computers, software, music and technological products are among the most widely used and competitive online retailers. Second, online retailers are increasingly using interactive features on their websites (e.g. mark ups such as del.ici.ous.com, or "I like", "Recommend this site to a friend" buttons), building communities for customer voice and shared experiences (e.g. Facebook page), and offering customer rewards for their effective referrals (e.g. discounts, product offers). These e-retailer marketing activities made it possible for us to examine customer's specific behaviors and motivations (i.e. site recommendation, voluntary collaboration or incentive seeking), which have been studied far less in the IS domain and EC settings. Taken together, the online retailer appears to offer a desirable empirical environment for testing the efficacy of the model. Then the customer base of the e-retailer was used to collect a sample of respondents. The online retailer was asked to post an invitation to participate in the survey on its website's homepage and included a link to a Web-based questionnaire. The online survey ran for eight weeks from June to early August 2011.

### 3.3.3 Sample characteristics and measures

Of the 577 participants who responded the online survey, a total of 308 completed the survey, resulting in a usable response rate of 53.4%. The analysis that follows is based on these 308 respondents, who participate in at least to 4 different online social networks. The sample's demographics are as follows: 62.3% were male and 37.7% were female, the vast majority 58.8% was between 25-39 years, and 69% had a university degree. We found that 47% had Internet shopping experience for more than 5 years, and about half of respondents spent more than 5 hours a day on the Internet. By inquiring about customer relationship with the e-retailer, we found that 49.7% had a relation between one and three years, and 30.5% had a relation for more than three years. The most represented online networks in the sample were Facebook (88.8%), Twitter (37.2%), LinkedIn (37.2%) and MySpace (18.0%). Other networks that were represented by fewer respondents are less expressive.

Table 3.1 Internet and social networks use of the sample

| Variable | Category | Frequency | Percent (%) |
|---|---|---|---|
| Internet usage per day | Less than 1 hour | 2 | 0,6 |
| | 1 or 2 hours | 51 | 16,6 |
| | 3 or 4 hours | 101 | 32,8 |
| | 5 or 6 hours | 61 | 19,8 |
| | 7 or 8 hours | 45 | 14,6 |
| | 9 or 10 hours | 22 | 7,1 |
| | More than 10 hours | 26 | 8,4 |
| Online shopping experience /use | 1 year or less | 43 | 14,0 |
| | Between 2 – 4 years | 117 | 38,0 |
| | Between 5 – 9 years | 110 | 35,7 |
| | 10 years or more | 38 | 12,3 |
| Primary virtual network membership [a] | Facebook | 267 | 88,8 |
| | Twitter | 104 | 37,2 |
| | MySpace | 50 | 18,0 |
| | LinkedIn | 104 | 37,2 |
| | Blog | 147 | 52,1 |
| | Other | 44 | 14,0 |
| Primary virtual network size | Less than 50 members | 67 | 21,8 |
| | 50–199 members | 117 | 38,0 |
| | 200–499 members, | 87 | 28,2 |
| | 500–999 members | 21 | 6,8 |
| | 1000 members or more | 16 | 5,2 |
| The level of posting on primary virtual network/ | Daily | 203 | 66,0 |
| | Weekly | 37 | 12,0 |
| | Monthly | 10 | 3,2 |
| | Less frequent | 58 | 18,8 |
| The function of posting on primary virtual networks/ communication platforms [a] | Interact for social reasons | 296 | 96,1 |
| | Chat and instantaneous messages | 196 | 63,6 |
| | Share photographs | 135 | 43,8 |
| | Interact for professional reasons | 217 | 70,5 |
| | Share or recommend product news | 115 | 37,3 |
| | Share documents | 185 | 60,1 |
| | Communication for professional career | 150 | 48,7 |
| | Other | 11 | 3,6 |

a Multiple answer question (frequencies of responses could exceed 100%). n= 308

**Classification of respondents**

*Network size*. We classified respondents as belonging to either small or large online social networks. We defined small online social networks as those with fewer than 50 members and large networks as those with 50 or more members. On the basis of responses to our survey question about network size (see the Appendix F), we classified 67 participants (21.8%) as belonging to small social networks and 241 (78.2%) as belonging to larger social networks.

### 3.3.4 Preliminary analysis

Our full-sample structural equation model included all survey respondents (n= 308), and we used it to test H1– 6; we used the small/large subsamples to test the moderation hypotheses (H7–8). We ran all the models that we describe subsequently using the AMOS 19 program, maximum likelihood (ML) estimation method (Arbuckle, 2010).

We assessed the goodness-of-fit of the models with chi-square tests, the root mean square error of approximation (RMSEA), the nonnormed fit index (NFI), and the comparative fit index (CFI). Discussions of these indexes can be found in the work of Bentler (1990), Hu and Bentler (1999), Marsh et al. (1996), and Browne and Cudeck (1993). Satisfactory model fits are indicated by nonsignificant chi-square tests, RMSEA value ≤ .08, and NFI and CFI values ≥ .90.

In examining the standardized residual values, we observe only one that exceeds the cutpoint of 2.58 (Jöreskog and Sörbom, 2001). As such, the residual value of 2.728 represents the only statistically significant discrepancy of note with the covariance between the two observed variables “recommendation intention - RECI5” and “voluntary collaboration - VOL1”. From this information, we exclude RECI5 from further analysis. An examination of the modification indices did not suggests any changes in the model.

*Normality assessment*. An assessment of the normal distribution of data shows that univariate skewness and kurtosis are within the accepted values. Kline (2005) considers the standardized kurtosis index rescaled (β2) values equal to or greater than 7 to be indicative of early departure from normality. An examination of the univariate kurtosis values reveals no item exceeds this value of 7, which is indicative of the presence of moderate kurtosis. When examined the C.R. value, which represents Mardia's (1974, 1970) normalized estimate of multivariate kurtosis, in practice, values greater than 5.00 are indicative of data that are nonnormally distributed (Bentler, 2005). In our data, the z-statistic of 35.884 is highly suggestive of nonnormality in the sample. Satorra and Bentler's (1994, 1988) statistic incorporates a scaling correction for the $\chi 2$ statistic (S–B$\chi 2$) when distributional assumptions are violated. However, this method is not available in the AMOS program. Therefore, we use the bootstrap as an applicable technique to handling the presence of multivariate nonnormal data (Efron and Tibshirani, 1993) to produce confidence intervals for parameter estimates, and to estimate standard errors, thus providing them with a type of generalizability using the survey data to test the model (Ping, 2004). Bootstrapping has also been suggested to improve the asymptotic correctness of a sample covariance matrix (Bentler, 2005; Jöreskog and Sörbom, 2001). Thus, we will continue to base our analyses on ML estimation using bootstrap method. We performed all analyses using covariance matrices as input to estimation and tests of significance of individual parameters, as well as, to testing for equivalence of covariance across groups (Baumgartner and Homburg, 1996; Cudeck, 1989).

## 3.4 Results

### 3.4.1 Measurement model evaluation

We built a confirmatory factor analysis (CFA) model with four latent constructs and a total of 14 measures. Recommendation behavior is measured with one single-item, (e.g. in which each item is a separated indicator) was not included, as we cannot compute reliabilities and validity using CFA as like multiple-item measures (Hair et al., 2006; Jöreskog and Sörbom, 2001). Following the authors' guidelines, the single-item construct will be examined further on, when included in the model to test a structural relationship between the latent constructs.

For model identification purposes, one item loading estimate ($\lambda$) relationship between the variable ($x$) and each latent construct ($\xi$), and the corresponding error ($\varepsilon$) term are fixed to 1. These constraints are sufficient to identify the model (Arbuckle, 2010). Further, when examining the number of parameters to be estimated they not exceed the number of distinct elements in the variance/covariance matrix on the observed variables (which implies that the number of degrees of freedom be nonnegative) providing the necessary condition for model identification. Table 3.2 shows, based on our measurement model, the means, standard deviations, composite reliability, average variance extracted, and correlations of the measures.

*Internal consistency*. We used two measures to evaluate the internal consistency of constructs. The composite reliability (CR) is a measure analogous to coefficient α (Fornell and Larcker, 1981, Eq. 10), whereas the average variance extracted (AVE) estimates the amount of variance captured by a construct's measure relative to random measurement error (Fornell and Larcker, 1981, Eq. 11). Estimates of CR greater than .60 and AVE greater than .50 are usually considered to support internal consistency (Bagozzi and Yi, 1988). As Table 3.2 shows, all values are significantly greater than these stipulated criteria (i.e., Cronbach's alpha ≥ 0.84, composite reliability ≥ 0.84, and average variance extracted ≥ 0.65), and therefore are indicative of good internal consistency.

Table 3.2 Means, standard deviations, and internal consistency statistics for construct measures

| Construct | Number of Measures | Mean | SD | CR | AVE | Correlations | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | 1 | 2 | 3 | 4 |
| 1. Voluntary Collaboration | 3 | 10.88 | 2.73 | .86 | .67 | **.82** | | | |
| 2. Incentive Seeking | 3 | 7.99 | 3.47 | .84 | .65 | .37 | **.81** | | |
| 3. Co-shopping Influence | 4 | 14.26 | 3.86 | .94 | .79 | .66 | .28 | **.89** | |
| 4. Recommendation Intention | 4 | 13.14 | 4.51 | .90 | .70 | .59 | .48 | .41 | **.84** |
| Recommendation Behavior | 1 | 2.62 | 1.66 | _ | _ | _ | _ | _ | _ |
| Network Size | 1 | 2.36 | 1.06 | _ | _ | _ | _ | _ | _ |

Notes: N= 308. Means are reported but not analyzed. SD = standard deviation; CR = composite reliability ≥ 0.7; AVE = average variance extracted ≥ 0.5. Value on the diagonal is the square root of AVE; Value below the diagonal is correlation; all correlations are significantly less than 1.00 at α .001. All item measures and loadings are presented in the Appendix F.

*Discriminant validity* is shown if the square root of the AVE of a measure is larger than its correlation coefficients with the other measures (Fornell and Larcker, 1981). From Table 3.2, we found that each of the scales met the criterion mentioned previously, again suggesting that all the measures of constructs in the measurement model achieve discriminant validity.

The results show that the model fit the data well. The goodness-of-fit statistics for the model are as follows: $\chi 2$ (69) = 117.14, $p \approx .000$, CMIN/DF = 1.698, CFI = .985, NFI = .964 and RMSEA = .048. The RMSEA with the 90% confidence interval ranging from .032 to .062, which is less than the value suggested by Browne and Cudeck (1993), albeit equal to the less conservative cut off value proposed by Hu and Bentler (1999), and according Jöreskog and Sörbom (2001) guidelines the p-value associated with this test of close fit is > .50 ($p = .585$). From these results, we can conclude that the hypothesized measurement model fits the data well.
In addition, the Expected Cross-Validation Index (ECVI) is central to model comparison statistics. We compare its ECVI value of .616 with those of both the saturated model (ECVI = .684) and the independence model (ECVI = 10.593). Given the lower ECVI value for our hypothesized model, compared with both the independence and saturated models (Hu and Bentler, 1995), we conclude that it represents the best fit to the data. Both the .05 and .01 Hoelter's (1983) Critical N (CN) values for our hypothesized model were > 200 (235 and 261, respectively) which leads us to conclude that the size of our sample (N = 308) is satisfactory according to Hoelter's benchmark that the CN should exceed 200. Thus, having established confidence in our measurement model, following we estimate the structural model testing the hypothesized structural relationships.

### 3.4.2 Structural model estimation

We assessed the structural model by checking the GOF indexes and putting more emphasis on the magnitude (size), direction and statistical significance of estimates of the structural weights. With respect to the fit statistics for the full model ($\chi 2$ [83] = 166.87, $p \approx .000$, RMSEA = .057, NFI = .95, and CFI = .97), the chi-square is significant ($p < .05$), which is usually the case for large sample sizes (> 200). All the other statistics are within the acceptable ranges, which indicate a good model fit. An examination of the unstandardized parameters reveals all estimates to be both reasonable and statistically significant ($p < .001$), except one ($p < .05$), and all standard errors appear also to be in good order (Bentler, 2005; Jöreskog and Sörbom, 2001).

We found that the impact of voluntary collaboration on site recommendation intention is significant and positive ($\gamma = .515$, standard error [s.e.] = .07), in support of H1, and its impact on co-shopping influence is significant and positive ($\gamma = .640$, s. e. = .07), in support of H5. As we expected, incentive seeking influences site recommendation intention positively ($\beta = .284$, s.e. = .06), in support of H2. Figure 3.2 summarizes these and other results. Furthermore, as we predicted, the impact of site recommendation intention on recommendation behavior is strong and positive ($\beta = .942$, s.e. = .11, $p < .001$), in support of H3, and the impact of recommendation behavior on co-shopping influence is significant and positive ($\beta = .115$, s.e. =.05, $p \approx .011$), in support of H4. Antecedents explain 40% of the variance in recommendation intention, 40% of the variance in recommendation behavior and 45% of the variance in co-shopping influence. The remaining main effect hypothesis addresses the interplay between co-shopping influence reciprocity mechanism on motivational incentive seeking related construct. In H6, we predicted a positive impact of co-shopping influence on incentive seeking; the results support significantly this prediction ($\beta = .270$, s.e. =.07, $p < .001$) as we expected. In addition, H6 receives support, and co-shopping influence explains only 8% of the variance in incentive seeking. Therefore, we found support for all the expected relationships in our proposed model (for details, see Figure 3.2).

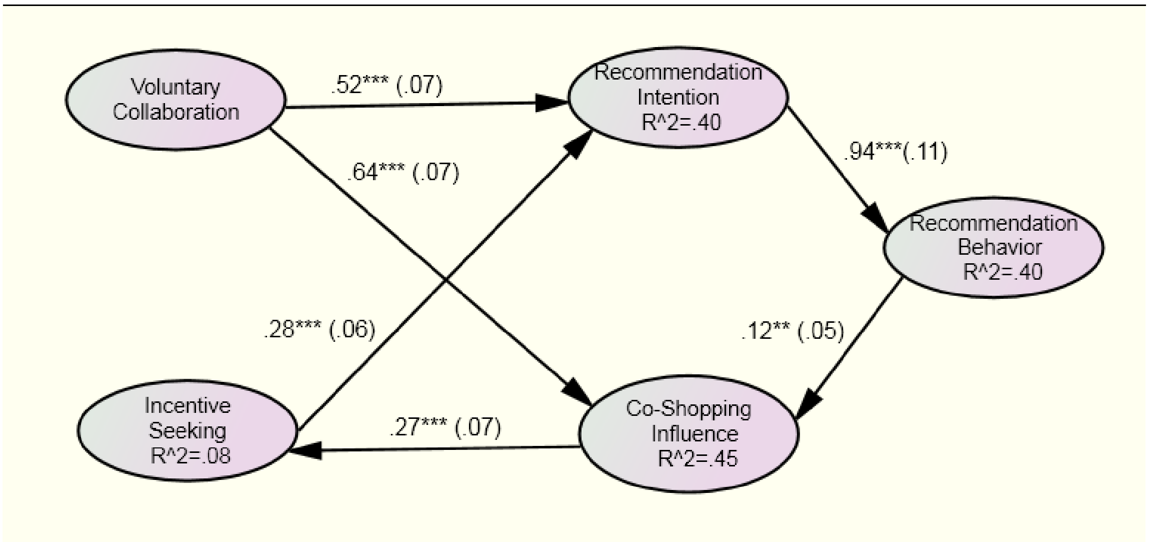
*Model identification and convergence*. As we early mentioned, each latent construct in our model is assessed with a minimum of three or four indicators in order to identify the model (Bollen, 1989), except one “recommendation behavior”. Baumgartner and Homburg (1996) point out that single item-constructs are commonly included in structural model to test relationships among other latent constructs (about 71% of SEM containing at least one single indicator construct); although it is less problematic for latent endogenous constructs, than for exogenous constructs, however it requires providing evidence of model identification. Regarding model identification, we established measurement units for the measurement indicator and latent construct ($\lambda$), and for the measurement indicator and unobservable variable ($\varepsilon$) error term: regression weights were fixed at 1. These two constraints are enough to make the model identified (Arbuckle, 2010, p.131). Despite the single-indicator construct of recommendation behavior, the variance of $\varepsilon$ is an identified parameter because of the over-identifying constraints in the model (Jöreskog and Sörbom, 2001). In this case, covariances among factors help to identify the system of equations (Baumgartner and Homburg, 1996).

Single item measures are widely used in SEM, however it requires carefully examination of measurement error. According to Jöreskog and Sörbom's (2001) guidelines, we further examine the modification indices, reliability and residuals to control for measurement error in the single item measure. Model results reveal no modification index for variance and regression parameters, suggesting no changes in model specification. When examined the estimated reliability, the recommendation behavior item loading $\lambda = 0.79$, the variance explained $\lambda^2 = 0.62$, and the error variance $\varepsilon = 0.38$ are within the acceptable values. The largest standardized residual (2.16) is below the inflexible cutoff value of 2.59 (two-tailed). Taken together, these results demonstrate that the model is identified, and indicate the observed recommendation behavior score is mostly error free and may represent the true behavior.

Next, we examine the model convergence. Our proposed model specifies a direct path from co-shopping influence to incentive seeking factor, and a return to co-shopping through recommendation intentions and behavior. This could occur when defining a cycle[13]. According Jöreskog and Sörbom (2001), a necessary and sufficient condition for convergence of the infinite series i.e. for the stability of the system is that all eigenvalues of **B** matrix are within the unit circle, which means the largest eigenvalue of **BB**' is less than one. The AMOS program prints the largest eigenvalue of **BB**' under the name of *Stability Index* (Bentler and Freeman, 1983; Fox, 1980). In our model the *Stability Index* of .091 provides evidence of model convergence and stability of the non-recursive cycle effect. From this result we can rely on values of regression weights of the well-defined linear interdependencies, and we can have confidence in our model.

[13] There may be a total effect of each $\eta$ on itself (although there are never direct effects of an $\eta$ on itself, which mean all diagonal elements of **B** are zero) in a non-recursive model. The non-recursive cycle total effect of $\eta$ will be the sum of the infinite geometric series, which is $\beta_{21}\beta_{12}$ / (1- $\beta_{21}\beta_{12}$) for $\beta_{21}\beta_{12} < 1$ (Jöreskog and Sörbom, 2001).

Figure 3.2 Estimated model




Notes: Unstandardized coefficients and standard errors are in parentheses. Significance levels ***p < .001; ** .01 < p ≤ .05.

### 3.4.3 Comparison with a rival model

One important criterion of a model's success is its performance compared with that of rival models (Bagozzi and Yi, 1988). Our proposed model is based on an elaborate theory that hypothesizes a specific nomological network of constructs. For example, our model allows no direct paths from antecedents, such as voluntary collaboration and incentive seeking, to recommendation behavior, and incentive seeking to co-shopping influence; therefore it assumes that behavioral intentions mediates all the effects. Moreover, the model also allows no direct paths from co-shopping influence to behavioral intentions constructs supposing that ongoing recommendations are fully mediated by extrinsic motivations i.e. incentives. A nonparsimonious rival model would hypothesize direct paths from the antecedent constructs to recommendation behavior and incentive seeking to co-shopping influence, as well from co-shopping influence to recommendation intentions. Such a model imposes relatively little nomological structure on the constructs.

We compared our hypothesized model with the rival model using the following criteria: overall fit, percentage of the model's statistically significant parameters, theoretical interpretation of the paths, and explained variance of the endogenous constructs. The overall fit for the rival model was about equal to that of our proposed model ($\chi2[79]$ = 141.2, $p \approx .000$, RMSEA = .05, NFI = .96, and CFI = .98), but it was accompanied by reduced parsimony. In our proposed model, all the 6 paths (100%) were significant, whereas only 5 out of 9 (55%) of the paths were significant in the rival model. The path from voluntary collaboration ($\gamma = .20$, s.e. = .14) and from incentive seeking ($\gamma = .05$, s.e. = .09) to recommendation behavior were both not significant ($p > .10$), which means that both effects are fully mediated by behavioral intentions. Even more problematic, several of the non-significant paths in the rival model did not make theoretical sense. For example, the path from incentive seeking to co-shopping influence ($\beta = – .02$, s.e. = .05, $p > .10$) and from co-shopping influence to recommendation intention ($\beta = – .18$, s.e. = .12, $p > .10$) were both negative[14]. Finally, the explained variances for all endogenous constructs were just about the same amount (barely passing the two decimals places) in the rival model: recommendation intention ($R^2_{rival} = .41$ versus $R^2_{proposed} = .40$); recommendation behavior ($R^2_{rival} = .42$ versus $R^2_{proposed} = .40$), and co-shopping influence ($R^2_{rival} = .48$ versus $R^2_{proposed} = .45$). On the basis of these findings, we acknowledge that this comparison provided added confidence to the nomological network in our conceptual model.

### 3.4.4 Moderating influence of network size

We conducted multiple sample analyses (Byrne, 2010; Kline, 2005) using AMOS 19 for the small/large network subsamples to test our hypotheses regarding the role of moderating variable on network externalities effects.

To test $H_7$–$H_8$, we built separate structural models for the small/large online social network subsamples, and we conducted tests of moderation to determine whether the respective path coefficients differed. Table 3.3 summarizes the analyses and results. The procedure that we used was the building of a multi-group model to test the equality of the paths between the two groups. In the first model, all paths were unconstrained between the two groups. This is the “no constraints” or baseline model in Table 3.3, and it was found to be exceptionally well fitting in its representation of the multi-group

[14] Detailed results for the rival model are available on request. We also tested other rival models that were more parsimonious and reflected current conventional wisdom about the value of co-shopping influence. Our hypothesized model out-performed both models. The detailed comparisons for these additional models are also available on request.

networked consumer data ($\chi2[166] = 281.4$, $p \approx .000$, CFI = .965, RMSEA = .048). In the second model, we constrained the relevant paths (e.g., incentive seeking to recommendation intention, co-shopping influence to incentive seeking, and recommendation intention to recommendation behavior for $H_7$) to be equal for both subsamples. This is the "equal paths" model.

Table 3.3 Results of multi-group analyses to test $H_7$–$H_8$

| | Small Versus Large Network Subsamples | | |
|---|---|---|---|
| **Hypothesis** | **Path Coefficients in Unconstrained Model** | **$\chi2$ Test Results** | **CFI Test Results** |
| Baseline model | | No constraints model:<br>$\chi2(166) = 281.360$ | No constraints model:<br>CFI=.965<br>RMSEA = .048 |
| $H_7$<br>INC → RECI,<br>RECI → REB, and<br>COSH → INC<br>are greater for large than for small subsamples | INC → RECI<br>$\beta_{(S)}{}^{a} = .05^{b}$ $(.09)^{c}$<br>$\beta_{(L)} = .36^{***}$ (.07)<br><br>RECI → REB<br>$\beta_{(S)} = .61^{**}$ (.24)<br>$\beta_{(L)} = 1.00^{***}$ (.12)<br><br>COSH → INC<br>$\beta_{(S)} = .17$ (.14)<br>$\beta_{(L)} = .31^{***}$ (.08) | Equal paths model:<br>$\chi2(169) = 293.544$<br>Test of $H_1$:<br>$\Delta\chi2(3) = 12.184$<br>$p \approx .006$<br>$H_7$ is supported. | CFI= .962<br>RMSEA = .049<br>ΔCFI = .003<br>Δ RMSEA = .001 |
| $H_8$<br>VOL → RECI,<br>VOL →COSH, and<br>REB → COSH are greater for small than for large subsamples | VOL → RECI<br>$\gamma_{(S)}{}^{a} = .45^{***}$ (.13)<br>$\gamma_{(L)} = .53^{***}$ (.08)<br><br>VOL → COSH<br>$\gamma_{(S)} = .47^{***}$ (.13)<br>$\gamma_{(L)} = .69^{***}$ (.08)<br><br>REB → COSH<br>$\beta_{(S)} = .29^{**}$ (.12)<br>$\beta_{(L)} = .07$ (.05) | Equal paths model:<br>$\chi2(169) = 285.558$<br>Test of $H_1$:<br>$\Delta\chi2(3) = 4.189$<br>$p > .24$<br>$H_8$ is not supported. | CFI= .964<br>RMSEA = .047<br>ΔCFI = .001<br>Δ RMSEA = .001 |

***p < .001, **p < .01.
a The subscript "S" refers to the small network subsample, and "L" refers to the large network subsample.
b Unstandardized coefficient.
c Standard error.
Notes: VOL = voluntary collaboration, INC = incentive seeking, RECI = site recommendation intention, REB = site recommendation behavior, and COSH = co-shopping influence.

The difference in chi-square values between the two models provides a test for the equality of the paths for the two groups.
Consider the first row of Table 3.3, in light of this procedure. For small network versus large network of consumers, the results indicate that the path from incentive seeking to recommendation intentions is stronger for the large subsample ($\beta$ = .36, s.e. = .07) than for the small network subsample ($\beta$ = .05, s.e. = .09), in support of $H_7$. Similarly, the path from recommendation intention to recommendation behavior is stronger for the large network subsample ($\beta$ = 1.00, s.e. = .12) than for the small network subsample ($\beta$ = .61, s.e. = .24), as well the path from co-shopping influence to incentive seeking is stronger for the large network subsample ($\beta$ = .31, s.e. = .08) than for the small network subsample ($\beta$ = .17, s.e. = .14). The test of difference in chi-square ($p \approx .01$) provides evidence that path coefficients are significantly different in both groups. Thus, $H_7$ is supported for the moderator variable network size.
With respect to the remaining hypothesis H8, the paths from voluntary collaboration to recommendation intention, voluntary collaboration to co-shopping influence, and recommendation behavior to co-shopping influence, are not different for large and small networks of consumers ($p > .10$). Thus, H8 is not supported for the moderator network size. On the whole, we found evidence that the interplay between incentive seeking, recommendation behavior and co-shopping influence is accentuated more for consumers belonging to large networks than small networks of connections.

## 3.5 Conclusion

In the current research, we studied the impact of consumers' virtual recommendation on co-shopping influence within networks of connections. We found support for our conceptual framework in a large sample of online consumers from a leading online store. These customers are actively participating in one or more online social networks, sharing information, social experiences and product recommendations (see Table 3.1). Broadly speaking, this finding points to the importance of purposely selecting, initiating, managing, and using online network interactions among customers when facilitating recommendation tools on retailers' websites.

In particular, our study contributes to existing networked consumer research in several ways. First, our model found that a customer's voluntary collaboration with his/her acquaintances was an influential antecedent to their intention to recommend the company site. This finding provides useful insights into current practice. Specifically, when soliciting highly motivated existing customers to freely give product and brand recommendations, they provide an excellent base to target new or potential customers. Their goal is to help their peers providing them with good business and purchase opportunities that match their needs. Our finding suggests that such approaches toward a new member acquisition only work well if the firm's goals are to enlist committed, active, network connected consumers to create a vibrant and highly participative site community.

Second, the impact of voluntary collaboration on co-shopping influence suggests that is more effective for a firm to solicit and enroll its existing customers who are self-motivated to freely recommend the product or site to their peers. Their reciprocating behaviors are recognition of their influence on other people's shopping decisions. As we noted previously, most customers are members of a specific social network, such as Facebook or Twitter, to name the most expressive. This finding may explain why social network interactions and personal bonds may also help foster co-shopping response. From a managerial perspective, discovering which customer is influential is useful as an effective tool for customer acquisition, which is crucial for firm value creation.

Third, it is noteworthy that the majority of e-retailers provide referral incentives on their websites. We find that such incentives can influence consumers' recommendations positively, and through feedback from co-shopping influence these incentives are perceived as positive future returns. This further reinforces the idea that co-shopping influence provides the structural route to keep ongoing recommendations under the effect of customer referral rewards. These findings have considerable relevance for e-managers. For example, designing different rewarding strategies for more influential customers, and making available not only recommendation tools but also feedback devices, informing customers of their referral effectiveness. In managerial parlance, an incentive seeking customer, like an “outsourced customer”, provides value both as a customer acquisition effectiveness device, as well as a customer retention tool.

Fourth, we find that network size can influence members’ motivations and behaviors differently. We show that network size moderates the relationships between incentive seeking and recommendation intention, recommendation intention and behavior, co-shopping influence and incentive seeking; we find that the strength of the paths in our model are greater in larger networks than in smaller ones (see Table 3.3).

This finding further reinforces the importance of network externality effects for both firms’ and customers’ profitability. For firms, it has considerable managerial value because, when online firms plan a great product diffusion and adoption, larger networks of customers are more appropriate under customer incentives, if their goal is to have greater recommendation diffusion and influence on product adoption or co-shopping behavior. As network size increases, this provides an enormous base for customer referral and product acceptance and adoption, which potentially makes available a base for “crowdsourcing” and social sales. For managers this provides particular value, because the highly networked customer, like an “e-linking” value, functions as a proxy for potential market attraction that is expensive and difficult to access. Another important managerial implication from the effect of network externalities is to use “push” strategy to increase recommendation diffusion, and consequently speed up the spread of new product information. Though potential and late adopter consumers still pay more attention to references from peers, a large network can increase this positive impact. As Van Den Bulte and Wuyts (2007) point out, innovative and e-leading “hubs” speed up the information diffusion process, and follower “hubs” increase the market size.

This study also contributes to existing knowledge on the network structure of ties (Bian, 1997; Granovetter, 1982), finding that incentive seeking seems to overcome the low-motivation problem of “*weak ties*” in large networks of individuals. Moreover, the role of incentives will help *bridging tie*s to foster and speed up market information diffusion. For customers, network externalities may also have a positive impact on profitability and value creation. This means that as network size increases it provides an enormous base for customer recommendations and reciprocal interactions, giving feedback about product acceptance and adoption, which potentially maximizes the utility of incentive rewards. For e-managers this finding has particular importance, suggesting that when firms give incentive rewards for their customers' referrals, they should also make available feedback devices informing customers of their referral effectiveness.

An interesting counterintuitive finding is that network size cannot influence the effect of voluntary collaboration and site recommendation behavior on co-shopping influence. This finding gives no support to the proposed theory of the strength of matched dyadic ties on social influence, in close networks of connections. This proposition refers to the fact that "small worlds" are structured on strong ties and close social bonds, and that "match dyads" are more exposed to social contagion (Watts, 1999) and have more influential power (Katona et al., 2011); however no empirical evidence of this is found in our study. We suggest that this finding should not be taken as a final conclusion, but rather as a preliminary finding that provokes further thought. Further research is therefore necessary to study this issue.

**Limitations and further research**

We conclude by addressing the limitations of our current study, and discussing future research topics. In our study we find that incentives can influence consumers' recommendations positively and through co-shopping influence feedback these incentives will produce ongoing recommendations. Notably, these reciprocal relationships give birth to a cycle effect. It should be noted that the model has revealed no problems with statistical identification and convergence. However, we used cross-sectional data. To confirm the cycle effect of these relationships, longitudinal data area required (Hair et al., 2006; Ferrer et al., 2004; Plewis, 2001). We thus encourage further research using longitudinal data that would help sort out this issue because the time sequence of events could be taken into account. Structural equation modeling could be used to track changes in constructs and relationships over time. For example, a significant co-shopping influence response in time period (t) will produce incentive seeking in time period (t + 1), and this relationship would help provide evidence of causality in that it will be consistent with a causal time sequence and establish covariance. It is easy to see how the model could be extended to more time periods.

Although this is not within the scope of our study, a theory of *crowdsourcing* could explain the large impact of network externalities (e.g. installed base). In addition, the phenomenon of social sales on the Internet also provides future research opportunities to study brand community building, whereby individuals shop together and get discounts.

## Appendix F - Summary of measures

| Construct | Measures [a] (Item Loading [b]) | α [c] |
|---|---|---|
| Constructs in Conceptual Model | | |
| *Voluntary Collaboration* | | .86 |
| | VOL1_ I like to share helpful information about new brands and products with my acquaintances. (.88***) | |
| | VOL2_ Recognition from others is my greatest reward to share with my friends, good business or purchase opportunities. (.75***) | |
| | VOL3_ I like helping my friends by providing them information about products, places to shop online, or sales, even if it may cost me time and effort. (.82***) | |
| *Incentive Seeking* | | .84 |
| | I will recommend the site: | |
| | INC1_ …because the company offers incentives such as monetary rewards, promotional deals or free samples.(.83***) | |
| | INC2_ …because the company gives me loyalty incentives for my continued recommendation. (.90***) | |
| | INC3_ …to get a monetary reward for my continued recommendation. (.67***) | |
| *Co-Shopping Influence* | | 93. |
| | COSH1_ In my network of connections we share information and opinion mutually about products, places to shop, or sales. (.87***) | |
| | COSH2_ In my network of connections we often give feedback about products, places to shop, or sales that we have recommended. (.91***) | |
| | COSH3_ My acquaintances and I, we often reply recognizing good business and purchase opportunities that we have recommended each other matched our needs. (.95***) | |
| | COSH4_ In my network of connections, the product recommendations we share, often influence us to shop at the same sites. (.82***) | |
| *Site Recommendation Intention* | | .91 |
| | RECI1_ I will recommend the website to anyone who seeks my advice. (.73***) | |
| | RECI2_ I would post positive messages and opinion about the website on some Internet message board. (.79***) | |
| | RECI3_ I will refer my acquaintances this is a good online store to do business with. (.86***) | |
| | RECI4_ I will invite friends and relatives to do business with this website. (.95***) | |
| *Site Recommendation Behavior* | | – |
| | RECB_ How many times have you recommended this site in the last 3 months? [d] | |
| **Moderator Variable** | | |
| *Network Size* | | – |
| | How many members does your primary online social network have? [e] | |

*** $p < .001$.

a Unless indicated otherwise, we obtained responses using five-point Likert scales, anchored by 1 = “strongly disagree” and 5 = “strongly agree.”

b We report standardized item loadings.

c Cronbach’s α

d This construct contains a single item and was elicited as a frequency through a question coded into the following seven categories: never, one to two times, three to four times, five to six times, seven to eight times, nine to ten times and more than ten times.

e The choices for this question were (1) less than 50 members, (2) 50–199 members, (3) 200–499 members, (4) 500–999 members, and (5) 1000 members or more.

# Conclusion

Online customer retention and attraction within a mutual value-based perspective, for both customers and online firms, has been a relevant and challenging research subject due to the intense competition in the electronic markets, high customer acquisition costs, and the perceived ease with which customers can switch between online suppliers. However, studying customer retention is relatively neglected in online business, because of the perceived low switching barriers and switching costs. To management, customer retention value is not only a measure of purchase value, frequency and relationship length, but also includes the customer potential for market attraction. Despite the potential of the networked customers, as a proxy to market attraction, there is scarce research on the social networking paradigm for the practice of marketing. In spite of the importance of studying online customer retention and market attraction in Internet commerce, the drivers and the links between them have not been much explored.

The first study shows the e-shopping experience index (e-SEI) model strongly predicts customer e-satisfaction and site recommendation intention. This finding seems to suggest that the higher order factor e-SEI, reflecting a higher level of abstraction of overall customer assessments and reactions concerning online shopping experience, is the leading factor that determines customers' overall satisfaction and recommendation intention. This finding also suggests that the Index scores rank provides a uniform and comparable system to benchmark data regarding current levels of e-retailer performance, as well as to conduct periodic checks to measure e-retailer performance improvement. More significantly, the research pointed out that it makes sense to evaluate the e-SEI model at both overall and dimension level. Regarding the dimension level it was also found that the strength of all "the big five" first order dimensions on e-SEI was quite uniform This finding suggests at dimension level the research instrument provides distinctive and additional information on each dimension, specifically, on the extent to which each dimension better represents e-shopping experience.

Another conclusion of the research showed that transaction and post-transaction dimensions are important to represent customers' evaluations of the perceived value of online shopping experience. The positive evaluations of dimensions reflect the degree to which an individual customer feels that the online provider fulfills and satisfies their personal needs. This conclusion is in line with Otim and Grover's (2006) finding that post-purchase stages become more critical as e-commerce matures. In light of this, the research data seems to be consistent with similar studies and the sample's characteristics (i.e. has considerable e-purchase experience) was shown to be appropriate for the research. The findings of multi-group analysis, in both groups of more and less e-experienced consumers, suggests that the instrument developed in this research proved the soundness of set of measures to capture customers' reactions to online shopping experiences in different conditions: both groups of customers rank the e-SEI indicator dimensions with very similar values. Again, this suggests that e-SEI is suitable to predict future customer behavior, of both e-experienced and e-novice customers, that eventually leads to customer maintenance with the incumbent online provider.

Another significant conclusion from this research is that there are other ways to retain online customers, taking a customer-value oriented approach in a highly competitive and non-contractual online retail setting. The findings of the second study provide strong support for a dual model, which posits that the commitment- and constraint-based mechanisms simultaneously, yet differentially, determine customers' reactions to online retail providers, and eventually will keep customers in the long run. Specifically, it was found that in the commitment-based mechanism, personalization and loyalty rewards are the customer perceived benefits which influence repurchase intentions. In the constraint-based mechanism, meanwhile, personalization influences search costs, and both are found to affect switching costs. It was found that the two mechanisms exhibit highly discernible patterns, but they are not completely independent of each other; this is because personalization relationships across the mechanisms - e.g. intermechanism relationships- are positive and significant, except the relationship between switching costs and repurchase intentions. These findings seem to suggest that customers do not remain with the online provider in a constraint manner, and only perceived benefits of personalization and loyalty rewards create customer value to explain the retention process.

Therefore, one of the major conclusions from the second study is that personalization and loyalty programs are key factors to retain customers in a value-oriented perspective. Personalization is the intervening factor of dual mechanism of online customer retention. Personalized product offerings provide customers other benefits to maintain the relationship with the incumbent provider. In fact, Internet technology and e-commerce will undoubtedly change the way business is done to create customer value. If all the interaction is via the website, it is simple for the web browser to capture and to manage the customer purchase history, in a way to suggest personalized products adapted to customers' profiles. It is also easy to create customer value, rewarding customers for their frequent purchases, but also for providing effective referrals to potential new customers. Consequently, another strategy of customer retention and attraction that it is expected to become more widespread in e-commerce is the loyalty rewards program. Rewarding customers for their frequent purchases will retain customers, and will increase sales volume. A personalized product recommendation is also key to retain customers in a constraint manner, because personalization benefits gives rise to the perception of increased search costs. In other words, this means the perceived benefits of personalization increases the perception of an additional cost, when customers intend to search for and switch to an alternative online provider.

A significant conclusion of the third study is that the structure of customers' network of connections can influence their motivations and behaviors differently. The network size acts as moderator between incentive seeking and recommendation intention, recommendation intention and behavior, co-shopping influence and incentive seeking: the strength of the paths of the relationships is greater in larger networks than in small social networks. This finding further reinforces the network externalities effects, for both customers and firms: customer' recommendation value increases as network size increases. For customers, the incentives system positively influences customers' recommendation, and through co-shopping influence feedback these incentives are perceived as increased returns, as the network expands. Therefore, co-shopping influence, through peer reciprocal interactions, provides the structural route to maintain ongoing recommendations, under customer reward incentives effects. For firms, the existence of network externalities potentially increases the size of the market and sales profitability, from both newly acquired customers and from the existing ones. Therefore, the existence of network externalities under customer incentives will increase the size of the market, and consequently overall welfare may easily be enhanced. This conclusion seems to be in line with Varian's (2000) point of view that "the success of e-commerce will depend on network externalities", which increasingly benefits from the new phenomenon of the networked customer in the digital world. Another conclusion from this study is that the customer's voluntary collaboration with their acquaintances was an influential antecedent of his or her intentions to recommend the company site and of co-shopping influence. Therefore, these customers self-motivated to freely recommend the product or site, their goal is to provide to their peers good business or purchase opportunities that match their needs. Their reciprocating behaviors are recognition of peer influence on shopping decisions. This seems to explain that the social network structure of close ties and match dyads may foster altruistic behaviors and also help foster co-shopping response. However, it was not found that network size (e.g. small networks) moderates the effect of voluntary collaboration and site recommendation behavior on co-shopping influence.

## Managerial implications

This research provides contribution for management practice of online business. One of the initial goals of this research is to develop an e-shopping experience index (e-SEI) to capture customers' reactions and evaluations regarding their online shopping experiences from a specific retailing site. The developed and validated measurement instrument provides contribution for managers on actions they can take. For instance, one way to use the measurement instrument, as a diagnostic tool, is by computing at an overall level the e-SEIndex. The index scores represent a uniform and comparable system of measurement that allows for systematic benchmark data regarding current levels of e-tail performance and across competitors, as well to conduct periodic "checks" to assess e-tail performance improvement. More importantly, the predictive power of e-SEI, as a diagnostic tool, to "check" customer intentional behavior (e.g. retention or to warn about defection) is of major relevance for online business.

Nowadays, more and more sites provide platforms for customers' reviews about products and online service, and they also provide direct links to social networks facilitating the recommendation of the site by online shoppers. Furthermore, e-managers can benchmark index ratings from more e-experienced, sophisticated and demanding customers on newly acquired customers to boost e-satisfaction.
Another way to use the measurement instrument, as a diagnostic tool, is by testing the five basic dimensions, that will allow online retailers to determine e-business areas that are weak and in need of improvement. More importantly, e-managers can gather information about the performance of outsourced third-party logistics companies (e.g. to pick, pack, delivery and return the products) that is difficult to control directly. Therefore, to deliver superior service and products that create value to customers, an online business must first understand how customers perceive and evaluate their e-shopping experience at specific dimension level.

Online retailers should increase firm-specific investments on a personalized product recommendation system, in order to match the customers' needs and wants in a more efficient way. Online firms today use information about customers' purchase history to build customer profiles, and to design personalized offerings matching these profiles. To do this successfully, however, firms must collect more explicit customer information. For this purpose, online managers should encourage customers to provide personal information so that the product recommendation can be tailored to the customer´s needs and desires. For example, online retailers need to actively encourage customers to customize their products, in terms of adapting product features or build it from zero. Such firm-investments in sophisticated personalization tools (e.g. providing customers personal accounts on the website for co-creation, co-design, intelligent agents tracking customer's searching needs) will retain customers in a specific webstore. Those personalization efforts are non-transferable customer-specific investments when they switch to another provider. Therefore, the amount of private information provided by customers will decrease the need for an additional search for other alternatives, and potentially will keep them with the current provider. A management tactic to inflate switching costs appears to be more effective in boosting customers' perceived benefits

of personalization features. In particular, in a highly competitive and non-contractual online retail context, managers should carefully exploit “positive” switching costs.
It is also important for online firms to enhance repurchase behavior by offering a variety of valuable customer benefits, such as loyalty rewards. Rewarding customers for frequent purchases will affect both short-term performance by an immediate increase of sales, and long-term success by offering ongoing incentives for repeated purchases. We believe that, in general, personalization and loyalty rewards tend to increase overall welfare, for both, online customers and e-retailers. Therefore, to effectively manage and build customer retention, online retailers should be aware of the importance of a constraint-oriented strategy that can complement the widely recognized commitment-oriented strategy.

A major implication of this research points to the importance of e-managers in selecting, initiating, managing, and using online networked customers while facilitating recommendation tools on a retailer’s website. It is noteworthy that the customers of the surveyed webstore are actively participating in one or more online social networks, sharing information, social experiences and product recommendations. Ideally, a company that wanted to know a customer’s full value would include a measure of that person’s ability to bring in profitable new customers. For managers, the strategic-level of customer recommendation resides in the e-linking value of networked customers, acting as a proxy to market attraction that is expensive and difficult to access. As customer’s networks increase, the potential for information diffusion and new market attraction also increases. Therefore, firms can replace or reduce marketing efforts and investments for market attraction promoting collaboration with highly valuable networked customers. These issues lie at the heart of e-commerce transformation, and could not be more timely for managing and creating alliances for cooperation with networked customers. For example, these networked customers provide a large base for crowdsourcing and social sales. Managers should build online brand communities to create a vibrant and exciting community for social sales, where members could buy products together and get bigger discounts.

Online managers should invest on customer referral program, since it has a positive impact on firm' profitability in the extent that potentially increases brand image, growing share-of-customer (e.g. cross-selling strategies to increase volume per customer), and can also increase market-share bringing new customers at a near zero cost. Actually, customer defection is not only a function of lost purchases but also a function of lost positive word-of-mouth effect on potential future sales.

For managers, personalization features could be an effective strategic tool for market segmentation and price discrimination. Personalized product offer may have high first set up costs, but very low incremental costs. For managers the challenge in pricing is to find a way to offer and sell to a broad enough customer base to cover those high first set up costs. One way to accomplish this is to version or bundle products. This means offering a product line of variations on the same underlying product. Versioning and bundling are common strategies of price discrimination for commodity goods and information goods, such as books, software or technological products. Moreover the flexibility of digital media offers many alternative forms of versioning (for details see Shapiro and Varian, 1998). Another challenge to managers is to find a way to offer and sell to a broad enough audience the same bundling product that matches other consumers' needs. Networked customers could be a strategic bridge to expand the market size.

## Contribution to extant knowledge

This research will help to incorporate empirical findings into a coherent body of knowledge in the online consumer behavior stream of research. The first study provides a set of validated e-commerce metrics which are suited for studying online customer reactions to e-retail business that offer a mix of consumer goods.

Measurement efforts of customer retention and market attraction drivers of real and e-experienced customers have not been much explored in the information systems and consumer behavior literature. A large body of research fails to develop and validate scales for measuring the full online shopping experience. One of the greatest limitations of the development and validation of e-scales has been the sample and industry context bias. This seems to occur because in the service industry context (i.e. online services, portals, brokerage industry), the critical dimensions of online service experiences are different from the physical retail (e.g. physical product delivery). This research provides several contributions to overcome the lacks of prior research.

This research fills this gap by proposing an e-shopping experience index that is suitable to measure both e-experienced and e-novice customers, and to predict customer retention and warn about customer defection. As far as we know, this research is a first step to propose an index for online retail by integrating a reflexive second order model. The “big five” first order dimensions are the enduring set of e-metrics of online retail. For research this contributes to confirm the theory that transaction and post-transaction are the critical dimensions of online shopping experiences, as e-commerce matures and online consumers become more experienced. As Straub and colleagues (2002) point out, Net-enablement and Net-enhancement e-commerce metrics began in the past decade and they picture an evolution that will see the development of metrics that suit emerging technologies and some that will endure over time.

Although, the development of measurement instruments does not move theory forward as much, both temporary and long lasting metrics will be valuable for academics and practitioners trying to understand the e-commerce phenomenon and e-consumer behavior.

The second study contributes to the literature by theoretically highlighting the duality of consumers’ reactions and empirically demonstrating that the repurchase intentions representing commitment, and switching costs representing constraints are the two mechanisms of customer retention in the online business-to-consumer domain. In addition, this study provides an innovative contribution, by empirically demonstrating that customers are intended to repeated behaviors, not in a constraint manner, when perceived benefits to maintain an ongoing customer-firm relationship are taken into account. While only aspects of the relationships in online contractual-services have been considered in order to lock-in customers, the present research fills a gap by revealing the limitations of the simplistic view of online customers’ constraints approach and shedding light on the powerful effects of perceived benefits of personalization and loyalty rewards, as firm-specific investments, have on customer retention. Personalization and loyalty rewards are likely to create customer value and both are the customer retention driving forces.

This research also contributes to information system literature by demonstrating that e-commerce has produced several myths and paradox theories. One of the most peculiar is what we label “the search costs paradox”. Some academics have predicted that customers’ search costs will be near to zero in the Internet marketplace, which will force price competition. Paradoxically, the information overload on the Internet will increase the cost of searching and comparing prices and products routinely bought.
As some researchers point out, despite the changes introduced by e-commerce, many of the fundamental principles of competition will still be relevant. In this sense, the second study contributes to an extant view of Internet technology usage to a more integrative theory of value-oriented approach, by considering firm-specific investments which will create customer value and the retention process. On the whole, the study contributes relevant knowledge to the information system literature showing the complex nature of online consumer behavior, clarifying seemingly complex post-consumption customer retention phenomena, in the online retail environment.

This research also contributes to the existing networked consumer theory, particularly on the effect of networked externalities. This effect is anchored in the network structure of ties. In fact, within larger social networks members are more likely to identify with the community as a whole rather than with specific people in it. Because of their larger exposure on the network, e-leading “hubs” have an important position in information access and transfer to the network: they speed up the information diffusion process and follower “hubs” increase the market size. The fundamental contribution is that e-linking-value of highly networked customers could be a proxy to market attraction.
The fundamental theory of networked customer supports the network externalities effects, in the sense that, a larger network will offer higher utility for any customer getting (a) incentives for effective product recommendation, and (b) feedback of co-shopping influence, will maximize the utility of incentives that lead to repeated recommendation behavior. In particular, this research provides a theory of network externalities effects for both customers and firms, in the sense that the potential value of

a product recommendation increases as the network of consumers expands, raises the size of the market, and consequently overall welfare and mutual value may easily increase.

The research also provides an innovative contribution, which is the new concept of co-shopping influence, defined as a feedback mechanism structured on the reciprocal interactions in the online social media, which also acts as a reinforcing mechanism of ongoing recommendation behavior. Moreover, for researchers the co-shopping construct provides a set of validated measures (e.g. good psychometric properties).

## Limitations and future research

One limitation of this research is that the findings are based on a one-site sampling scheme, which limits their generalizability. Despite this limitation, this research provides important theoretical and practical contributions.

The research's limitation also suggests directions for future investigation. In future, surveying diverse samples and conducting cross-sites study will help to confirm if the e-SEI is equivalent across-sites considering site and/or product heterogeneity. Despite the changes introduced by e-commerce, we believe "the big five" fundamental dimensions of e-SEI will still be relevant. However, the Internet is a fast changing environment, and the e-SEI is not the final word in measurement instruments. As technology changes researching another dimensions of net-enhanced and net-enable business, would require continuous investigation in the field.

One of the major conclusions of this research is that the implementation of loyalty rewards programs seems particularly fruitful, because it may be also used as a customer retention and acquisition strategic tool. To determine the long-term efficacy of loyalty rewards programs, further research is needed to quantify the loyalty program's influence on repurchase behavior and increased market size.

Another conclusion of this research is that personalization of benefits increases consumers' perceived search costs. However the study does not incorporate into the model the role of peer recommendations and the moderator effect of product heterogeneity on the relationship between personalization and search costs. It is likely that consumers perceive information search to find relevant attribute information is indeed more costly and difficult for experience products than for search products, as found in prior research. Further research is certainly required for a better understanding of the role that product recommendations through online peer communications, play in regulating search costs and behavioral outcomes across various product categories (i.e. search, experience and credence products).

Another limitation of this research is that it focuses on the extent of personalization benefits as a whole without paying much attention to the specific features of personalization at a micro level. For example, personalization features that address the needs of consumers who are more willing to invest in co-creation, co-design or bundling products. Moreover, personalization features also involves customer-specific investments, namely customers' willingness to provide explicit personal information. Therefore, we encourage researchers to perform a feature level analysis to gain better insights into the dual component of personalization, as perceived benefits and customer-specific investments, which could affect customer retention.

An additional research area that requires future investigation is the study of dynamic price competition on the Internet, more specifically examining the interplay between dynamic prices, search costs and customer buying response.

The social media research stream also presents increasing challenges and opportunities for business and consumers. The movement of firms toward using networks and social media to enhance their businesses will likely take decades, an evolution that will see the development of metrics that suit emerging technologies and some that will endure over time. Both temporary and long lasting metrics will be valuable for academics and practitioners trying to understand this phenomenon. Therefore continuous research is needed.

# Bibliography


Agarwal, R. and V. Venkatesh (2002), "Assessing a Firm's Web Presence: A Heuristic Evaluation Procedure for the Measurement of Usability", *Information Systems Research*, Vol. 13, Nº 2, pp. 168-186.

Ajzen, I. (1991), "The Theory of Planned Behavior", *Organizational Behavior and Human Decision Processes*, Vol. 50, Nº 2, pp. 179–211.

Algesheimer, R., U. M. Dholakia, and A. Herrmann (2005), "The Social Influence of Brand Community: Evidence from European Car Clubs", *Journal of Marketing*, Vol. 69, Nº 3, pp. 19-34.

Anderson, E. T., K. Hansen, and D. Simester (2009), "The Option Value of Returns: Theory and Empirical Evidence", *Marketing Science*, Vol. 28, Nº 3, pp. 405-423.

Anderson, E. W. and C. Fornell (2000), "Foundations of the American Customer Satisfaction Index", *Total Quality Management*, Vol. 11, Nº 7, pp. 869-882.

Anderson, E. W. and S. A. Mansi (2009), "Does Customer Satisfaction Matter to Investors? Findings from the Bond Market", *Journal of Marketing Research (JMR)*, Vol. 46, Nº 5, pp. 703-714.

Anderson, R. E. and S. S. Srinivasan (2003), "E-Satisfaction and E-Loyalty: A Contingency Framework", *Psychology & Marketing*, Vol. 20, Nº 2, pp. 123-138.

Arbuckle, J. L. (2010), *AMOS TM 19 User's Guide*, Chicago: IBM:SPSS.

Awad, N. F. and M. S. Krishnan (2006), "The Personalization Privacy Paradox: An Empirical Evaluation of Information Transparency and the Willingness to Be Profiled Online for Personalization", *MIS Quarterly*, Vol. 30, Nº 1, pp. 13-28.

Bagozzi, R. and Y. Yi (1988), "On the Evaluation of Structural Equation Models", *Journal of the Academy of Marketing Science*, Vol. 16, Nº 1, pp. 74–94.

Bagozzi, R. P. (1980), "Performance and Satisfaction in an Industrial Sales Force: An Examination of Their Antecedents and Simultaneity", *Journal of Marketing,* Vol. 44, Nº 2, pp. 65-77.

Bagozzi, R. P. and U. M. Dholakia (2006), "Antecedents and Purchase Consequences of Customer Participation in Small Group Brand Communities", *International Journal of Research in Marketing,* Vol. 23, Nº 1, pp. 45-61.

Bagozzi, R. P. and T. F. Heatherton (1994), "A General Approach to Representing Multifaceted Personality Constructs: Application to Self Esteem", *Structural Equation Modeling,* Vol. 1, Nº 1, pp. 35– 67.

Bagozzi, R. P. and Y. Yi (1990), "Assessing Method Variance in Multitrait-Multimethod Matrices: The Case of Self-Reported Affect and Perceptions at Work", *Journal of Applied Psychology,* Vol. 75, Nº 5, pp. 547–560.

Bagozzi, R. P., Y. Yi, and L. W. Philips (1991), "Assessing Construct Validity in Organizational Research", *Administrative Science Quarterly,* Vol. 36, Nº 3, pp. 421–458.

Bakos, Y. J. (1997), "Reducing Buyer Search Costs: Implications for Electronic Marketplaces", *Management Science,* Vol. 43, Nº 12, pp. 1676–1692.

Balabanis, G., N. Reynolds, and A. Simintiras (2006), "Bases of E-Store Loyalty: Perceived Switching Barriers and Satisfaction", *Journal of Business Research,* Vol. 59, Nº 2, pp. 214-224.

Balasubramanian, S. and V. Mahajan (2001), "The Economic Leverage of the Virtual Community", *International Journal of Electronic Commerce,* Vol. 5, Nº 3, pp. 103-138.

Baron, R. M. and D. A. Kenny (1986), "The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic and Statistical Considerations", *Journal of Personality and Social Psychology,* Vol. 51, Nº 6, pp. 1173-1182.

Baumgartner, H. and C. Homburg (1996), "Applications of Structural Equation Modeling in Marketing and Consumer Research: A Review", *International Journal of Research in Marketing,* Vol. 13, Nº 2, pp. 139-161.

Bearden, W. O., R. G. Netemeyer, and M. F. Mobley (1993), *Handbook of Marketing Scales: Multi-Item Measures for Marketing and Consumer Behavior Research*, Newbury Park, CA: Sage Publications.

Belanger, F., J. S. Hiller, and W. J. Smith (2002), "Trustworthiness in Electronic Commerce: The Role of Privacy, Security, and Site Attributes", *Journal of Strategic Information Systems,* Vol. 11, Nº 3-4, pp. 245–270.

Benbasat, I. and G. DeSanctis (2001), "Communication Challenges: A Value Network Perspective", in G. W. Dickson and G. DeSanctis (Eds.), *Information Technology and the Future Enterprise: New Models for Managers*, pp. 144-162, Upper Saddle River, NJ: Prentice Hall.

Bendapudi, N. and L. L. Berry (1997), "Customers' Motivations for Maintaining Relationships with Service Providers", *Journal of Retailing,* Vol. 73, Nº 1, pp. 15-37.

Bentler, P. M. (1990), "Comparative Fit Indexes in Structural Models", *Psychological Bulletin,* Vol. 107, Nº 2, pp. 238–246.

Bentler, P. M. (2005), *EQS 6 Structural Equations Program Manual*, Encino, CA: Multivariate Software.

Bentler, P. M. and E. H. Freeman (1983), "Tests for Stability in Linear Structural Equation Systems", *Psychometrika,* Vol. 48, Nº 1, pp. 143–145.

Besanko, D. and R. Braeutigam (2005), *Microeconomics,* (Second ed.): John Wiley and Sons, Inc.

Bhattacherjee, A. (2001), "Understanding Information Systems Continuance: An Expectation-Confirmation Model", *MIS Quarterly,* Vol. 25, Nº 3, pp. 351-370.

Bian, Y. (1997), "Bringing Strong Ties Back In: Indirect Ties, Network Bridges, and Job Searches in China.", *American Sociological Review,* Vol. 62, Nº 3, pp. 366-385.

Blau, P. M. (1964), *Exchange and Power in Social Life*, New York, NY: Wiley.

Bollen, K. A. (1989), *Structural Equations with Latent Variables*, New York: Wiley.

Bollen, K. A. and R. Lennox (1991), "Conventional Wisdom on Measurement: A Structural Equation Perspective", *Psychological Bulletin,* Vol. 110, Nº 2, pp. 305-314.

Bollen, K. A. and R. Stine (1990), "Direct and Indirect Effects: Classical and Bootstrap Estimates of Variability", *Sociological Methodology,* Vol. 20, Nº 1, pp. 115–140.

Bolton, R. N. (2004), "Linking Marketing to Financial Performance and Firm Value", *Journal of Marketing,* Vol. 68, Nº 4, pp. 73-75.

Bolton, R. N., K. N. Lemon, and P. C. Verhoef (2004), "The Theoretical Underpinnings of Customer Asset Management: A Framework and Propositions for Future Research", *Journal of the Academy of Marketing Science,* Vol. 32, Nº 3, pp. 271-292.

Bonifield, C., C. Cole, and R. L. Schultz (2010), "Product Returns on the Internet: A Case of Mixed Signals?", *Journal of Business Research,* Vol. 63, Nº 9-10, pp. 1058-1065.

Bressolles, G., F. Durrieu, and M. Giraud (2007), "The Impact of Electronic Service Quality's Dimensions on Customer Satisfaction and Buying Impulse", *Journal of Customer Behaviour,* Vol. 6, Nº 1, pp. 37-56.

Browne, M. W. and R. Cudeck (1993), "Alternative Ways of Assessing Model Fit", in K. A. Bollen and J. S. Long (Eds.), *Testing Structural Equation Models* pp. 136–162, Newbury Park, CA: Sage.

Brynjolfsson, E. and M. Smith (2000), "Frictionless Commerce? A Comparison of Internet and Conventional Retailers", *Management Science,* Vol. 46, Nº 4, pp. 563–585.

Burke, R. R. (2002), "Technology and the Customer Interface: What Consumers Want in the Physical and Virtual Store", *Journal of the Academy of Marketing Science,* Vol. 30, Nº 4, pp. 411-432.

Burnham, T., J. Frels, and V. Mahajan (2003), "Consumer Switching Costs: A Typology, Antecedents, and Consequences", *Journal of the Academy of Marketing Science,* Vol. 31, Nº 2, pp. 109-126.

Byrne, B. M. (2010), *Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming*, Routledge, NY: Taylor & Francis Group.

Chan, K. W. and S. Y. Li (2010), "Understanding Consumer-to-Consumer Interactions in Virtual Communities: The Salience of Reciprocity", *Journal of Business Research,* Vol. 63, Nº 9-10, pp. 1033-1040.

Chang, H. H. and S.-S. Chuang (2011), "Social Capital and Individual Motivations on Knowledge Sharing: Participant Involvement as a Moderator", *Information & Management,* Vol. 48, Nº 1, pp. 9-18.

Chen, P.-Y. and L. M. Hitt (2002), "Measuring Switching Costs and the Determinants of Customer Retention in Internet-Enabled Businesses: A Study of the Online Brokerage Industry", *Information Systems Research,* Vol. 13, Nº 3, pp. 255-274.

Chen, Y.-H., I. C. Hsu, and C.-C. Lin (2010), "Website Attributes That Increase Consumer Purchase Intention: A Conjoint Analysis", *Journal of Business Research,* Vol. 63, Nº 9-10, pp. 1007-1014.

Cheung, G. W. and R. B. Rensvold (2002), "Evaluating Goodness-of-Fit Indexes for Testing Measurement Invariance", *Structural Equation Modeling: A Multidisciplinary Journal,* Vol. 9, Nº 2, pp. 233–255.

Childers, T. L. and A. R. Rao (1992), "The Influence of Familiar and Peer-Based Reference Groups on Consumer Decisions", *Journal of Consumer Research,* Vol. 19, Nº 2, pp. 198-211.

Churchill, G. A., Jr. (1979), "A Paradigm for Developing Better Measures in Marketing", *Journal of Marketing Research,* Vol. 16, Nº February, pp. 64–73.

Cohen, J. (1988), *Statistical Power Analysis for the Behavioral Sciences*, Hillsdale, NJ: Lawrence Erlbaum Associates.

Cohen, J. (1992), "A Power Primer", *Psychological Bulletin,* Vol. 112, Nº 1, pp. 155-159.

Cole, M. (2007), "The Networked Consumer: A Critical Review and Assessment", *Journal of Customer Behaviour*, Vol. 6, Nº 1, pp. 5-18.

Coleman, J. S. (1990), *Foundations of Social Theory*, Cambridge, Mass.: Harvard University Press.

Cudeck, R. (1989), "Analysis of Correlation Matrices Using Covariance Structure Models", *Psychological Bulletin,* Vol. 105, Nº 2, pp. 317–327.

Cudeck, R. and M. W. Browne (1983), "Cross-Validation of Covariance Structures", *Multivariate Behavioral Research,* Vol. 18, Nº 2, pp. 147–167.

Dabholkar, P. A., D. I. Thorpe, and J. O. Rentz (1996), "A Measure of Service Quality for Retail Stores: Scale Development and Validation", *Journal of the Academy of Marketing Science,* Vol. 24, Nº 1, pp. 3-16.

Davis, F. (1989), "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology", *MIS Quarterly,* Vol. 13, Nº 3, pp. 319-340.

Devaraj, S., F. Ming, and R. Kohli (2002), "Antecedents of B2c Channel Satisfaction and Preference: Validating E-Commerce Metrics", *Information Systems Research,* Vol. 13, Nº 3, pp. 316-333.

Dholakia, U. M., R. P. Bagozzi, and L. K. Pearo (2004), "A Social Influence Model of Consumer Participation in Network- and Small-Group-Based Virtual Communities", *International Journal of Research in Marketing,* Vol. 21, Nº 3, pp. 241-263.

Diamantopoulos, A. and H. Winklhofer (2001), "Index Construction with Formative Indicators: An Alternative to Scale Development", *Journal of Marketing Research,* Vol. 38, Nº 2, pp. 269-277.

Dick, A. S. and K. Basu (1994), "Customer Loyalty: Toward an Integrated Conceptual Framework", *Journal of the Academy of Marketing Science,* Vol. 22, Nº 2, pp. 99-113.

Dunham, R. B., J. A. Grube, and M. B. Castañeda (1994), "Organizational Commitment: The Utility of an Integrative Definition", *Journal of Applied Psychology,* Vol. 79, Nº 3, pp. 370-380.

Eagly, A. H. and S. Chaiken (1993), *The Psychology of Attitudes*, Fort Worth, TX: Harcourt Brace Jovanovich.

Eastlick, M. A., S. L. Lotz, and P. Warrington (2006), "Understanding Online B-to-C Relationships: An Integrated Model of Privacy Concerns, Trust, and Commitment", *Journal of Business Research,* Vol. 59, Nº 8, pp. 877–886.

Edwards, J. R. (2001), "Multidimensional Constructs in Organizational Behavior Research: An Integrative Analytical Framework", *Organizational Research Methods,* Vol. 4, Nº 2, pp. 144-192.

Edwards, J. R. and R. P. Bagozzi (2000), "On the Nature and Direction of the Relationship between Constructs and Measures", *Psychological Methods,* Vol. 5, Nº 2, pp. 155-174.

Efron, B. and R. J. Tibshirani (1993), *An Introduction to the Bootstrap*, New York: Chapman and Hall.

Fader, P. S. and B. G. S. Hardie (2009), "Probability Models for Customer-Base Analysis", *Journal of Interactive Marketing,* Vol. 23, Nº 1, pp. 61-69.

Ferrer, E., F. Hamagami, and J. J. McArdle (2004), "Modeling Latent Growth Curves with Incomplete Data Using Different Types of SEM and Multi-Level Software", *Structural Equation Modeling,* Vol. 11, Nº 3, pp. 452-483.

Foa, U. G. (1971), "Interpersonal and Economic Resources", *Science,* Vol. 171, Nº 3969, pp. 345-351.

Fornell, C. (1992), "A National Customer Satisfaction Barometer: The Swedish Experience", *Journal of Marketing,* Vol. 56, Nº 1, pp. 6–21.

Fornell, C., M. D. Johnson, E. W. Anderson, C. Jaesung, and B. E. Bryant (1996), "The American Customer Satisfaction Index: Nature, Purpose, and Findings", *Journal of Marketing,* Vol. 60, Nº 4, pp. 7-18.

Fornell, C. and D. F. Larcker (1981), "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error", *Journal of Marketing Research,* Vol. 18, Nº 1, pp. 39–50.

Fox, J. (1980), "Effect Analysis in Structural Equation Models.", *Sociological Methods and Research,* Vol. 9, Nº 1, pp. 3–28.

Francis, J. E. and L. White (2002), "Pirqual: A Scale for Measuring Customer Expectations and Perceptions of Quality in Internet Retailing", paper presented at the AMA Winter Educators' Conference Proceedings.

Friedkin, N. E. (2011), "Spine Segments in Small World Networks", *Social Networks,* Vol. 33, Nº 1, pp. 88-97.

Gefen, D., I. Benbasat, and P. A. Pavlou (2008), "A Research Agenda for Trust in Online Environments", *Journal of Management Information Systems,* Vol. 24, Nº 4, pp. 275-286.

Gefen, D., E. Karahanna, and D. Straub (2003), "Trust and Tam in Online Shopping: An Integrated Model", *MIS Quarterly,* Vol. 27, Nº 1, pp. 51–90.

Gefen, D., D. Straub, and M. Boudreau (2000), "Structural Equation Modeling and Regression: Guidelines for Research Practice", *Communications of Association for Information Systems,* Vol. 7, Nº (August), pp. 1-78.

Gerbing, D. W. and J. C. Anderson (1984), "On the Meaning of within-Factor Correlated Measurement Errors", *Journal Consumer Research,* Vol. 11, Nº 1, pp. 572– 580.

Gerbing, D. W., J. G. Hamilton, and E. B. Freeman (1994), "A Large-Scale Second-Order Structural Equation Model of the Influence of Management Participation on Organizational Planning Benefits", *Journal of  Management,* Vol. 20, Nº 4, pp. 859–885.

Gilmore, J. and B. J. Pine (2002), "Customer Experience Places: The New Offering Frontier", *Strategy and Leadership*, Vol. 30, Nº 4, pp. 4-11.

Granovetter, M. S. (1973), "The Strength of Weak Ties", *American Journal of Sociology*, Vol. 78, Nº 6, pp. 1360-1380.

Granovetter, M. S. (1982), "The Strength of Weak Ties: A Network Theory Revisited", in P. V. Marsden and N. Lin (Eds.), *Social Structure and Network Analysis*, pp. 105-130, Beverly Hills, Calif.: Sage Publications.

Greenwald, A. and J. O. Kephart (1999), "Shopbots and Pricebots", paper presented at the International Joint Conference on Artificial Intelligence, July-August, Stockholm.

Gruca, T. S. and L. L. Rego (2005), "Customer Satisfaction, Cash Flow, and Shareholder Value", *Journal of Marketing*, Vol. 69, Nº 3, pp. 115-130.

Guide, V. D. R. J., G. C. Souza, L. N. Van Wassenhove, and J. D. Blackburn (2006), "Time Value of Commercial Product Returns", *Management Science*, Vol. 52, Nº 8, pp. 1200-1214.

Gupta, P. and J. Harris (2010), "How E-Wom Recommendations Influence Product Consideration and Quality of Choice: A Motivation to Process Information Perspective", *Journal of Business Research*, Vol. 63, Nº 9-10, pp. 1041-1049.

Gupta, S. (2009), "Customer-Based Valuation", *Journal of Interactive Marketing*, Vol. 23, Nº 2, pp. 169-178.

Gupta, S. and D. R. Lehmann (2003), "Customers as Assets", *Journal of Interactive Marketing*, Vol. 17, Nº 1, pp. 9-24.

Gupta, S. and V. Zeithaml (2006), "Customer Metrics and Their Impact on Financial Performance", *Marketing Science*, Vol. 25, Nº 6, pp. 718-739.

Hair, J. F., W. C. Black, B. J. Babin, R. E. Anderson, and R. L. Tatham (2006), *Multivariate Data Analysis*, NJ: Prentice-Hall.

Hars, A. and S. Qu (2002), "Working for Free? Motivations for Participating in Open-Source Projects", *International Journal of Electronic Commerce,* Vol. 6, Nº 3, pp. 25.

Hausman, A. V. and J. S. Siekpe (2009), "The Effect of Web Interface Features on Consumer Online Purchase Intentions", *Journal of Business Research*, Vol. 62, Nº 1, pp. 5-13.

Heide, J. B. and A. M. Weiss (1995), "Vendor Consideration and Switching Behavior for Buyers in High-Technology Markets", *Journal of Marketing,* Vol. 59, Nº 3, pp. 30-43.

Hernández, B., J. Jiménez, and M. J. Martín (2010), "Customer Behavior in Electronic Commerce: The Moderating Effect of E-Purchasing Experience", *Journal of Business Research,* Vol. 63, Nº 9-10, pp. 964-971.

Ho, J. Y. C. and M. Dempsey (2010), "Viral Marketing: Motivations to Forward Online Content", *Journal of Business Research,* Vol. 63, Nº 9-10, pp. 1000-1006.

Hoelter, J. W. (1983), "The Analysis of Covariance Structures: Goodness-of-Fit Indices", *Sociological Methods & Research,* Vol. 11, Nº 3, pp. 325–344.

Hsu, S. H. (2008), "Developing an Index for Online Customer Satisfaction: Adaptation of American Customer Satisfaction Index", *Expert Systems with Applications,* Vol. 34, Nº 4, pp. 3033-3042.

Hu, L.-T. and P. M. Bentler (1995), "Evaluating Model Fit", in R. H. Hoyle (Ed.), *Structural Equation Modeling: Concepts, Issues, and Applications*, pp. 76–99, Thousand Oaks, CA: Sage.

Hu, L.-T. and P. M. Bentler (1999), "Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria Versus New Alternatives", *Structural Equation Modeling,* Vol. 6, Nº 1, pp. 1–55.

Hunter, J. E. and D. W. Gerbing (1982), "Unidimensional Measurement, Second-Order Factor Analysis and Causal Models", in B. M. Staw and L. L. Cummings (Eds.), *Research in Organizational Behavior*, Vol. IV, pp. 267– 320, Greenwich (CT): JAI Press.

Hwang, H., T. Jung, and E. Suh (2004), "An LTV Model and Customer Segmentation Based on Customer Value: A Case Study on the Wireless Telecommunication Industry", *Expert Systems with Applications*, Vol. 26, Nº 2, pp. 181-188.

Iwarrden, J. v., T. v. d. Wiele, L. Ball, and R. Millen (2004), "Perceptions About the Quality of Web Sites: A Survey Amongst Students at Northeastern University and Erasmus University", *Information & Management*, Vol. 41, Nº 8, pp. 947–959.

Jarvis, D., S. MacKenzie, and P. Podsakoff (2003), "A Critical Review of Construct Indicators and Measurement Model Misspecification in Marketing and Consumer Research", *Journal of Consumer Research*, Vol. 30, Nº 3, pp. 199-218.

Jasperson, J., P. E. Carter, and R. W. Zmud (2005), "A Comprehensive Conceptualization of the Post-Adoptive Behaviors Associated with Information Technology Enabled Work Systems", *MIS Quarterly*, Vol. 29, Nº 3, pp. 525-557.

Jones, M. A., D. L. Mothersbaugh, and S. E. Beatty (2000), "Switching Barriers and Repurchase Intentions in Services", *Journal of Retailing*, Vol. 76, Nº 2, pp. 259-274.

Jones, M. A., D. L. Mothersbaugh, and S. E. Beatty (2002), "Why Customers Stay: Measuring the Underlying Dimensions of Services Switching Costs and Managing Their Differential Strategic Outcomes", *Journal of Business Research*, Vol. 55, Nº 6, pp. 441-450.

Jöreskog, K. and D. Sörbom (2001), *LISREL 8: User's Reference Guide,* (Second ed.), Chicago: Scientific Software International.

Jöreskog, K. G. (1970), "A General Method for Analysis of Covariance Structures", *Biometrika*, Vol. 57, Nº 1, pp. 239– 251.

Jöreskog, K. G. (1971), "Simultaneous Factor Analysis in Several Populations", *Psychometrika*, Vol. 36, Nº 4, pp. 409–426.

Kaplan, A. M. and M. Haenlein (2010), "Users of the World, Unite! The Challenges and Opportunities of Social Media", *Business Horizons,* Vol. 53, Nº 1, pp. 59-68.

Karahanna, E., D. W. Straub, and N. L. Chervany (1999), "Information Technology Adoption across Time: A Cross-Sectional Comparison of Pre-Adoption and Post-Adoption Beliefs", *MIS Quarterly,* Vol. 23, Nº 2, pp. 183-213.

Katona, Z., P. P. Zubcsek, and M. Sarvary (2011), "Network Effects and Personal Influences: The Diffusion of an Online Social Network", *Journal of Marketing Research (JMR),* Vol. 48, Nº 3, pp. 425-443.

Katz, M. L. and C. Shapiro (1985), "Network Externalities, Competition, and Compatibility", *American Economic Review,* Vol. 75, Nº 3, pp. 424-440.

Katz, M. L. and C. Shapiro (1986), "Technology Adoption in the Presence of Network Externalities", *Journal of Political Economy,* Vol. 94, Nº 4, pp. 822-841.

Keh, H. T. and Y. H. Lee (2006), "Do Reward Programs Build Loyalty for Services?: The Moderating Effect of Satisfaction on Type and Timing of Rewards", *Journal of Retailing,* Vol. 82, Nº 2, pp. 127-136.

Kim, S. S. and J.-Y. Son (2009), "Out of Dedication or Constraint? A Dual Model of Post-Adoption Phenomena and Its Empirical Test in the Context of Online Services", *MIS Quarterly,* Vol. 33, Nº 1, pp. 49-70.

Klemperer, P. (1987), "Markets with Consumer Switching Costs", *The Quarterly Journal of Economics,* Vol. 102, Nº 2, pp. 375-394.

Kline, R. B. (2005), *Principles and Practice of Structural Equation Modeling,* (2nd ed.), New York: Guilford.

Kozinets, R. V., A. Hemetsberger, and H. Schau (2008), "The Wisdom of Consumer Crowds: Collective Innovation in the Age of Networked Marketing", *Journal of Macromarketing,* Vol. 28, Nº 4, pp. 339-354.

Kumar, V., J. A. Petersen, and R. P. Leone (2007), "How Valuable Is Word of Mouth?", *Harvard Business Review,* Vol. 85, Nº 10, pp. 139-146.

Kumar, V., I. D. Pozza, J. A. Petersen, and D. Shah (2009), "Reversing the Logic: The Path to Profitability through Relationship Marketing", *Journal of Interactive Marketing*, Vol. 23, Nº 2, pp. 147-156.

Lam, S. Y., V. Shankar, M. K. Erramilli, and B. Murthy (2004), "Customer Value, Satisfaction, Loyalty, and Switching Costs: An Illustration from a Business-to-Business Service Context", *Journal of the Academy of Marketing Science*, Vol. 32, Nº 3, pp. 293-311.

Law, K. S. and C.-S. Wong (1999), "Multidimensional Constructs in Structural Equation Analysis: An Illustration Using the Job Perception and Job Satisfaction Constructs", *Journal of Management*, Vol. 25, Nº 2, pp. 143-160.

Law, K. S., C. Wong, and W. H. Mobley (1998), "Toward a Taxonomy of Multidimensional Constructs", *Academy of Management Review*, Vol. 23, Nº 4, pp. 741-755.

Lee, T. Q., Y. Park, and Y.-T. Park (2008), "A Time-Based Approach to Effective Recommender Systems Using Implicit Feedback", *Expert Systems with Applications*, Vol. 34, Nº 4, pp. 3055-3062.

Lee, W.-P., C.-H. Liu, and C.-C. Lu (2002), "Intelligent Agent-Based Systems for Personalized Recommendations in Internet Commerce", *Expert Systems with Applications*, Vol. 22, Nº 4, pp. 275-284.

Lee, Y. and G. C. O'Connor (2003), "New Product Launch Strategy for Network Effects Products", *Journal of the Academy of Marketing Science*, Vol. 31, Nº 3, pp. 241-255.

Leenheer, J. and T. H. A. Bijmolt (2008), "Which Retailers Adopt a Loyalty Program? An Empirical Study", *Journal of Retailing and Consumer Services*, Vol. 15, Nº 6, pp. 429–442.

Lewis, M. (2004), "The Influence of Loyalty Programs and Short-Term Promotions on Customer Retention", *Journal of Marketing Research*, Vol. 41, Nº 3, pp. 281–292.

Liu, Y. (2007), "The Long-Term Impact of Loyalty Programs on Consumer Purchase Behavior and Loyalty", *Journal of Marketing*, Vol. 71, Nº 4, pp. 19–35.

Loiacono, E. T., R. T. Watson, and D. L. Goodhue (2007), "Webqual: An Instrument for Consumer Evaluation of Web Sites", *International Journal of Electronic Commerce,* Vol. 11, Nº 3, pp. 51-87.

MacCallum, R. C., M. Roznowski, M. Mar, and J. V. Reith (1994), "Alternative Strategies for Cross-Validation of Covariance Structure Models", *Multivariate Behavioral Research,* Vol. 29, Nº 1, pp. 1–32.

MacKenzie, S. B. (2003), "The Dangers of Poor Construct Conceptualization", *Journal of the Academy of Marketing Science,* Vol. 31, Nº 3, pp. 323-326.

MacKenzie, S. B., P. M. Podsakoff, and C. B. Jarvis (2005), "The Problem of Measurement Model Misspecification in Behavioral and Organizational Research and Some Recommended Solutions", *Journal of Applied Psychology,* Vol. 90, Nº 4, pp. 710-730.

Mangleburg, T. F., P. M. Doney, and T. Bristol (2004), "Shopping with Friends and Teens' Susceptibility to Peer Influence", *Journal of Retailing,* Vol. 80, Nº 2, pp. 101-116.

Mardia, K. V. (1970), "Measures of Multivariate Skewness and Kurtosis with Applications", *Biometrika,* Vol. 57, Nº 3, pp. 519–530.

Mardia, K. V. (1974), "Applications of Some Measures of Multivariate Skewness and Kurtosis in Testing Normality and Robustness Studies", *Sankhya,* Vol. B36, pp. 115–128.

Marsh, H. W., J. R. Balla, and K. T. Hau (1996), "An Evaluation of Incremental Fit Indices: A Clarification of Mathematical and Empirical Properties", in G. A. Marcoulides and R. E. Schumacker (Eds.), *Advanced Structural Equation Modeling: Issues and Techniques,* pp. 315–353, Mahwah, NJ: Lawrence Erlbaum Associates.

Mathwick, C., N. Malhotra, and E. Rigdon (2001), "Experiential Value: Conceptualization, Measurement and Application in the Catalog and Internet Shopping Environment", *Journal of Retailing,* Vol. 77, Nº 1, pp. 39-56.

Meyer-Waarden, L. (2007), "The Effects of Loyalty Programs on Customer Lifetime Duration and Share of Wallet", *Journal of Retailing,* Vol. 83, Nº 2, pp. 223-236.

Mithas, S., N. Ramasubbu, M. S. Krishnan, and C. Fornell (2006), "Designing Web Sites for Customer Loyalty across Business Domains: A Multilevel Analysis", *Journal of Management Information Systems*, Vol. 23, Nº 3, pp. 97.

Nelson, M. R. and C. C. Otnes (2005), "Exploring Cross-Cultural Ambivalence: A Netnography of Intercultural Wedding Message Boards", *Journal of Business Research,* Vol. 58, Nº 1, pp. 89-95.

Netemeyer, R. G., W. O. Bearden, and S. Sharma (2003), *Scaling Procedures: Issues and Applications*, Thousand Oaks, CA: Sage Publications.

Nitzan, I. and B. Libai (2011), "Social Effects on Customer Retention", *Journal of Marketing,* Vol. 75, Nº 6, pp. 24-38.

Novak, T. P., D. L. Hoffman, and Y.-F. Yung (2000), "Measuring the Customer Experience in Online Environments: A Structural Modeling Approach", *Marketing Science,* Vol. 19, Nº 1, pp. 22-42.

Nunes, J. C. and X. Drèze (2006), "Your Loyalty Program Is Betraying You", *Harvard Business Review,* Vol. 84, Nº 4, pp. 124–131.

Oliver, R. L. (1999), "Whence Consumer Loyalty?", *Journal of Marketing,* Vol. 63, Nº 4, pp. 33-44.

Otim, S. and V. Grover (2006), "An Empirical Study on Web-Based Services and Customer Loyalty", *European Journal of Information Systems,* Vol. 15, Nº 6, pp. 527-541.

Palmer, J. W. (2002), "Web Site Usability, Design, and Performance Metrics", *Information Systems Research,* Vol. 13, Nº 2, pp. 151-167.

Pan, X., B. T. Ratchford, and V. Shankar (2002), "Can Price Dispersion in Online Markets Be Explained by Differences in E-Tailer Service Quality?", *Academy of Marketing Science,* Vol. 30, Nº 4, pp. 433–445.

Parasuraman, A. and D. Grewal (2000), "Serving Customers and Consumers Effectively in the Twenty-First Century: Emerging Issues and Solutions", *Journal of the Academy of Marketing Science*, Vol. 28, Nº 1, pp. 9-16.

Parasuraman, A., V. Zeithaml, and A. Malhotra (2005), "E-S-Qual a Multiple-Item Scale for Assessing Electronic Service Quality", *Journal of Service Research,* Vol. 7, Nº 3 (February), pp. 213-233.

Parasuraman, A. and G. M. Zinkhan (2002), "Marketing to and Serving Customers through the Internet: An Overview and Research Agenda", *Journal of the Academy of Marketing Science,* Vol. 30, Nº 4, pp. 286-295.

Pavlou, P. A. and D. Gefen (2004), "Building Effective Online Marketplaces with Institution-Based Trust", *Information Systems Research,* Vol. 15, Nº 1, pp. 37-59.

Petersen, J. A. and V. Kumar (2009), "Are Product Returns a Necessary Evil? Antecedents and Consequences", *Journal of Marketing,* Vol. 73, Nº 3, pp. 35-51.

Petersen, J. A., L. McAlister, D. J. Reibstein, R. S. Winer, V. Kumar, and G. Atkinson (2009), "Choosing the Right Metrics to Maximize Profitability and Shareholder Value", *Journal of Retailing,* Vol. 85, Nº 1, pp. 95-111.

Ping, R. A. (2004), "On Assuring Valid Measures for Theoretical Models Using Survey Data", *Journal of Business Research,* Vol. 57, Nº 2, pp. 125-141.

Plewis, I. (2001), "Explanatory Models for Relating Growth Processes", *Multivariate Behavioral Research,* Vol. 36, Nº 2, pp. 207-225.

Price, L. L., L. F. Feick, and A. Guskey (1995), "Everyday Market Helping Behavior", *Journal of Public Policy & Marketing,* Vol. 14, Nº 2, pp. 255-266.

Reibstein, D. J. (2002), "What Attracts Customers to Online Stores, and What Keeps Them Coming Back?", *Journal of the Academy of Marketing Science,* Vol. 30, Nº 4, pp. 465-473.

Reichheld, F. and W. E. Sasser (1990), "Zero Defections: Quality Comes to Services", *Harvard Business Review,* Vol. 68, Nº 5, pp. 105-111.

Reichheld, F. F. and P. Schefter (2000), "E-Loyalty", *Harvard Business Review,* Vol. 78, Nº 4, pp. 105-113.

Reinartz, W. J. and V. Kumar (2003), "The Impact of Customer Relationship Characteristics on Profitable Lifetime Duration", *Journal of Marketing,* Vol. 67, Nº 1, pp. 77-99.

Rezabakhsh, B., D. Bornemann, U. Hansen, and U. Schrader (2006), "Consumer Power: A Comparison of the Old Economy and the Internet Economy", *Journal of Consumer Policy,* Vol. 29, Nº 1, pp. 3-36.

Rindskopf, D. and T. Rose (1988), "Some Theory and Applications of Confirmatory Second-Order Factor Analysis", *Multivariate Behavioral Research,* Vol. 23, Nº 1, pp. 51 – 67.

Satorra, A. and P. M. Bentler (1988), "Scaling Corrections for Chi-Square Statistics in Covariance Structure Analysis", in A. S. Association (Ed.), *Proceedings of the Business and Economics Section*, pp. 308–313, Alexandria, VA: American Statistical Association.

Satorra, A. and P. M. Bentler (1994), "Corrections to Test Statistics and Standard Errors in Covariance Structure Analysis", in A. von Eye and C. C. Clogg (Eds.), *Latent Variables Analysis: Applications for Developmental Research*, pp. 399–419, Thousand Oaks, CA: Sage.

Schaupp, L. C. and F. Belanger (2005), " A Conjoint Analysis of Online Consumer Satisfaction", *Journal of Electronic Commerce Research,* Vol. 6, Nº 2, pp. 95-111.

Senecal, S. and J. Nantel (2004), "The Influence of Online Product Recommendations on Consumers' Online Choices", *Journal of Retailing,* Vol. 80, Nº 2, pp. 159-169.

Seraj, M. (2012), "We Create, We Connect, We Respect, Therefore We Are: Intellectual, Social, and Cultural Value in Online Communities", *Journal of Interactive Marketing,* Vol. 26, Nº 4, pp. 209-222.

Shankar, V., A. K. Smith, and A. Rangaswamy (2003), "Customer Satisfaction and Loyalty in Online and Offline Environments", *International Journal of Research in Marketing,* Vol. 20, Nº 2, pp. 153-175.

Shapiro, C. and H. R. Varian (1998), *Information Rules: A Strategic Guide to the Network Economy*, Boston, MA: Harvard Business School Press.

Shin, D.-H. and W.-Y. Kim (2008), "Forecasting Customer Switching Intention in Mobile Service: An Exploratory Study of Predictive Factors in Mobile Number Portability", *Technological Forecasting & Social Change,* Vol. 75, Nº 6, pp. 854-874.

Shrout, P. E. and N. Bolger (2002), "Mediation in Experimental and Nonexperimental Studies: New Procedures and Recommendations", *Psychological Methods,* Vol. 7, Nº 4, pp. 422-455.

Simon, C. J. and J. T. Warner (1992), "Matchmaker, Matchmaker: The Effect of Old Boy Networks on Job Match Quality, Earnings, and Tenure", *Journal of Labor Economics,* Vol. 10, Nº 3, pp. 306-330.

Smith, M. D. (2002), "The Impact of Shopbots on Electronic Markets", *Journal of the Academy of Marketing Science,* Vol. 30, Nº 4, pp. 446-454.

Smith, M. D., J. Bailey, and E. Brynjolfsson (2000), "Understanding Digital Markets: Review and Assessement", in E. Brynjolfsson and B. Kahin (Eds.), *Understanding the Digital Economy: Data, Tools, and Research*, pp. 99-136, Cambridge, Mass.: MIT Press USA.

Sobel, M. E. (1982), "Asymptotic Confidence Intervals for Indirect Effects in Structural Equation Models", in S. Leinhardt (Ed.), *In Sociological Methodology*, pp. 290-313, San Francisco: Jossey-Bass.

Srinivasan, S. S., R. Anderson, and K. Ponnavolu (2002), "Customer Loyalty in E-Commerce: An Exploration of Its Antecedents and Consequences", *Journal of Retailing,* Vol. 78, Nº 1, pp. 41-50.

Stanley, S. M. and H. J. Markman (1992), "Assessing Commitment in Personal Relationships", *Journal of Marriage and the Family* Vol. 54, Nº 3, pp. 595-608.

Sung, Y., Y. Kim, O. Kwon, and J. Moon (2010), "An Explorative Study of Korean Consumer Participation in Virtual Brand Communities in Social Network Sites", *Journal of Global Marketing,* Vol. 23, Nº 5, pp. 430 - 445.

Symeonidis, P., A. Nanopoulos, A. N. Papadopoulos, and Y. Manolopoulos (2008), "Collaborative Recommender Systems: Combining Effectiveness and Efficiency", *Expert Systems with Applications,* Vol. 34, Nº 4, pp. 2995-3013.

Szymanski, D. M. and D. H. Henard (2001), "Customer Satisfaction: A Meta-Analysis of the Empirical Evidence", *Journal of the Academy of Marketing Science,* Vol. 29, Nº 1, pp. 16.

Szymanski, D. M. and R. T. Hise (2000), "E-Satisfaction: An Initial Examination", *Journal of Retailing,* Vol. 76, Nº 3, pp. 309-322.

Tirole, J. (1988), *The Theory of Industrial Organization*, Cambridge, MA: MIT Press.

Torres, A. and F. V. Martins (2005), "Developing an E-Satisfaction Scale for Internet Services (Websat): A Comparative Study with Servqual Scale", paper presented at the IADIS International Conference e-Commerce 2005, Porto, Portugal.

Torres, A. and F. V. Martins (2007a), "The Internet Shopper Profile", paper presented at the International Conference of e-Activity and Leading Technologies of IASK International Association of Scientific Knowledge, Porto, Portugal.

Torres, A. and F. V. Martins (2007b), "Is Online Consumer Price Sensitive? A Comprehensive Framework and Implications for Developing E-Pricing Strategies", paper presented at the IADIS International Conference e-Commerce 2007, Algarve, Portugal.

Torres, A. and F. V. Martins (2009), "The Conflicting Role of Online Switching Costs: The Main and Interaction Effects on Customer Retention", paper presented at the IADIS International Conference e-Commerce 2009, Algarve, Portugal.

Torres, A. and F. V. Martins (2011), "Virtual Recommendation Diffusion and Co-Shopping Influence: The Role of Dyadic Network-Based Interactions", paper presented at the IADIS International Conference e-Commerce 2011, Rome, Italy.

Torres, A. and F. V. Martins (2012), "Online Social Networks: Virtual Recommendation Diffusion and Co-Consumption Influence. (Accepted for Publication)", in M. M. Cruz-Cunha, F. Moreira and J. Varajão (Eds.), *Handbook of Research on Enterprise 2.0: Technological, Social, and Organizational Dimensions*, Hershey, PA: IGI Global, USA.

Tsai, H.-T. and H.-C. Huang (2007), "Determinants of E-Repurchase Intentions: An Integrative Model of Quadruple Retention Drivers", *Information & Management,* Vol. 44, Nº 3, pp. 231-239.

Tsai, H.-T., H.-C. Huang, Y.-L. Jaw, and W.-K. Chen (2006), "Why on-Line Customers Remain with a Particular E-Retailer: An Integrative Model and Empirical Evidence", *Psychology & Marketing,* Vol. 23, Nº 5, pp. 447-464.

Turban, E., D. King, J. K. Lee, and D. Viehland (2006), *Electronic Commerce 2006: A Managerial Perspective*: Prentice Hall.

Van den Bulte, C. and Y. V. Joshi (2007), "New Product Diffusion with Influentials and Imitators", *Marketing Science,* Vol. 26, Nº 3, pp. 400-421.

Van den Bulte, C. and S. Stremersch (2004), "Social Contagion and Income Heterogeneity in New Product Diffusion: A Meta-Analytic Test", *Marketing Science,* Vol. 23, Nº 4, pp. 530-544. .

Van Den Bulte, C. and S. Wuyts (2007), *Social Networks and Marketing*, Cambridge, Mass: Marketing Science Institute.

Varian, H. R. (2000), "Market Structure in the Network Age", in E. Brynjolfsson and B. Kahin (Eds.), *Understanding the Digital Economy: Data, Tools, and Research*, pp. 137-150, Cambridge, Mass.: MIT Press USA.

Wang, X., C. Yu, and Y. Wei (2012), "Social Media Peer Communication and Impacts on Purchase Intentions: A Consumer Socialization Framework", *Journal of Interactive Marketing,* Vol. 26, Nº 4, pp. 198-208.

Wasko, M. M. and S. Faraj (2005), "Why Should I Share? Examining Social Capital and Knowledge Contribution in Electronic Networks of Practice", *MIS Quarterly,* Vol. 29, Nº 1, pp. 35-57.

Watts, D. J. (1999), "Networks, Dynamics, and the Small-World Phenomenon", *American Journal of Sociology,* Vol. 105, Nº 2, pp. 493–527.

Weijters, B., E. Cabooter, and N. Schillewaert (2010), "The Effect of Rating Scale Format on Response Styles: The Number of Response Categories and Response Category Labels", *International Journal of Research in Marketing,* Vol. 27, Nº 3, pp. 236-247.

Wolfinbarger, M. and M. C. Gilly (2003), "eTailQ: Dimensionalizing, Measuring and Predicting eTail Quality", *Journal of Retailing,* Vol. 79, Nº 3, pp. 183-198.

Wu, J.-J., Y.-H. Chen, and Y.-S. Chung (2010), "Trust Factors Influencing Virtual Community Members: A Study of Transaction Communities", *Journal of Business Research,* Vol. 63, Nº 9-10, pp. 1025-1032.

Wulf, K. D. and G. Odekerken-Schröder (2001), "A Critical Review of Theories Underlying Relationship Marketing in the Context of Explaining Consumer Relationships", *Journal for the Theory of Social Behaviour,* Vol. 31, Nº 1, pp. 73-101.

Yang, J. and E. Mai (2010), "Experiential Goods with Network Externalities Effects: An Empirical Study of Online Rating System", *Journal of Business Research,* Vol. 63, Nº 9-10, pp. 1050-1057.

Yang, Z. and R. T. Peterson (2004), "Customer Perceived Value, Satisfaction, and Loyalty: The Role of Switching Costs", *Psychology & Marketing,* Vol. 21, Nº 10, pp. 799-822.

Yi, Y. and J. Hoseong (2003), "Effects of Loyalty Programs on Value Perception, Program Loyalty, and Brand Loyalty", *Journal of the Academy of Marketing Science,* Vol. 31, Nº 3, pp. 229-240.

Yoo, B. and N. Donthu (2001), "Developing a Scale to Measure the Perceived Quality of an Internet Shopping Site (Sitequal)", *Quarterly Journal of Electronic Commerce,* Vol. 2, Nº 1, pp. 31-45.

Yu, C.-C. and C.-S. Wang (2008), "A Hybrid Mining Approach for Optimizing Returns Policies in E-Retailing", *Expert Systems with Applications,* Vol. 35, Nº 4, pp. 1575-1582.

Zauberman, G. (2003), "The Intertemporal Dynamics of Consumer Lock-In", *Journal of Consumer Research,* Vol. 30, Nº 3, pp. 405-419.

Zeithaml, V. A. (1988), "Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence", *Journal of Marketing,* Vol. 52, Nº 3, pp. 2-22.

Zeithaml, V. A., A. Parasuraman, and A. Malhotra (2002), "Service Quality Delivery through Web Sites: A Critical Review of Extant Knowledge", *Journal of the Academy of Marketing Science,* Vol. 30, Nº 4, pp. 362-375.

Zhang, Z. J., K. Aradhna, and K. D. Sanjay (2000), "The Optimal Choice of Promotional Vehicles: Front-Loaded or Rear-Loaded Incentives?", *Management Science,* Vol. 46, Nº 3, pp. 348-362.

Zhu, K. and K. L. Kraemer (2002), "E-Commerce Metrics for Net-Enhanced Organizations: Assessing the Value of E-Commerce to Firm Performance in the Manufacturing Sector", *Information Systems Research,* Vol. 13, Nº 3, pp. 275-295.

Zviran, M., C. Glezer, and I. Avni (2006), "User Satisfaction from Commercial Web Sites: The Effect of Design and Use", *Information & Management,* Vol. 43, Nº 2, pp. 157-178.