UNDERSTAND OMNICHANNEL CUSTOMER VALUE AND THE

HUMAN-MACHINE USER EXPERIENCE WHEN USING MOBILE APPLICATION

A Dissertation Proposal presented to

the Faculty of the Graduate School

at the University of Missouri-Columbia

In Partial Fulfillment

of the Requirements for the Degree

Doctor of Philosophy

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by

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July 2022

The undersigned, appointed by the dean of the Graduate School, have examined the dissertation entitled

UNDERSTAND OMNICHANNEL CUSTOMER VALUE AND THE HUMAN-MACHINE USER EXPERIENCE WHEN USING MOBILE APPLICATION

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ACKNOWLEDGEMENTS

I owe my appreciation to all those people who have helped to make this dissertation possible and because of whom my PhD program experience has been one that I will cherish forever. My deepest gratitude is to my advisor, Dr. Li Zhao, for guiding me throughout the whole Ph.D. pursuing process. I have been incredibly fortunate to have an advisor who equipped me with the knowledge and abilities necessary to be an independent researcher and a successful educator. Your patience, encouragement, and support helped me get over my weakness, build up my confidence, and helped me to finally complete this dissertation.

I would like to express my sincere thanks to Dr. Ha-Brookshire, Dr. Youn, and Dr. Yunxin Zhao. I sincerely appreciate each of you for your insightful remarks, constructive criticism, and guidance in keeping my thoughts focus on my ideas at various stages of my research. Throughout the dissertation process and my time as a doctoral student, each of you has been a major source of inspiration and guidance.

I am also indebted to all my friends at the University of Missouri. In particular, I am greatly honored to study with the graduate students of Textile and Apparel Management. You are best friends and colleagues who always encourage and support me with your best wishes.

Most importantly, none of this would have been possible without my family's love and patience. I would like to express my heartfelt gratitude to my parents, my husband and my mother-in-law, who has been an unending source of love, concern, support, and strength over the years. And I will never forget the nights that I held my daughter Yuning in one arm and reviewed the dissertation draft using the other arm.

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ABSTRACT

This research was designed to explore the human-machine user/consumer experience when customers use retail mobile applications under the omnichannel context. Customer reviews from retail mobile application were crawled and investigated by text-mining methods, including textual data pre-processing, LDA topic modeling, sentimental analysis, word co-occurrence network. This is the first attempt to quantify fashion retailing data using text-mining methods to thoroughly investigate the user/consumer experience in omnichannel shopping. Based on the customer value theory and components of the user experience model, the study findings were expected to provide further evidence of the importance of the user experience in human-machine interfaces when adopting omnichannel strategy. The findings would also help to optimize the performance of the retail mobile applications and improve user experience to achieve a seamless omnichannel shopping experience. Meanwhile, the findings help retailers to develop practical strategies to convey consistent customer value via mobile applications, based on their positioning and business features.

CHAPTER I. INTRODUCTION

Chapter I includes the following sections: (a) background of the study, (b) purpose of the study, (c) significance of the study, (d) definition of key terms, (e) guiding paradigms and research assumptions, (f) organization of this study.

Background of the Study

Recent advances in mobile computing technology are blurring the distinctions between traditional and online retailing, allowing retailers to interact with customers through multiple touchpoints. Customers are not only shopping either online or offline but are merging their online and offline activities. As the distinction between online and offline channels blurs, a new approach to channel integration and a seamless shopping experience emerges: omnichannel (Piotrowicz & Cuthbertson, 2014). "Omni" is a Latin word that means "all" or "universal" (Lazaris & Vrechopoulos, 2014). In the current context, this term originates from business practitioners in IDC's Global Retail Insights research unit reports (Parker & Hand, 2009). It is suggested that an "omnichannel" shopper is an evolution of the multichannel consumer who, rather than using channels in parallel, uses them all simultaneously." Nowadays, the term "omnichannel" has gained much academic and industrial attention (Cai & Lo, 2020).

Evolution of Omnichannel Retailing

Retailing has changed dramatically over the last two decades as a result of the introduction of the online channel and ongoing digitalization. With the growth of Internet retailing, it is vital that retailers revise their practices to include the potential roles of the Internet (Schoenbachler & Gordon, 2002). To counteract these trends, many retailers have implemented multichannel strategies and delivering products to customers through one or more channels. They abandon single business model approaches, such as catalog-only operations or stand-alone physical stores, but attempt to link store operations with e-commerce, call center, and catalog (Haydock, 2000). A multichannel strategy is defined as "… a distribution strategy to serve customers using more than one selling channel or medium such as the Internet, television and retail outlets" (Stone et al., 2002). According to the definition, retailers implement multichannel strategies based on each channel, making it engaging and simple to use for the majority of their customers. With multichannel strategy, retailers are able reach out to their audience or customer through the right channel, delivering the right message at the right time. The aim of a multichannel strategy is to enable customers to reach out to brands on the maximum number of channels (Stone et al., 2002). It focuses more on using channels to increase customer engagement.

In recent decades, consumers are becoming increasingly accustomed to various interface technologies, not only websites, but also multiple wireless devices, to interact with firms (Rangaswamy & Van, 2005). Consumers are increasingly using multiple channels at various stages of their decision-and-shopping cycles. For example, consumers may get product information through websites, place orders through mobile applications, and collect purchased items from a nearby physical store. Consumers want to interact with brands freely and seamlessly across multiple channels; therefore, the use of multichannel retailing will eventually no longer be sufficient, forcing retailers to adopt omnichannel retailing (Rangaswamy & Van, 2005).

Omnichannel retailing is defined as an integrated shopper experience that merges the physical store with the information-rich digital environment, with the aim of providing excellent shopper experiences across all touchpoints (Frazer & Stiehler, 2014). While the term “multichannel” implies a separation of online and offline stores, in the omnichannel context, within a single transaction process, consumers can freely move between websites, mobile devices, and physical stores. During this process, consumers will not lose their place when switching between channels, since the omnichannel strategy ensures that all aspects of the process are fully integrated (Verhoef et al., 2015). An omnichannel approach is more customer-centric and aims to build stronger customer relationships by connecting channels and creating a seamless and unified experience.

Advantages of Omnichannel

For retailers, adopting an omnichannel strategy could increase sales and traffic dramatically. According to a study from Harvard Business Review (Sopadjieva et al., 2017), only 7% of consumers shop exclusively online, while 20% are store-only shoppers, and 73% shop across multiple channels during their shopping journey. Furthermore, with every additional channel used, consumers spent more. Consumers who used more than four channels spent 9% more than those who used one channel. Companies with extremely strong omnichannel customer engagement increase annual revenue by 9.5 percent year over year, compared to 3.4 percent for companies with weak omnichannel strategy (Knexus, 2021). According to a joint study conducted by Google, Ipsos MediaCT, and Sterling Brands, 75% of consumers are more likely to visit a store if they find local retail information online (thinkwithGoogle, 2014). Omnichannel retailing not only increases revenue from online retail, but also drives significant traffic to stores, increasing revenue even further, by leveraging multiple channels.

Meanwhile, omnichannel retailing allows businesses to build long-term customer relationships by providing information, products, services, and support through multiple synchronized channels, thereby increasing customer retention and lifetime value and enhancing brand loyalty. Companies with the strongest omnichannel customer engagement strategies retain an average of 89 percent of their customers, compared to 33 percent for companies with weak omnichannel strategies, according to Aberdeen Group Inc (Fois, 2014). Based on the previous study from Harvard Business Review (Sopadjieva et al., 2017), Customers who had an omnichannel shopping experience were 23 percent more likely to return to the retailer's stores and were more likely to recommend the retailer/brand to others than customers who had only used one channel.

Furthermore, omnichannel strategies enable retailers to make better use of shared data in order to integrate marketing analytics and provide cross-channel insights. Omnichannel analytics facilitates interaction with customer data from all channels, resulting in a more transparent marketing strategy and, as a result, lower marketing costs. (Adobe, 2020). A comprehensive view of shared channel data can help retailers better meet customer needs, predict inventory, and improve overall supply chain efficiency.

Regarding customers, omnichannel retailing offers them a seamless, convenient, and comfortable way to shop (Brynjolfsson et al., 2013). Omnichannel customers prefer retailer touchpoints, such as smartphone apps for price comparison and coupon downloads, as well as in-store digital tools such as interactive catalogs, tablets, and price checkers. The consumer research from UC found that nine out of ten consumers stated that they want an omnichannel experience with seamless service (Roberts, 2019). For many consumers, an omnichannel strategy is not even negotiable, as 40% of customers say that they are unwilling to do business with companies if their preferred channels are unavailable (Roberts, 2019).

Mobile Application Use in Omnichannel Retailing

The emergence and increasing ubiquity of the Internet, mobile devices, and social media has dramatically transformed customers' shopping experiences. The increasing popularity of location-based apps on mobile devices is critical to these changes. More than half of cell phone owners in the United States own smartphones, and more than 70% of those respondents have used their mobile applications for shopping comparison (Statista, 2021). According to Statista (2021), nearly 80% of US consumers already have at least one retailer app on their smartphone. Mobile applications bridge the gap between online and offline channels, transforming the purchasing process and experiences of consumers (Brynjolfsson et al., 2013). Previously, e-commerce provided consumers with unique benefits that were not available in physical stores, such as instant price comparison, fast checkouts, recommendation systems, and so on. With the constant evolution of smartphone hardware and innovative software, it is now possible to provide consumers with convenient access to online retailing environments anywhere there is Wi-Fi, including physical stores (Lazaris et al., 2015). Mobile devices can have an impact on almost every stage of the purchasing process, including purchase planning, purchase execution, and more. It is estimated that 78% of young adults use their mobile devices while shopping in stores (Briggs, 2019). During the first quarter of 2019, mobile devices accounted for 46% of all digital retail orders and 65% of traffic to retail websites (Charlton, 2020). Many retailers are capitalizing on the opportunities provided by location-based mobile applications in order to foster an effective omnichannel strategy. Some retailers, for example, offer customers electronic coupons on their phones as soon as they enter the physical store, as well as free Wi-Fi, and customers can scan QR codes on products to view online product reviews, prices, and exclusive offers (Brynjolfsson et al., 2013). The distinction between physical and online stores will fade as the retailing industry evolves into a seamless "omnichannel retailing" experience, aided by the development of mobile applications. It is critical that retailers reconsider their competitive strategies and advantages. Retailers could use their product, order, and customer data to improve the overall shopping experience by evolving omnichannel capabilities through mobile services (Lawry & Bhappu, 2021).

In the field of fashion, there also has been increasing awareness of the need to develop efficient mobile marketing strategies (Lee & Kim, 2019) in order to booster omnichannel retailing. Many retailers have launched mobile apps. Unlike the e-commerce giants like Amazon, these retailers have numerous brick-and-mortar stores, which facilitates the integration of physical and online channels to provide comprehensive service for shoppers. The online and offline channels of retailers are increasingly complementary. Consumers benefit from the convenience of online channels, while offline channels provide opportunities for consumer engagement and brand building. In this digital world, many retailers have started to adopt omnichannel retailing strategies. For example, Nordstrom has been undergoing a digital transformation to drive customer loyalty and achieve a seamless customer experience by leveraging powerful data and in-store experiences (Morgan, 2019). Therefore, it is important to understand the omnichannel customer experience in retail stores, and further explore the challenges and opportunities that retailers might face with.

Despite many studies having investigated the effect of e-commerce strategies (Mittal, 2013) and social media marketing strategies (Stephen, 2016) on consumer behaviors, few have explored customer experiences of using mobile applications in the fashion retailing field. Therefore, it is essential to understand the customer experience in omnichannel retailing from the perspective of department store retail mobile application usage, to further study the opportunities and challenges in achieving a convenient and comfortable shopping experience.

Customer Reviews and Customer Experience

Merchants selling products on digital platforms frequently ask their customers to review the products and services they have purchased. As a venue for customers to convey their feedback (Wu et al., 2021), customer reviews provide insight into the customer's experience throughout the purchase process (Xu, 2019). According to a Qualtrics report, 91% of customers aged 18–34 years trust online reviews similar as personal recommendations, and 93 % of the consumers say online reviews influence their purchasing decisions (Kaemingk, 2020).

In the era of big data, online customer reviews are an innovative way to access a large amount of feedback to gain a holistic understanding of the customer experience, including praise/complaints, benefit/cost, of the shopping process. Many studies have utilized online reviews in consumer research. For example, Jia (2018) investigated consumers' needs by extracting consumer satisfaction levels toward product attributes and the service quality from customer reviews and found that while Chinese yoga consumers were satisfied with teachers and courses, they felt that more supporting staff and cheaper membership prices were needed. Xu (2019) also utilized hotel customer reviews to investigate the significance of core attributes in relation to customer experience and investigated customers' different needs toward different tiers of hotels. In the field of fashion, consumers' comments posted on company websites mainly convey their attitudes toward the fashion products sold online. Guo et al. (2009) utilized customer reviews to extract and categorize the product features through aspect-based opinion mining. See-To & Ngai (2018) investigated product information from the big data stream of customer reviews to achieve a more effective insight into demand distribution and sales nowcasting. Customer reviews from third-party review platforms may provide a more holistic understanding of fashion website shopping experiences, including website navigation and customer service provided by the retailing company. For example, Lang et al. (2020) investigated the motivations and barriers of the online fashion rental experience, such as easy navigation, slow refund, etc., through real consumers' feedback toward online rental companies posted on third-party review platforms. Therefore, customer reviews are important and useful data source for researchers to understand customer experience in different shopping channels.

Customer Reviews in Mobile Applications

Nowadays, smartphones have played an important role in integrating retailing channels, and merchants urgently need mobile application user reviews. For example, in Apple iOS, app developers tend to request customers to rate and review apps at appropriate times throughout the using experience, such as when customers have completed an action or task (Developer, 2021). For customers who purchase products via mobile applications, their reviews reflect their mobile application usage experience as well as their consumption experience.

There are various scenarios wherein mobile applications can be used in omnichannel retailing. For example, customers can place orders in the company's mobile application and collect their item in-store or compare prices online via mobile applications (Brynjolfsson et al., 2013). In these scenarios, the mobile devices enable customers to leave praise or complaints through online reviews, expressing their satisfaction or raising issues about various aspects of the entire omnichannel shopping experience, at any place and time. Meanwhile, other potential users and consumers could read existing reviews to gain an overview about not only the mobile application performance, but also the omnichannel experience of the company or brand and thus make an informed decision about whether to adopt the touchpoint (Hsu et al., 2017). As a result, customer feedback on mobile applications is critical in omnichannel strategy and provide substantial useful information related to consumer omnichannel experience, for both practitioners and potential consumers.

In the fashion retailing field, researchers have attempted to consider the role of mobile shopping usage in moderating product returns/sales through analysis of mobile application ratings (Lohse et al., 2017). However, few studies have utilized the textual content of retail mobile application reviews and explored what consumers attempt to convey through this important channel.

Customer Reviews and Data Mining

Given the growing reliance on the Internet as the source of information for decision-making, it is critical for retailers and researchers to use available customer review information to better understand their customers and improve shopping performance (Sparks & Browning, 2011). However, because the online medium generates so much information, it may be difficult for researchers and practitioners to review and evaluate it all (Lau et al., 2005). Online data are generally unstructured, which is hard to analyze manually and objectively. Therefore, established data-mining methods are used to conduct deep analysis in order to capture subjectivity in terms of the semantic orientation associated with text constituents. In addition, when compared to traditional data analysis techniques, this effective analysis of unstructured data enables real-time customer feedback analysis (Liau & Tan, 2014).

For example, Sezgen et al., (2019) utilized sentimental analysis and latent semantic analysis to examine airline user-generated reviews to determine which service attributes lead to passenger satisfaction and dissatisfaction across different airline business models and service classes. In terms of the mobile application reviews, Chung et al., (2022) applied topic modeling and text regression to online app reviews for five music streaming services and discovered that customers comment on factors related to usage environments, price plans, and content, from a data-drive standpoint. Through these data-mining methods, these studies offer alternative ways to reveal the hidden meaning of the customer reviews accurately and efficiently.

Human-Machine User Experience in Omnichannel Retailing

Website graphic user interfaces have long served as retail storefronts for selling products and services. People who interact with web-based retail stores are both online shoppers and users of a human-machine interface. A user interface consists of a physical medium and content presentation (Griffith et al., 2001). Researchers have previously analyzed the influence of web-based user interface involvement on consumer response in e-commerce and discovered that greater interface involvement increases user involvement with the retailer's products, and that greater consumer involvement results in more positive consumer responses (Griffith et al., 2001).

Nowadays, consumers interact with multiple touchpoints throughout the shopping experience in omnichannel retailing. Currently, human-machine user interface in an omnichannel context translates to mobile commerce. It was found that roughly 80% of US mobile Wi-Fi users use their mobile devices while shopping in-store (Lazaris &

Vrechopoulos, 2014). Customers switch between different channels or interfaces to get the best deals and the best support (Broekhuizen et al., 2021). For instance, a consumer may visit a web-based retail store to search for and evaluate a product or service. and subsequently visit a physical store to purchase the products through the user interface available in-store, which could be connected easily via mobile applications and QR code. Alternatively, they could go to a physical store to look at products before purchasing them through the mobile app at a lower price. Therefore, the user interface is critical in the omnichannel shopping process, particularly when mobile applications are used.

The significance of today's omnichannel research initiatives has been previously highlighted (Lazaris & Vrechopoulos, 2014). However, no existing research has adequately investigated the emerging user-consumer behavioral pattern in omnichannel retailing.

Purpose of the Study

Human-machine interface plays an important role in the omnichannel approach. If customers were unable to have a satisfying experience during the usage of human-machine interface, this would make it more difficult for them to gain a seamless shopping experience, thereby further limiting their involvement in the omnichannel experience. Mobile applications are the key device bridging online and offline shopping and the most widely adopted user interface in omnichannel retailing. Therefore, considering the gap in the human-machine interface user experience in research on omnichannel retailing consumer behavior, this research aims to explore mobile application user/consumer experience under omnichannel context, integrating the human-machine user experience components, based on customer value theory and the user experience model. Particularly, this research was designed to explore mobile application user/consumer experience through real customer feedback utilizing innovative text-mining methods. Further, through the comparison of mobile applications experiences of different types of retailers, this study seeks to comprehend customers' expectations and the targeted value. regarding to different types of omnichannel retailers, and explored the challenges and opportunities that retail mobile applications faced with under the omnichannel retailing context, based on retailers' different positioning strategies and competitive advantages.

Significance of the Study

The findings of this research not only build a conceptual model to understand the user/consumer experience when utilizing retail mobile applications in an omnichannel setting, but also assist retail practitioners and researchers in considering the importance of human-machine interface in omnichannel retailing.

First, this is the one of the few studies to have investigated the user/consumer experience in the context of retail mobile applications. Numerous studies have focused on consumer behavior in e-commerce and on social media platforms to understand multichannel retailing experience. Meanwhile, this research attempts to utilize retail mobile applications as an example of human-machine interface to holistically understand the mobile application use experience and shopping/consumption experience under the omnichannel context, since mobile applications bridge the online and offline channels and are a key interface that omnichannel shoppers are most likely to use.

Second, this is the one of few studies to have utilized cutting-edge text-mining methods to study mobile application reviews and explore the knowledge of consumer research in the context of omnichannel retailing. Text-mining methods, including topic modeling, sentiment analysis and collocation analysis, provide an innovative way to quantify fashion retail big data. The new research scheme could be an innovative and efficient way to discover knowledge from textual data sources, especially customer reviews. Using this research scheme, researchers could efficiently and accurately identify, classify, investigate, compare, and analyze topics, themes, and the underlying causes of customers' praises and complaints. Therefore, this research scheme provides an innovative way to utilize fashion retail big data to better understand consumers in this digital world.

Third, this study helps to reveal the underlying causes of positive/negative user/consumer experience when using retail mobile applications. By investigating the positive/negative customer reviews from different types of retail mobile applications, this study explores the customers' expectation towards different types of retail mobile applications and the potential causes of customers' praises and complaints in the whole shopping experience. The findings were expected to shed light on how to target the segments of omni shoppers and improve the human-machine interface experience, thereby facilitating a more seamless omnichannel shopping experience.

Definition of Key Terms

This research discusses several key concepts and the definitions of key terms are presented in Table 1.

Table 1. Definition of Key Terms

Key Term	Definitions
Omnichannel Shopping	An integrated shopper experience that merges the physical store with the information rich digital environment, with the aim of providing excellent shopper experiences across all touch points (Frazer & Stiehler, 2014).

User Experience	A person's perceptions and responses that result from the use or anticipated use of a product, system or service (ISO 9241-210, 2010, p.7).
Customer Value	Consumer's overall assessment of the utility of a product based on perceptions of what is received and what is given" (Zeithaml, 1988).
Ease of Use	The degree to which an individual believes that using a particular system would be free of physical and mental effort (David, 1989).
Usability	The extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use (ISO 9241-11,1998).
Fluency	The extent to which customers feel cross-platform experience natural, unhindered, and continuous (Shen et al., 2018).
Personalization	Consumer's recognition that information is personalized and tailored for that specific consumer (Vesanen, 2007).
Aesthetics	The degree to which a person believes that the website is aesthetically pleasing to the eye (Dion et al., 1972).
Hedonic Value	An overall assessment (i.e., judgment) of experiential benefits and sacrifices, such as entertainment and escapism (Babin et al., 1994).
Utilitarian Value	Functional benefits delivered by the performance of the applications that is instrumental in achieving valued outcomes distinct from the usage itself, which include application quality and utility (Xu et al., 2014).
Text mining	The discovery by computer of new, previously unknown information, by automatically extracting information from different written resources (Hearst, 2003).
Topic Modeling	A type of statistical modeling for discovering the abstract topics th at occur in a collection of documents (Yau et al., 2014).

Guiding Paradigms and Research Assumptions

The universe is a complex, dynamic flow of mostly obscure, one-of-a-kind, and frequently unrepeatable phenomena. Therefore, it is important for researchers to employ guiding paradigms and assumptions to understand phenomena and making sense of reality (Jaccard & Jacoby, 2010). Two guiding paradigms used in this research are (a) structuralism and (b) critical realism.

The first guiding paradigm that underlies this research is structuralism, focusing on discovering how people think rather than what people think (Jaccard & Jacoby, 2010). The author assumes that beneath the surface structure of phenomena lies a deeper underlying structure representing a set of organizing principles (Jaccard & Jacoby, 2010). Through the lens of structuralism, this research strives to discover the user/consumer experience pattern when using mobile application under the omnichannel context. By following this guiding paradigm, it is assumed that there will be an underlying structure to assist in understanding human-machine user experience and customer benefit gained in omnichannel retailing.

Another guiding paradigm of this study is critical realism, which presumes that our world necessitates and justifies empirical science... to create concepts that can accommodate the obstinate nature of the empirical world (Jaccard & Jacoby, 2010). Reality is seen through the lens of human perceptions. The empirical world either supports or rejects human conceptions. Critical realism researchers assume that reality exists and attempt to learn about it through questions and data collection (Jaccard & Jacoby, 2010). In this research, the conceptual model was proposed based on customer value theory and components of user experience model, and data was collected to reflect this model. Using this approach, the research investigates what is going on in today's society (Jaccard & Jacoby, 2010), and user/consumer experience when using mobile applications.

Organization of the study

This dissertation is divided into five chapters. Chapter 1 discusses the study's background, purpose, and significance, as well as key terms, guiding paradigms and research assumptions, and study organization. Chapter 2 contains a literature review of the theoretical framework for the study. Research gaps are proposed along with a conceptual model. Meanwhile, a short review of text-mining application is also presented. The research methods, including data collection and analysis methods, are presented in Chapter 3. The text-mining research schema is described in detail. Chapter 4 discusses the results of data collection and data analysis, including topic modeling results, sentimental analysis results, collocation analysis results, and comparative analysis results. Finally, Chapter 5 summarizes the research by discussing the major findings, contributions, and implications, as well as limitations and future research opportunities.

CHAPTER II. LITERATURE REVIEW

Chapter II includes the following: (a) theoretical framework, and (b) research hypotheses development.

Theoretical Framework

In this research, the retail mobile application experience is explored through two aspects, the human-machine user experience and the omnichannel shopping experience. This research utilizes the user experience (UX) model to understand human-machine interaction experience when using retail mobile applications in omnichannel retailing. The customer value theory is also adopted to understand customer benefit gained in omnichannel shopping experience in retail mobile applications.

The Components of the User Experience Model

The term "User experience" has been adopted by the human-computer interaction community for a very long time (Hassenzahl & Tractinsky, 2006). However, there has been a lot of debate about the scope of UX and how it should be defined. The traditional usability framework focuses primarily on user cognition and performance in human-technology interactions, while many researchers and user interface designers have recognized that UX emphasizes non-utilitarian aspects of interactions, the emphasis has shifted to user affect and sensation (Law et al., 2009). The term UX is associated with a wide range of meanings, ranging from traditional usability to beauty, hedonic, affective, or experiential aspects of technology use (Forlizzi & Battarbee, 2004).

The most widely accepted definition of UX is "a person's perceptions and responses that result from the use or anticipated use of a product, system or service" in ISO (ISO 9241-210, 2009, p.7). This definition suggests that usability or UX can be measured during or after using a product, system, or service. While this definition is still too broad, researchers attempt to find alternatives to define this term more precisely and specify how it can be measured and categorized. Blythe and Wright (2005) suggested that future UX research must incorporate enjoyment and overall hedonic characteristics. Mahlke (2005) recognized this trend and incorporated perceived hedonic quality, perceived usefulness, and perceived ease of use into his web UX model. Hassenzahl and Tractinsky (2006) divided UX into three perspectives, namely, the user's internal state, the system's characteristics, and the context of use. According to Wright and McCarthy (2004), UX can be measured in terms of usability, aesthetics, emotions, and pleasure.

Overall, this research is based on the position by Thüring and Mahlke (2007) that has been validated and supported by several studies. Thüring and Mahlke (2007) developed a component of the UX model to explain why people prefer one system/device over another in human-machine interaction. Thüring and Mahlke (2007) contended that, in addition to usability, other factors such as personal experience with technology, system aesthetics, and preferred working styles, should all be considered important aspects of UX. Meanwhile, the emotional side of UX has also been long neglected in research on human-machine interaction. The component of the UX model is shown in Figure 1. While the efficiency, effectiveness, usability are definitely important determinants of human-technology interaction, other aspects, such as the aesthetic of system design and emotional experience during usage, also impact the appraisal and further adoption of the system (Hassenzahl, 2006). Therefore, Thüring & Mahlke (2007) presented a broader perspective that regards human-machine UX as a compound of three elements: the perception of instrumental qualities, the perception of non-instrumental qualities, and the user’s emotional responses. Instrumental qualities concern the experienced support the system provides and the ease of its use, including the controllability of the system, the effectiveness, usability, etc. Non-instrumental qualities concern the look and feel of the system, including visual aesthetics and haptic quality. The emotional components here are characterized as subjective feelings accompanied by specific physiological reactions and expressive behaviors.

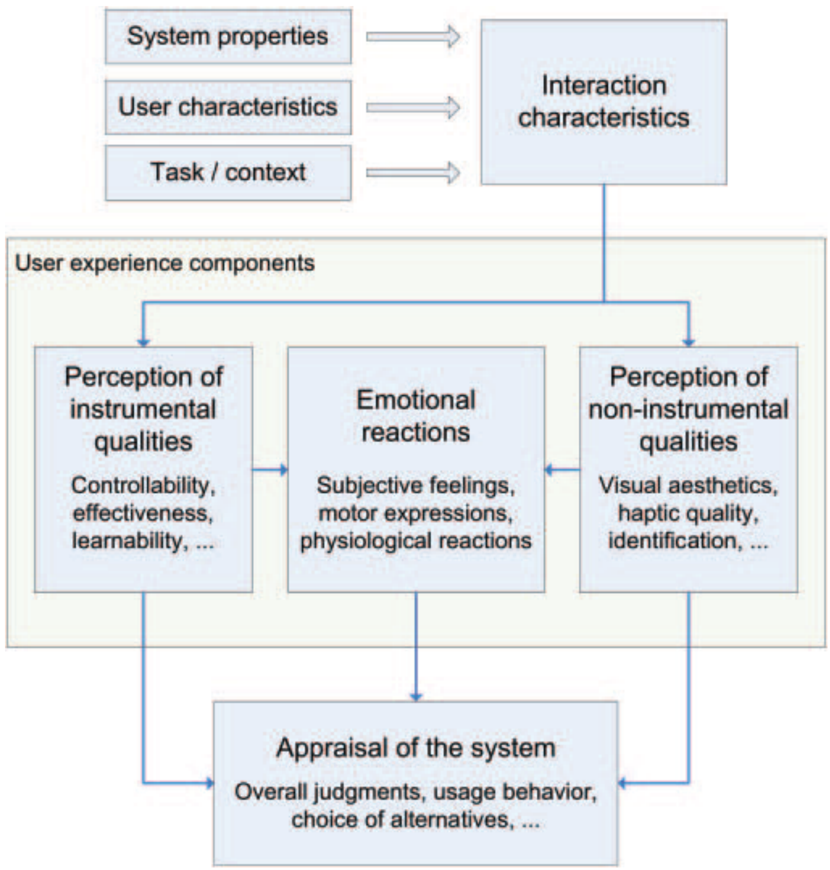

Figure 1. The Components of the UX Model (Thüring & Mahlke, 2007)

Meanwhile, according to this theory, UX is gained when interacting with a technical device. During this experience, user attributes such as knowledge, personality, and skills, as well as system features such as functionality and interface design, may influence the interaction and determine the major UX components (Thüring & Mahlke, 2007). Systems with high levels of usability and attractiveness received higher ratings than their impaired counterparts. Overall, this model demonstrated the concept of UX as a synthesis of emotions and perceptions of both instrumental and non-instrumental qualities. All three UX components would influence the overall evaluation of the system, influencing the user's future decisions and behavior.

This comprehensive and robust model has been widely used and tested in the area of human-machine interaction. For instance, Aizpurua et al. (2016) explored the relationship between web accessibility and UX, based on the UX model, and found that the perceived accessibility is highly related to hedonic and pragmatic qualities. Minge et al. (2017) created a new questionnaire for a standardized measurement of UX based on the components model of UX. This questionnaire consists of four major constructs, namely, instrumental and non-instrumental product perceptions, user emotions, consequences of usage, and an overall judgment of attractiveness. According to the test results, this questionnaire is a valuable and cost-effective tool for measuring key aspects of UX. Aranyi and Schaik (2015) modeled the human-computer interaction with new websites, through the integration of the components model of UX and the technology acceptance model. Therefore, this components of UX model could be utilized to holistically understand the human-machine interface UX and could inform a valuable and cost-effective tool for measuring key aspects of UX.

However, despite the important role of human-machine UX in omnichannel retailing, there are no studies investigating the UX components when using retail mobile application under omnichannel context, based on the components of UX model.

User Experience in Mobile Application

With the rapid and growing development, mobile application is becoming one of the most popular daily human-machine interfaces. Mobile applications offer their users numerous advantages in terms of portability, position consciousness (location awareness), and accessibility. Because several software products that previously ran in computers, now are running using smart phone technologies, the user experience of mobile application has become an important topic. Mobile device manufacturers intend to increase user experience through the features of devices. The Guidelines of Apple iOS Human Interface, for example, state that the platform of iOS features must be considered during the application development process, and should display different resolutions and dimensions, collaboration with multi-touch screen, device orientation gestures and changes, such as pinch, flick, and tap (Apple, 2022). Meanwhile, to find the issues and better optimize the user experience, many researchers in software development field proposed ways to assess user experience of mobile applications. Hussain et al., (2017) carried out laboratory-based user experience evaluation on the Amazon Kindle application, using 15 users who performed 5 tasks on the Kindle e-book mobile application. Overall, they examined four user experience factors, namely, perceived visibility, perceived efficiency, perceived ease-of-use, and perceived enjoyability. Arhippainen and Tähti (2003) performed user experience evaluations through observation and interviews while test users were using adaptive mobile application prototypes.

Researchers also have utilized the components of the user experience model to explore user experience in mobile applications. For example, Chen & Zhu (2011) proposed a quantitative assessment to evaluate user experience through analytic hierarchy process with the guidance of the components of user experience model. This study proposed a four-dimensional assessment system for mobile app user experience, consisting of user characteristics, app properties, app system supports, and context parameters. Meanwhile, Silvennoinen et al. (2014) investigated user experiences and preferences in relation to the visual elements of color and perceived dimensionality of two different mobile application contexts using the components of the user experience model. The findings indicate that visual elements contribute to the pragmatic user experience component in terms of visual usability and to the hedonic user experience component in terms of subjective visual aesthetic preferences.

All those researches explored general user experience in mobile applications from a technique perspective. In the retailing field, however, there is no study evaluating user experience in mobile application under an omnichannel retailing context.

Customer Value Theory

According to Thüring and Mahlke (2007), the components of the UX would have an effect on the overall evaluation of the system and thus influence the user's future decisions and behavior. In the omnichannel retailing context, the human-machine interface UX would then influence the whole shopping/consumption experience of customers. To cover and better measure customers’ omnichannel experience, including both online and offline customer experiences, we use the customer value theory. Early interpretations of customer value emphasized only the benefit and sacrifice components, as reflected by perceived quality and price (Grewal et al., 1998), which is believed to be too simplistic.

The most common definition of customer value is “a consumer’s overall assessment of the utility of a product based on perceptions of what is received and what is given" (Zeithaml, 1988). Value is considered to be a trade-off between the perceived benefits and the perceived costs of acquiring or using a product (Boksberger & Melsen, 2011). Day (1999) introduced a "value equation," which is "*Customer's Perceived Benefits - Customer's Perceived Costs = Perceived Customer Value*" (p. 142). Early marketing studies focused on perceived product quality as the main "benefit" component. For example, Lai (1995) proposed a model to stress the consumer's product valuation and defined eight generic product benefits in regard to perceived product quality: functional, social, affective, epistemic, aesthetic, hedonic, situational, and holistic. Tsiotsou (2005) also demonstrated the positive effect of perceived product quality on consumers' overall satisfaction. Customer value consists of various value dimensions that make different contributions in different choice situations. Therefore, besides perceived product quality, many other factors were explored. Sweeney & Soutar (2001) incorporated three relevant dimensions of customer consumption value: functional, emotional, and social. Functional value is the perceived utility of a product based on the product's capacity for functional, utilitarian, or physical performance, and emotional value is the perceived utility of a product based on the product's capacity to arouse feelings or affective states. The emotional value principally depends on how the product looks and the emotive aspects of the customer's experience with the product.

According to Hartnett (1998), "when [retailers] satisfy people-based needs, they are delivering value, which puts them in a much stronger position in the long term." Kim et al. (2015) investigated the positive influence of customer value components on customer purchase behavior by evaluating the firm's product's customer value performance based on the purchase decision-making process. Meanwhile, customer value is also an important factor in technology-adoption intentions. For instance, according to Khadem and Mousavi (2013), customers who perceive internet banking as useful, simple, and cost-effective, and who are willing to use technology, have a higher value perception regarding internet banking and are more willing to adopt internet banking. Roostika (2014) also proved that customer benefit, including usefulness and enjoyment, has a positive influence on mobile internet acceptance among university students. Overall, Potential customers who believe they will receive high product/service value from the provider should have more positive behavioral intentions than those who believe they will receive low service value (Roostika, 2012). In examining an omnichannel customer experience, customer value should be included to better understand and predict customer behavior, especially adoption intentions.

There are multiple factors that might affect customer perceived value. For instance, Kumar et al. (2010) examined the cognitive influences of atmospherics on customer value, indicating that store size, design changes, lighting, and architectural makeover would all affect customer perceived value, due to the influence of the emotional state, such as pleasure and arousal. Tzavlopoulos et al. (2019) also found that a high level of service quality in an e-commerce platform, such as the ease of use of websites, design, responsiveness, and security, all lead to higher levels of customer perceived value. Meanwhile, strong customer relationship management, positive brand image, and company reputation (Cretu & Brodie, 2007) could all increase the level of customer perceived value. Therefore, in an omnichannel approach, the emotional component and other instrumental and non-instrumental qualities in human-machine UX should also strongly influence the customer value in the whole shopping experience.

Many studies have explored customer value in the context of online shopping. Chen and Dubinsky (2003) proposed a conceptual model of perceived customer value in the e-commerce field. Perceived customer value is associated with the product price, product quality, e-retailer reputation, privacy risk, and valence of online experience, such as ease of website use, relevant information, and customer service. Lang et al. (2020) also identified experiential value, financial value, ease of use, and utilitarian value as the four major perceived benefits of online fashion renting, while unsatisfactory service, poor product performance, and insufficient inventory were three major perceived costs discovered through a text-mining method from the customer reviews.

The benefit/cost components of customer value vary within different consumption contexts. In terms of the customer value in mobile applications, Xu et al. (2015) define utilitarian benefits of mobile applications as the functional benefits delivered by the performance of applications that are instrumental, and they define hedonic benefits of mobile applications as the non-functional benefits delivered by the performance of apps to obtain fun and self-fulfillment. They found that those customers' perceived value increased customer satisfaction, and finally positively influenced customers' intention to recommend mobile applications. Wang et al. (2013) also demonstrated that the consumption value, including functional value, social value, emotional value, and epistemic value, positively affected the behavioral intention to use mobile applications.

Customer Value in Omnichannel Retailing

In the context of omnichannel retailing, value creation entails thinking about the customer experience in terms larger than a single transaction or shopping process. According to Yrjölä et al. (2018), omnichannel customers appear to prioritize hedonic aspects of consumption in their value propositions. Retailers regard shopping as a pleasurable activity. For example, Neiman Marcus's mobile application enables customers to use a photo of an item of clothing to determine whether the retailer offers a similar product, and Apple's customers can make voice-controlled purchases at home through their Apple TV. According to Jindal et al. (2021), when comparing customer value between Amazon and Walmart, it was discovered that Amazon should provide an opportunity for product freshness and quality validation, whereas Walmart should provide a stronger incentive for customers who value assortment, price, and convenience.

In the fashion retailing field, Lynch and Barnes (2020) developed a framework for describing each stage of the omnichannel customer decision-making journey for high-involvement fashion consumers. This framework depicts the emotional experiences, devices, and channels that consumers encounter, and enables retailers to find issues within the customer and brand experience. Kopot and Brenda (2021) investigated customers' perspectives on omnichannel fashion department store shopping channels and discovered that customers were more likely to purchase from a fashion department store that provided consistent content and processes across all shopping channels. All these studies provided contributions for retailing practitioners to improve their websites, products, and services to deliver superior customer value and better meet customers' expressed needs. However, there is no study utilizing customer value theory to understand the omnichannel customer experience when using retail mobile applications.

Customer Value in Different Types of Retailers

There are also many studies investigate customer value provided from different types of retailers based on their positioning. In terms of high-end fashion retailers, previous research has helped to identify and conceptualize customer value. Because the strategic mission of luxury brands is based on providing enough value to compensate for the high product price (Dubois & Duquesne, 1993), creation of customer value through closer and more special relationships leads to satisfaction, trust, affective commitment and loyalty (Bick, 2009). Choo et al. (2012) conceptualized luxury customer value and developed a four-value structure model composed of utilitarian, hedonic, symbolic and economic values. The in-store experience for the high-end customer has traditionally been the focus of luxury retail. However, during the pandemic, many high-end fashion retailers took efforts to expand and accelerate established digital programs and adopted omnichannel strategies. Bai (2018) explored luxury fashion retailers' omnichannel distribution and communication strategies. Lawry and Choi (2013) found that custom QR codes could enhance the visual appeal of a luxury window display, which supported an inter-channel transference of experiences. However, there is few studies attempting to explore how luxury retailers keep consistent customer experience and convey customer value through omnichannel approach, especially via mobile applications.

housewares, wine, books, leather goods, and so on) and take pride in their customer service. Mid-tier retailers provide value to customers primarily by providing services and assisting them in making product selections (Dennis, 2018). They can also improve consumers' perceptions of product value by making buyers' shopping experiences easier or more convenient, such as offering free delivery or an online shopping option (Dennis, 2018). Compared with high-end fashion retailers, mid-tier retailers have much more physical store. For example, in 2022, there were 508 Macy's stores, while there were only 86 Bloomindale's stores in the U.S (ScrapeHero, 2022). Therefore, the mid-tier retailers' customers are more likely to transit between online and offline channels. However, there is not study exploring how mid-tier retailers keep seamless customer experience and add customer value through mobile applications under the omnichannel context.

Brands have excess inventory that they cannot sell at full price (or even at a slight discount) in stores, and in order to maintain proper cash flow and business success, they typically look to off-price retailers to sell the products to consumers at significantly lower prices than those found in boutiques, department stores, and other full-price retailers (Inturn, 2022). Off-price retailers sell brand name and designer products for a fraction of their original price, allowing customers to shop for bargains and gain financial value whenever they want, without having to wait for annual sales. Hedonic value is another component of customer value. When customers enter the store, they have no idea what they will end up purchasing. They enjoy looking for the best deal, price, or product (Inturn, 2022). Now that many off-price retailers launched their mobile applications, it is more convenient for consumers to search the deals. It is necessary to understand the opportunities and challenges that off-price retailers faced with to achieve omnichannel strategy.

Instrumental Qualities

According to the components of the UX model, instrumental qualities refer to the experienced support the system provides and the ease of its use, including the controllability of the system, the effectiveness, usability, etc. Since its early days, the majority of the human-computer interaction research was devoted to achieving instrumental value (Mahlke, 2005). For example, Hussain et al. (2021) evaluated the instrumentality of a novel eWallet mobile application, such as task completion rates, ease or difficulty of task completion, time spent on a task, errors, etc. In the omnichannel retailing context, consumers expect high performance on not only each channel, but also the channel integration and the whole service quality. Fluent experience with consistent information in the human-machine interface when shopping is also an important aspect of instrumental qualities. Meanwhile, personalization is instrumental in two ways: first, it helps to understand the unique needs of each individual consumer, and second, it helps to tailor offerings to those needs (Bashar & Rabbani, 2021). In the case of mobile applications, personalization entails tailoring the web content, design, interface, and overall atmosphere to each customer's preferences. In this light, instrumental qualities can be categorized into four dimensions: ease of use, usability, fluency, and personalization.

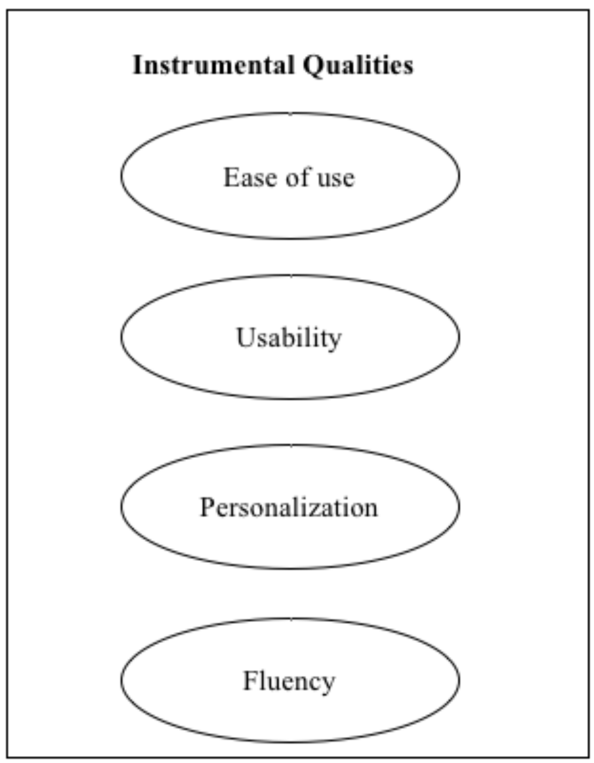

Figure 2. The Major Components of Instrumental Qualities

Ease of Use

David (1989) postulated that users' attitudes toward using a computer system consisted of a cognitive appraisal of the design features and an affective response to the system. This attitude then influences actual computer system use or adoption. The two major design features are the perceived *ease of use* of the system (operating as an intrinsic motivator) and the *perceived usefulness* of the system (operating as an extrinsic motivator). Perceived ease of use is "the degree to which an individual believes that using a particular system would be free of physical and mental effort" (David, 1989). It refers to the extent to which an individual considers that making use of a specific technology would be effortless. Ease of use pertains to the performance impacts related to the process. The ease of use of a technological system is determined by how the system enables the customer to perform tasks while increasing productivity, performance, and efficiency (Chau & Lai, 2003). The greater the perceived ease of use of the system, the greater the likelihood of actually using the system. Consumers dislike using technology that they perceive to be difficult to use, even if they believe the technology is useful. David (1989) also mentioned that perceived ease of use was assumed to have a significant direct effect on perceived usefulness. When two systems perform the same task, the user should find the system that is easier to use to be more useful than the other. According to the components of the UX model, instrumental qualities also include ease of use of the system.

Many studies show the importance of the role of ease of use in the determination of use intention. For example, Henderson and Divett (2003) assess the positive influence effect of perceived ease of use on the adoption of electronic supermarket systems, including the use of deliveries, purchase value, and number of log-ons to the system. In the mobile application research area, Min et al. (2019) used the diffusion of innovation theory and the technology acceptance model to discover that perceived ease of use would lead to consumers' intention to use the Uber mobile application, due to their attitude. Enhanced instrumental qualities of smartphones, such as ease of use and responsiveness, may influence users' utilitarian value perceptions and their hedonic enjoyment (Chun et al., 2012). In the omnichannel context, Silva et al. (2018) also demonstrated the direct influence of perceived ease of use on use intention in the omnichannel approach to shopping. The findings of Mclean et al. (2018) highlighted the importance of utilitarian factors, including ease of use, customization, and convenience, in driving an effective customer experience in the omnichannel approach. When consumers have easy access to and use of mobile services, they can achieve their goals more efficiently (Ozturk et al., 2016). Furthermore, when consumers believe that using a mobile service is easy, their hedonic value perception rises (Yang, 2010).

In the human-computer interaction area, Hussain et al. (2021) assess the ease of use of a mobile application through the ease of navigation, ease of finding help, and ease of completing a task. Therefore, ease of use is an important aspect of instrumental qualities in the UX and could further influence the users' appraisal of the system as well as use intention. In this study, ease of use refers to the degree to which a user believes that adopting the human-machine interface will be free of effort.

Usability

Usability is an important attribute of software that has several methods and metrics that can be used for assessment. Although usability has its academic roots in software engineering communities and human-computer interaction, the term is still not defined in a consistent way (Hoehle & Venkatesh, 2015). Shackel (1991) described usability as a system's capability to be used by humans effectively and easily. Preece (1994) defined it as "a measure of the ease with which a system can be learned or used, its safety, effectiveness and efficiency, and the attitude of its users towards it." ISO 9241-11 (1998) defined usability as "the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use." This definition of usability has been accepted widely, and usability is considered a multidimensional characteristic of a system (Jokela et al., 2004).

There are several models available to identify the attributes of perceived usability. According to the definition of ISO (1998), *effectiveness* refers to the extent to which a task goal is successfully achieved (e.g., the proportion of users that are able to complete a given task). *Efficiency* indicates the amount of resources a user spends to reach a task goal (e.g., task completion time). *Satisfaction* can be considered as an attitude toward the product. It is a subjective measure that is typically collected in usability tests by means of questionnaire items. Each factor influences how the software is designed overall, as well as how users interact with the system. Another usability model identified by Nielson (1994) has five attributes: efficiency, learnability, satisfaction, errors, and memorability. Harrison et al. (2013) developed a usability model, which is the latest and most frequently used model in recent research on usability. It combines elements of both Nielsen's model and the ISO standard.

Perceived usability is one of the basic components of UX. Researchers in software engineering communities measure the usability of a system through various methods and scales. For example, Alturki and Gay (2017) used the completion rate of tasks to measure effectiveness, and they used the time taken to finish a task to measure efficiency. Pal and Vanijja (2020) used the System Usability Scale (SUS), a human-computer interaction-based approach, to determine the perceived usability of Microsoft Teams as an online learning platform during the COVID-19 pandemic. Holden and Rada (2011) adapted scale items of usability from Preece (1994), finding that the integration of perceived usability into the technology acceptance model was more influential to attitude/behavior elements when investigating the acceptance and usage behavior of educational technology.

Finstad (2010) adapted the measures from the SUS and created the Usability Metric for User Experience to assess the subjective usability of an application. This measurement reflects the three attributes from the definition of ISO, which have been widely tested. For example, Lewis (2018) compared this measurement with the SUS, and concluded that, even though these questionnaires have different items, they appear to be assessing the same construct, perceived usability.

Personalization

Personalization is a process in which consumers are provided with custom-made products or services that are specifically designed based on their individual preferences through consumer data (Tuzhilin, 2009). It requires advanced technology, such as data mining, collaborative technology, usage pattern detection, transaction history, location detection, etc. Thurman and Schifferes (2012) defined personalization as a form of interaction between user and system which depends on "technological features to adapt the content, delivery, and arrangement of communication to individual users' explicitly registered and/or implicitly determined preferences." Companies nowadays use a variety of personalization strategies to build and maintain customer relationships and gain a sustainable competitive advantage (Erevelles et al., 2016). For example, personalizing communication or messages, making personalized recommendations based on consumer data, using personalized virtual models to determine clothing fit, and so on (Tam & Ho, 2006). From consumers' perspectives, perceived personalization is defined as a consumer's recognition that information is personalized and tailored for that specific consumer (Vesanen, 2007). When a consumer recognizes these personalization cues, the information is encoded in relation to the self, and the experience is perceived to be more personalized. Personalized products/services allow consumers to save time searching for information while also receiving customized services that more precisely address their needs (Nyheim et al., 2015). According to a Forbes report, 80% of consumers are willing to make a purchase from retailers that personalize their buying experience, and 87% of consumers indicated that they prefer to buy from a brand that "understands the real me" (Morgan, 2020).

Many researchers have conducted studies related to the importance of perceived personalization on retailing and marketing strategies, as well as consumer behavior. Komiak and Benbasat (2006) articulated theory and empirically examined the positive effect of perceived personalization on trust and further adoption of web-based recommendation agents. Smink et al. (2020) investigated whether perceived personalization could enhance purchase intentions in augmented reality. In mobile app usage, Cheng et al. (2020) demonstrated the importance of personalization in consumers' continuous use of mobile news apps. Kang and Namkung (2019) investigated consumers' attitudes toward personalized services provided by branded mobile apps in the food service industry.

Despite the enormous potential of mobile apps as retailing tools, there are few researchers who have explored the personalization of products/services of mobile apps as a driver for further adoption of omnichannel retailing.

Fluency

Perceived fluency refers to the subjective experience of feeling ease or difficulty in any form of mental processing (Reber et al., 2004). Research shows that processing fluency is a key concept that influences various domains of human judgment and subsequent behavior (Labroo & Lee, 2006). In the offline context, if consumers read the product information fluently, the assessed ease of processing information may result in a positive affective response to the product described in the text. In the online context, researchers investigated the impact of the three dimensions of processing fluency (perceptual fluency, positive affect, and cognitive effort) on consumers' choice satisfaction with an online shopping task (Mosteller et al., 2014). In a multichannel service context, Cassab and MacLachlan (2006) define interaction fluency as the degree to which the firm's multiple interfaces facilitate flowing, effortless, and accurate interactions with customers, and they utilize interaction fluency to evaluate customer-firm interaction during service delivery and other functional quality dimensions of service.

Originating from information processing research, some studies extend the concept of fluency to a cross-platform context (Shen et al., 2018). To holistically measure the instrumental qualities of a human-machine interface in an omnichannel context, the fluency performance in a cross-platform human-machine interface should also be considered. Majrashi and Hamiltion (2015) consider fluency as the capacity of services to support the fluency of user activity across a platform in their cross-platform usability model. For instance, if a user moves activity from a service on their PC to a service on their mobile app, the fluency degree the mobile application could support would influence the efficiency and effectiveness of the system.

There are different types of fluency, including task, content, interaction, cognition, and feeling fluency (Majrashi & Hamiltion, 2015). Task fluency refers to the capability of services in supporting the fluency of a task. Content fluency means the capability of cross-platform services to support continuity of reading or exploring the contents after switching from one platform to another. Interaction fluency refers to the capability of services in supporting fluency of user interaction when users are carrying out a task cross-platform. Cognition fluency indicates the capability of services in helping users remain at the same level of engagement after transition of the activity to another device. And feeling fluency indicates the capability of services in helping users to remain at the same level of feeling after transition (Majrashi & Hamiltion, 2015). Therefore, perceived fluency was associated with continuity after cross-platform transitions, and it plays an important role in measuring cross-platform UX.

Shen et al. (2018) define “perceived fluency” as the extent to which customers feel a cross-platform experience is natural, unhindered, and continuous, and they demonstrate that perceived fluency in cross-platform activity exerts a positive impact on omnichannel service usage. Kopot and Cude (2021) found that the perceived fluency of omnichannel fashion consumers would positively affect their brand attitude, therefore perceived fluency acts in an important role in developing a sustainable omnichannel business strategy.

In this research, the instrumental qualities of a human-machine interface, including mobile applications and in-store interfaces, should provide a natural, unhindered, and continuous UX to guarantee a seamless omnichannel shopping experience. Therefore, perceived fluency is considered an aspect of instrumental qualities of human-machine interfaces in the omnichannel retailing context.

Non-instrumental Qualities

Quality aspects beyond the instrumental value of an interactive human-machine system are one area of research in the field of UX. Jordan (2000) claimed that, along with the functionality and usability of the product, different aspects of pleasure are also important to enhance the user's interaction with it. Rafaeli and Vilnai-Yavetz (2004) presented a model and proposed that systems be examined using three distinct criteria: instrumentality, aesthetics, and symbolism. Aesthetics and symbolism represent two categories of non-instrumental quality. Aesthetics refers to the sensual experience a product elicits and the extent to which this experience fits individual goals and spirits. And symbolism refers to the meanings and associations that are evoked by the products. According to the components of the UX model, non-instrumental qualities of a human-machine interface system mainly concern the look and feel of the system, including visual aesthetics and haptic quality. In the human-machine interaction area, researchers began to realize the importance of non-instrumental qualities, and they attempted to assess their interface, not only focusing on the instrumental qualities but also on the aesthetical aspect. For example, Irshad et al. (2018) assessed the UX of mobile augmented reality systems using non-instrumental quality attributes, focusing on the visual aesthetics.

Aesthetics

Traditionally, the primary focus of the field of human-computer interaction has been on the system's effectiveness and efficiency, such as time to learn, error rate, time to complete a task, and so on (Butler, 1996). Aesthetics were discovered to be important in development, marketing strategies, and the retail environment. Bloch (1995) said that the "physical form or design of a product is an unquestioned determinant of its marketplace success." The importance of aesthetics in various aspects of computing has recently emerged. The visual appearance of a computer, for example, has become an important factor in buyers' purchasing decisions, and the Apple MacBook was heralded as the "aesthetic revolution in computing" (Postrel, 2001). Lavie and Tractinsky (2004) proposed an assessment of perceived website aesthetics, resulting in a two-dimensional structure of perceived website aesthetics. The first dimension, "classical aesthetics," is represented by items that refer to the following design attributes of the website: aesthetic, pleasant, clean, clear, and symmetrical. The second dimension, "expressive aesthetics," is represented by the following design attributes: creative, using special effects, original, sophisticated, and fascinating. According to the research of Oyibo et al. (2018), when designing utilitarian systems, classical aesthetics have a stronger influence on perceived credibility than expressive aesthetics. Therefore, this research takes an approach focusing on the classical aesthetics.

In most empirical studies, visual design refers to the balance, emotional appeal, or aesthetics of an interaction system, and it may be expressed through colors, shapes, font type, music, or animation. Furthermore, the sensory experience of the website can influence whether or not a user stays and shops. Drawn from the psychology literature, perceived aesthetics was defined as “the degree to which a person believes that the website is aesthetically pleasing to the eye” (Dion et al., 1972). The response to an interface system's aesthetic design is influenced not only by specific design factors (such as form or surface attributes), but also by individual characteristics such as age, personality, cultural background, or gender (Crilly et al., 2004).

According to empirical studies in the field of human-computer interaction, the aesthetic aspect of computing products plays an important role in shaping users' attitudes. Schenkman and Jönsson (2000), for example, investigated how users perceive web pages aesthetically. Van der Heijden (2003) mentioned in research that the visual attractiveness of the website refers to its visual elements, including the colors used and its overall layout, and examined that this perceived visual attractiveness is one of the major drivers of website traffic. Especially in the mobile commerce area, Cyr et al. (2006) discovered that visual design aesthetics have a significantly impact on the hedonic aspect in the shopping experience and ultimately influenced users’ loyalty intentions toward a mobile service. Meanwhile, according to Lindgaard (2007), one might speculate that aesthetically pleasing technology might put the user at ease, thereby increasing user performance (e.g., reduced task completion time). Sonderegger and Sauer (2010) empirically show that the attractive model's visual appearance has a positive effect on user performance, resulting in shorter task completion times.

Emotional Components

Besides the instrumental qualities and non-instrumental qualities, emotional components are also important to measure UX in human-machine interactions. According to the components of the UX model, the emotional components here are characterized as subjective feelings accompanied by specific physiological reactions and expressive behaviors. They consist of the perceptual, physiological feelings, and thinking activities, and they cause a change in the emotional state of the users (Li et al., 2012).

Internal emotions can be aroused by multiple external sensory modalities, including sounds, tactile impressions, and visual images (Holbrook & Hirschman, 1982). A large number of stimulus-organism-response (SOR) studies have found empirical evidence supporting the relationship between some emotional responses (e.g., enjoyment, pleasure, and arousal) and behaviors. For example, Wang et al. (2011) indicated that consumers' cognitive and affective states can be significantly influenced by aesthetic stimuli, and these consumers' psychological reactions would influence online consumers' intentional behavioral tendencies. According to the SOR model, emotional responses consist of two dimensions: pleasure and arousal (Koo & Ju, 2010). Pleasure is defined as "the degree to which a person feels good, joyful, happy, or satisfied in a situation." And arousal refers to "the degree to which a person feels stimulated, active, or alert" (Menon & Kahn, 2002). In the information system area, several empirical studies supported the notion that the emotional response, such as flow, perceived enjoyment, liking, joy, pride, dislike, frustration, and fear, would impact user behavior. For example, Li et al. (2012) interpreted consumers' emotions in the context of mobile commerce from an experiential standpoint, implying that emotion played a significant role in the mobile consumption experience. Among these emotional states, enjoyment could be considered as one of the major factors that positively impact user/consumer experience.

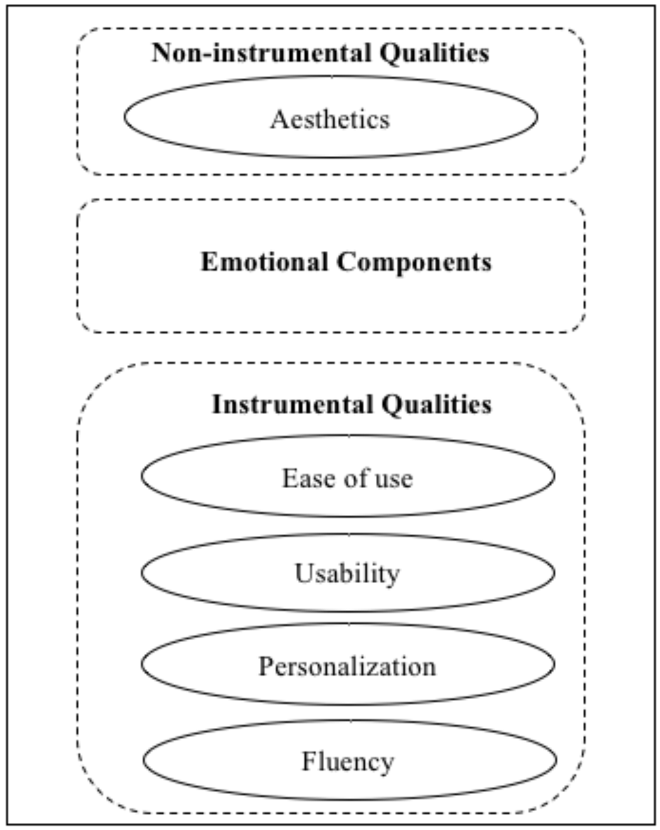

Figure 3. The Components of UX in a Human-machine Interaction

Customer Value in Shopping Experience

Customer value roots from the reconciliation of what the customer receives (e.g., quality, worth, benefits), and what the customer gives up acquiring the benefits (e.g., price, sacrifices) (Zeithaml, 1988). It is a complex and multi-dimensional construct. It is crucial in predicting customer preferences and future repurchase intentions (Zeithaml, 1988). Utilitarian value and hedonic value appear to be the most universal value dimensions (Babin et al., 1994). Existing research has established that people shop for hedonic or utilitarian reasons. For example, researchers indicated that both the utilitarian value and hedonic value are positively associated with buyers' repeat purchase intentions in a B2C e-commerce context (Chiu et al., 2014). Irani and Hanzaee (2011) investigated the effects of utilitarian and hedonic value on the apparel shopping experience. Xu et al. (2015) also broke customer benefits down into utilitarian benefits and hedonic benefits to understand the influence of customer benefits gained in mobile application usage on mobile application recommendation. Therefore, in this research, we primarily focus on utilitarian value and hedonic value to understand the customer benefit gained in the omnichannel context.

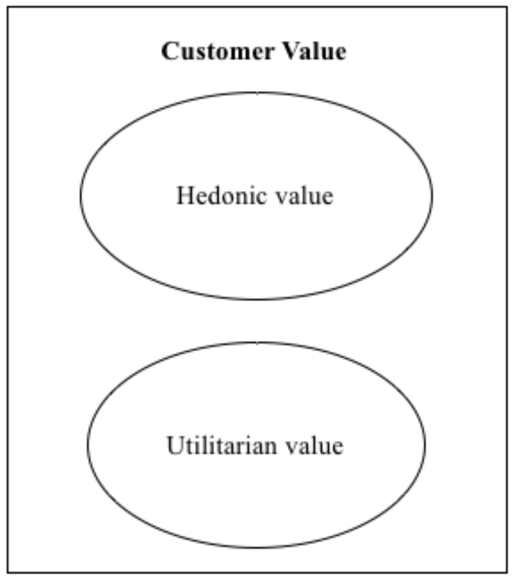

Figure 4. The Major Dimensions of Customer Value

Utilitarian Value

Utilitarian value is described as “resulting from some type of conscious pursuit of an intended consequence” (Babin et al., 1994). Therefore, it is task-oriented and rational. It primarily entails meeting the instrumental expectations that customers may have for the product or service. It is regarded as a means to an end, frequently equated with rational motives of time, place, and possession requirements. Consumers are concerned with purchasing products in an efficient and timely manner in order to achieve their goals, according to utilitarian theory (Ryu et al., 2010).

Chiu et al. (2014) proposed four major utilitarian benefits of online shopping as the dimensions of utilitarian value: convenience, product offerings, product information, and monetary savings. Convenience is the most compelling benefit of online shopping, in that customers are able to shop anywhere at any time. Online buyers are also variety-seeking. It is critical to fulfill their need for broad product offerings to drive them to shop online again. Rich product information is another key advantage of online shopping, as online shoppers are only a few clicks away from receiving more extensive and higher quality product information. In the mobile application context, Xu et al. (2014) defined utilitarian benefits of mobile applications as functional benefits delivered by application performance that are instrumental in achieving valued outcomes separate from the usage itself, which include application quality and utility. When consumers perceived the mobile application as useful for information-seeking, file-synchronization, and shopping, and when consumers perceived the mobile application as reliable and responsive, they were more likely to recommend the mobile application.

Hedonic Value

Traditional product-acquisition explanations failed to capture the total value of a consumption experience. The numerous intangible and emotional benefits would be overlooked if consumption activities were solely evaluated on the benefits of goods or services acquired, which would fail to fully explain the consumption experience (Babin et al., 1994). Therefore, many researchers have brought hedonic value into studies of customer value in online shopping. Hedonic value is defined as an overall assessment (i.e., judgment) of experiential benefits and sacrifices, such as entertainment and escapism (Babin et al., 1994). It is more subjective and personal than its utilitarian counterpart, and it stems from playfulness and fun rather than task completion. Consumers frequently shop for the sake of the experience rather than simply to complete a task. Hedonic value is non-instrumental, experiential, and affective in nature, and it is frequently associated with non-tangible retailer/product attributes (Ryu et al., 2010). In the technology context, hedonic value could be considered as fun or pleasure that results from technology use (Venkatesh et al., 2012). However, it varies depending on the retail format (Arnold & Reynolds, 2003). For example, in the online context, consumers value adventure, authority, and status, whereas hedonic shoppers value enjoyment, entertainment, and exploration in the physical store context.

Overall, the user/consumer experience in retail mobile application could be understood by the guidance of components of user experience model and the customer value theory. The conceptual model of this study is shown in Figure 5.

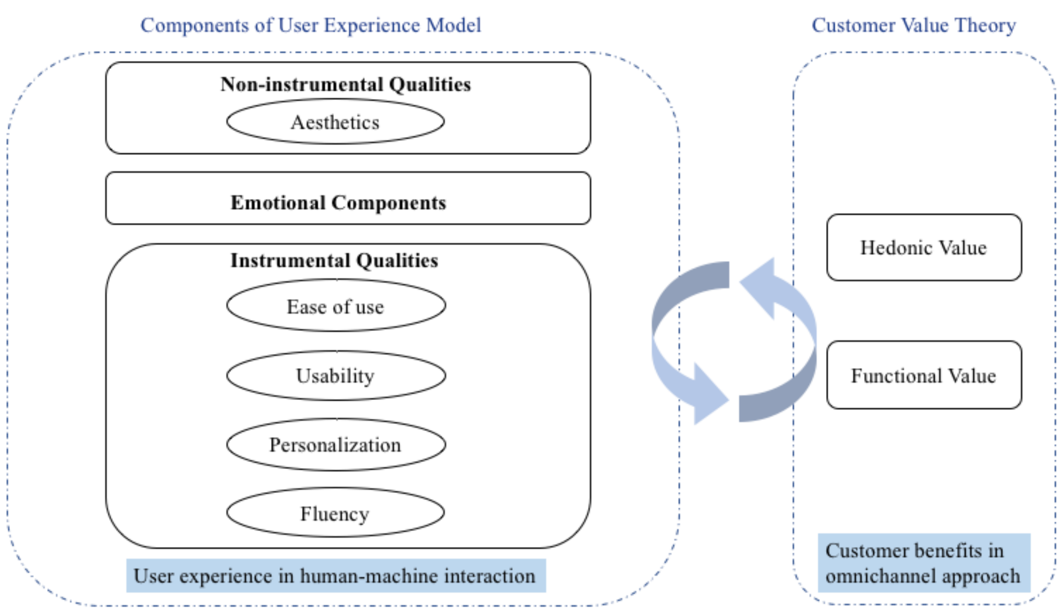

Figure 5. Research Conceptual Model

Text Mining in Customer Reviews

Surveys have traditionally been used to learn about customer expectations and satisfaction. However, Lucini et al. (2020) criticized such survey methods because the aspects focused tend to be based on management or researcher knowledge and may not reflect the customer's actual needs, resulting in inconsistent measurement of perceived service quality.

With the increased accessibility of Web 2.0 technologies and the expansion of social media websites, more customers are freely expressing their opinions/experiences about a product or service on online forums (Rajendran, 2021). Despite the fact that online customer reviews are subjective and represent a subset of actual customers, they are regarded as highly reliable for understanding a customer's point of view (Srinivas & Rajendran, 2019). Besides, online customer reviews also influence the decisions made by potential customers (Salehan & Kim, 2016). Negative online customer reviews can harm a company's reputation and spread five to six times faster than positive ones. As a result, businesses must comprehend and analyze these unstructured review data (Salehan & Kim, 2016). Furthermore, these reviews have become widely available and simple to access, allowing businesses to easily understand their strengths and weaknesses from the perspective of their customers (Salehan & Kim, 2016). Hence it is presumed that the retailers can also use customer reviews to understand and improve user/customer experience.

The raw data of online customer reviews are all unstructured textual data. And it is difficult to evaluate the large amount of online user-generated-data manually and objectively (Lau et al., 2005). Therefore, many studies have utilized text mining methods, the established data-mining methods aiming to analyze textual data source, to explore knowledge from customer reviews (Berezina et al., 2016; Tuck & Kim, 2021). Text mining is “the discovery by computer of new, previously unknown information, by automatically extracting information from different written resources” (Hearst, 2003). It aims to reveal hidden information using methods that, on the one hand, can deal with the large number of words and structures in natural language and, on the other hand, can deal with ambiguity, uncertainty, and fuzziness (Hearst, 2003). Text mining research is currently addressing issues such as text representation, classification, clustering, information extraction, and the search for and modeling of hidden patterns.

Text mining can be used in conjunction with exploratory data analysis. Unlike content analysis, which is used to (re-)construct a “reality” based on the interpretations of a text made by researchers, Text mining is based on the positivist research philosophy of "hard science," and it seeks universal generalizations through quantifiable measures (Rynes & Gephart, 2004). Text mining also employs natural language processing (NLP) to detect patterns and provide predictive information based on a more sophisticated understanding of language. NLP, as a subfield of artificial intelligence and computational linguistics, focuses on the automatic analysis of human language using algorithms capable of dealing with complex structures (Nadkarni et al., 2011). Text mining uses NLP to analyze data as if it were read by a human coder. Text mining has the potential to improve not only the ability to analyze large, complex data sets, but also the reliability, reproducibility, and flexibility of analysis (Lang et al., 2020). It ensures consistency across results and provides an objective measure of accuracy. It also has the potential to be improved by incorporating more data. Considering this, our study introduces text mining to accurately and efficiently retrieve, manage, and interpret customer reviews.

Text Preprocessing

Pre-processing text documents and storing the information in a data structure that is more appropriate for further processing than a plain text file is required for mining large document collections. The majority of text mining approaches are based on the idea that a text document can be represented by a set of words, i.e. a text document is described based on the set of words it contains (bag-of-words representation) (Hotho et al., 2005). And, in order to define at least the importance of a word within a given document, a vector representation is typically used, with each word storing a numerical "importance" value.

The set of words describing the documents can be reduced by filtering and lemmatization or stemming methods to reduce the size of the dictionary and thus the dimensionality of the description of documents within the collection (Hotho et al., 2005).

Filtering methods remove words from the dictionary and, as a result, from documents. Stop word filtering is a common filtering method. Stop word filtering removes words with little or no content information, such as articles, conjunctions, prepositions, and so on. Furthermore, words that occur extremely frequently can be said to have little information content to distinguish between documents, and words that occur very rarely are likely to have no statistical relevance and can be removed from the dictionary (Hotho et al., 2005).

Lemmatization is an important preprocessing step for many text mining applications. Natural language processing also makes use of it. Methods of lemmatization attempt to map verb forms to the infinite tense and nouns to the singular form (Hotho et al., 2005). It usually refers to word morphological analysis, which seeks to eliminate inflectional endings. It aids in returning the lemma, or base or dictionary form, of a word.

A lot of work has been carried out filtering and word lemmatization as part of text preprocessing. For example, Sezgen et al. (2019) adopted a text-mining approach to compare satisfied and dissatisfied airline customer online reviews. In the text-preprocessing, Sezgen et al. (2019) removed all of the English stop words as well as airline names, and also applied lemmatization techniques to bring single word concepts together.

Topic Modeling

It is critical in text analysis to determine what events or concepts a document is discussing. A human reading a document would understand this information, but a program is only given the text as it is written, not the subject matter of each document. Data scientists use a technique known as topic modeling to accomplish this task in a program (Vayansky & Kumar, 2020). Topic modeling is a type of statistical modeling used to identify the abstract topics that appear in a set of documents (Yau et al., 2014). It can aid in the organization of large-scale datasets for easier access. Researchers used topic modeling methods to organize databases of journals and articles into groups based on similar subject matter (Blei et al., 2013). Liu et al. (2016) developed a topic model application and provided an outlook on the use of topic models in the development of bioinformatics applications. Hong and Davison (2010) proposed several schemes for training a standard topic model and comparing its quality and effectiveness in understanding social media messages.

Many topic modeling methods have been developed to extract topics from textual datasets accurately and efficiently. The first method developed for this task was known as the tf-idf reduction scheme, and it was proposed in the field of information retrieval by (Salton, 1983). Each individual document in a corpus is regarded by its vocabulary in this method, and the number of occurrences of each word is tallied to form a count value to form a term frequency count (tf) specific to that document for that word. The total number of instances of a word across the entire corpus, known as the inverse document frequency count (idf), is also computed. Although effective at identifying sets of words that distinguish documents in a collection, the reduction in description length was minor, and the approach yielded little meaningful information about statistical relationships within or between documents. Deerwester et al. (1990) developed another dimensionality reduction method known as latent semantic indexing or analysis (LSI/LSA). When applied to large corpora, LSI can achieve significant data compression; however, a more direct method of analysis could be implemented by developing a generative model and fitting it with probabilistic methods (Blei et al., 2003). This enhancement, known as the probabilistic LSI or LSA, was proposed by (Hofman, 1999). This approach, however, lacked a probabilistic model for determining the mixture proportions of documents.

Latent Dirichlet Allocation (LDA) is currently one of the most popular topic modeling algorithms, and it is frequently used to extract and identify topics from documents (Blei et al., 2003). LDA is a powerful tool for discovering and exploiting hidden thematic structure in large text archives, and it works well on a variety of document types (Blei et al., 2003). LDA has been used by researchers for a variety of purposes. Kumar and Raghuveer (2012) proposed a method for generating a short summary from a given legal judgment using LDA topics. The developed topic-based document summarization model is capable of producing effective short summaries. Frick et al. (2015) presented an application of LDA to measure disease similarity using textual descriptions. They evaluated the approach's performance by comparing results to manually curated relationships and demonstrated that their unsupervised model could recover curated Disease Ontology relations from records. Researchers also have utilized LDA to explore knowledge from user-generated-data. For example, Srinivas and Rajendran (2019) discovered company- and competitor-specific intelligence from customer online reviews using LDA. Through this unsupervised text analytics approach, Srinivas and Rajendran (2019) comprehended the critical dimensions of service quality from the perspective of the passenger and tailored service offerings for competitive advantage. Wamuyu and Mursi (2020) examined customer engagement on Twitter of four Kenyan banks in order to better understand customer interactions with businesses. The extracted latent models can not only provide insight into consumer behavior but also help any company improve its social customer relationship management. In fashion retailing field, Lang et al. (2020) utilized LDA to explore barriers and motivations of online fashion rental from online customer feedback. All these studies demonstrated the efficient and accurate performance of LDA algorithm in extracting topics and understand the content of large textual dataset.

Word-Network

Although the sophisticated signals provided by short text make it a promising source for topic modeling, its extreme sparsity and imbalance pose unprecedented challenges to conventional topic models such as LDA and its variants, because the goal of most commonly used topic models is to maximize the probability of the observed data, and they tend to sacrifice performance on rare topics (Blei et al., 2013). LDA models, in general, group semantically related words into a single topic by utilizing document-level word co-occurrence information, making them extremely sensitive to document length and the number of documents related to each topic (Blei et al., 2013). Because the short text contains few words, those models will fail to provide an accurate picture of how words are related to one another.

A word co-occurrence network-based model has been widely used to address sparsity and imbalance at the same time (Zuo et al., 2016). When texts are short, word-by-document space is extremely limited, but word-by-word space is still quite dense. Instead of learning topics for each document, the word co-occurrence network models the distribution over topics for each word, successfully increasing the semantic density of data space without introducing too much time or space complexity. The word co-occurrence network is less sensitive to document length or topic distribution heterogeneity, making it more general in real-world applications.

Nodes in a word co-occurrence network are words found in the corpus, and an edge between two words indicates that the two words have co-occurred in the same context at least once. The number of times two words appear together is accumulated and defined as the weight of the corresponding edge between them (Lang et al., 2020). It should be noted that a pair of words may be counted multiple times, which is known as word pair weighting.

Researchers have utilized this text-mining method to understand the content from large scale of textual dataset, especially short texts. For example, Zuo et al., (2016) have employed the word co-occurrence network discovering newly emerging topics or unexpected events in social media user-generated-content, and they demonstrate its potential in precisely analyze textual data through the comparison with other baseline methods. Kim et al., (2020) also propose a word network model for examining public perceptions of renewable energy resources from Twitter and Instagram, indicating that the proposed model can extract users' hidden perceptions about renewable energy issues. Researchers also have attempted to utilize word co-occurrence network to explore customer reviews. For example, Lang et al (2020) used this method to compare the similarities and differences in the benefits and costs of fashion online renting from three different types of rental companies and discovered that consumers place different values on and have slightly different expectations of rental companies' products and services based on their business features.

Overall, these text-mining methods are proved to be accurate and efficient ways to discover knowledge from large scale of textual dataset, such as customer reviews. Details of the text-mining application in customer reviews are presented in the following chapters.

CHAPTER III. METHODS

Chapter III describes the research methods applied to achieve the objectives of the study. The methods section includes the following: (a) research flow, (b) research design, (c) data collection, (d) data analysis procedure.

Research Flow

Figure 6 presents the research flow of this study. To reveal the user/consumer experience in mobile application under omnichannel context, this study adopts the components of user experience model and customer value theory to guide the data collection and data analysis. To get more detailed user experience and customer value information guided by the theories, this study utilizes the real customer feedback from retail mobile applications. A series of text-mining methods were conducted to extract topics and categorize themes from those customer reviews. Then the adopted theories help to analyze the topics/themes and find the root causes of praises/complaints through an inductive approach. Finally, the meaningful data analysis and deep further discussion based on theories achieves a holistic understanding of the user/consumer experience in mobile applications.

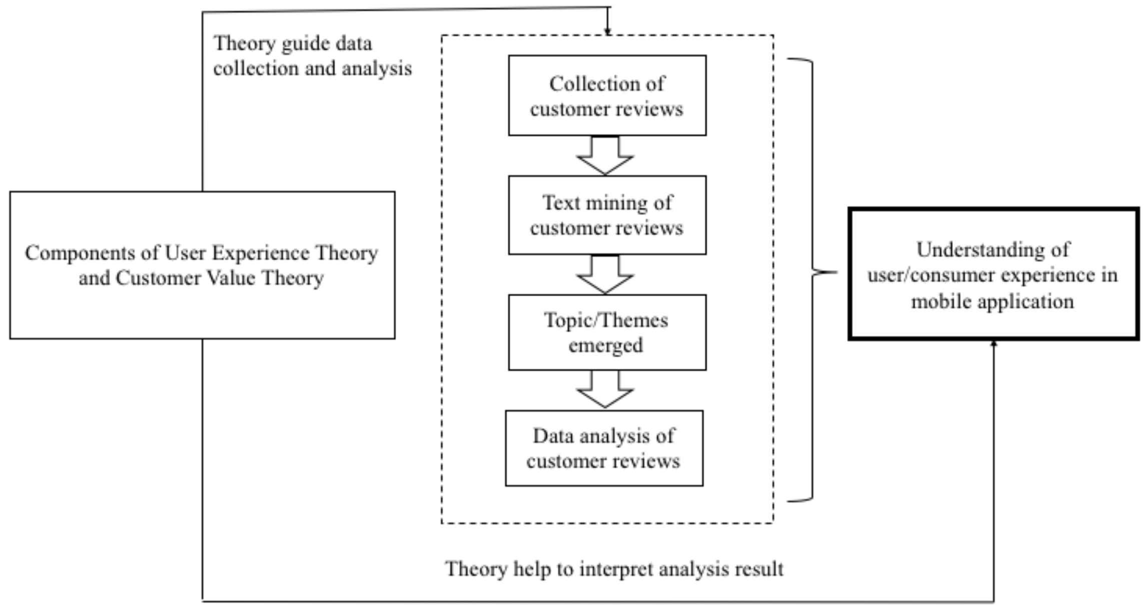

Figure 6. Research Flow of the Study

Research Design

In this research, user-generated content has been utilized to reach the research goal. User-generated content is created by ordinary people who voluntarily contribute data, information, or media that is then displayed to others in a useful or entertaining manner. Researchers have demonstrated how user-generated content can aid in the discovery of patterns in human behavior (Krumm et al, 2008).

To analyze the user-generated-data, the text mining methods were employed. Text mining is the process of extracting interesting and non-trivial patterns or knowledge from text documents. It is also known as text data mining or knowledge discovery from textual databases (Tan, 1999). Because text is the most natural form of storing information, text mining is thought to have a high potential for knowledge discovery (Tan, 1999).

Text mining is now widely used as an effective research tool for assisting in the creation of knowledge by preparing and organizing unstructured textual data and assisting in the extraction of relevant information from large amounts of unstructured textual data via automatic pre-selection based on user-defined criteria (Dörre et al, 1999). The use of automated mining processes to organize and scan massive amounts of textual data can significantly improve the efficiency and quality of textual data analysis (Dörre et al, 1999).

The aim of this study is to understand the mobile application user experience and omnichannel customer behavior. The user-generated-data is analyzed through text-mining methods by the guidance of conceptual model developed in Chapter II.

Data Collection

To achieve the research goals, we collected customer reviews from the retailer mobile application as a reliable user generated data source. These customer reviews imply customers' praise and complaints after an actual task or purchase and could reflect the benefit/cost during the whole using and shopping experience. Overall, 10 iOS applications of the retailers were chosen to draw a holistic understanding of consumers' shopping experiences using mobile applications. These retailers all provide a wide variety of merchandise, and they have numerous brick-mortar stores, which makes it possible to integrate physical and online channels to provide the best of both worlds for shoppers. These well-known retailers have developed mobile applications to bridge the gap between online and offline channels and have been available online for at least two years. All the mobile applications have received a large number of reviews.

These retailers are Bloomingdale's, Nordstrom, Nordstrom Rack, Saks Fifth Avenue, Macy's, JCPenney, NET-A-PORTER, TJ-Maxx, Target, and Kohl's. These retailers could be categorized based on different positioning strategies and competitive advantages, thus, to further understand the customers' expectations and the focused value regarding to different types of omnichannel retailers. Overall, three types of retailers are categorized to investigate the opportunities and challenges of various types of retailers based on their business features and competitive advantages in the omnichannel world. Among these retailers, Bloomingdale's, Nordstrom, Saks Fifth Avenue, and NET-A-PORTER could be considered as high-end fashion department stores, who mainly provides luxury fashion products. Macy's, JCPenney, and Kohl's could be categorized as mid-tier retailers, who offer not only fashion products but also a variety of home products. Nordstrom Rack and TJ-Maxx are categorized as off-price retailers, since they sell high-quality products at cheap prices, attracting customers through deals and sales. These three different types of retailers have different positioning and business features and provide different customer value. High-end fashion department stores have been about the in-store experience for the high-end customer. Mid-tier retailers' customers are more likely to transit between different channels. And off-price retailers' customers enjoy hunting for the best deal, price, or item. It is necessary to explore how these retailers adopt omnichannel strategy in mobile applications and add customer value and whether customers have gain the consistent customer benefit in mobile application shopping.

In this research, the user-generated-data were all imported for certain mobile apps on the iTunes App Store via the public reviews RSS feed. An RSS (Really Simple Syndication) feed is an online file that contains information about all of the content that a website has published. When a website publishes new content, information about that content is automatically generated in the file and displayed in reverse chronological order (Greene, 2021). In the RSS feed of iOS application, the user-generated-data includes customer reviews, review titles, apple IDs, review dates, etc. Then Beautiful Soup in Python was utilized to scrape and get each customer review. Beautiful Soup is a Python library used for web scraping to extract data from HTML files. It generates a parse tree from page source code, which can be used to extract data in a more hierarchical and readable format (Maithani, 2020). Figure 7 presents 10 entries of collected data as an example. Each entry includes the rate, the title and the body part of the review.

	review_rate	review_title	review_text
0	5	Love bloomingdales app	Can shop easily online with the app
1	5	Ãber quality	My place decidedly matters to me. Itâs me. ...
2	1	Racist app	This app puts black charites in your check out...
3	5	In love with bloomiesâ¤ï¸	Bloomingdales has always come through for me! ...
4	1	Failed	I placed an order using curbside pickup. When ...
5	1	Not up to date	My order of 2 handbags was not fulfilled becau...
6	3	Fix these bug issues	The app is generally good. Please fix these is...
7	5	Black Beauties	I received my shoes and was VERY excited! They...
8	5	Satisfied	One of my favorite stores
9	2	Need bigger font capability on the app	Due to a very bad visual problem I am having p...

Figure 7. Example Entries of Collected Data

To get the evaluation of the app experience from the latest app version, 500 latest iOS mobile application reviews from each retailer were crawled from each app in June 2021. In total, 5,000 app reviews were collected.

A text-mining research schema was built to demonstrate the information from the text data source, as shown in Figure 8.

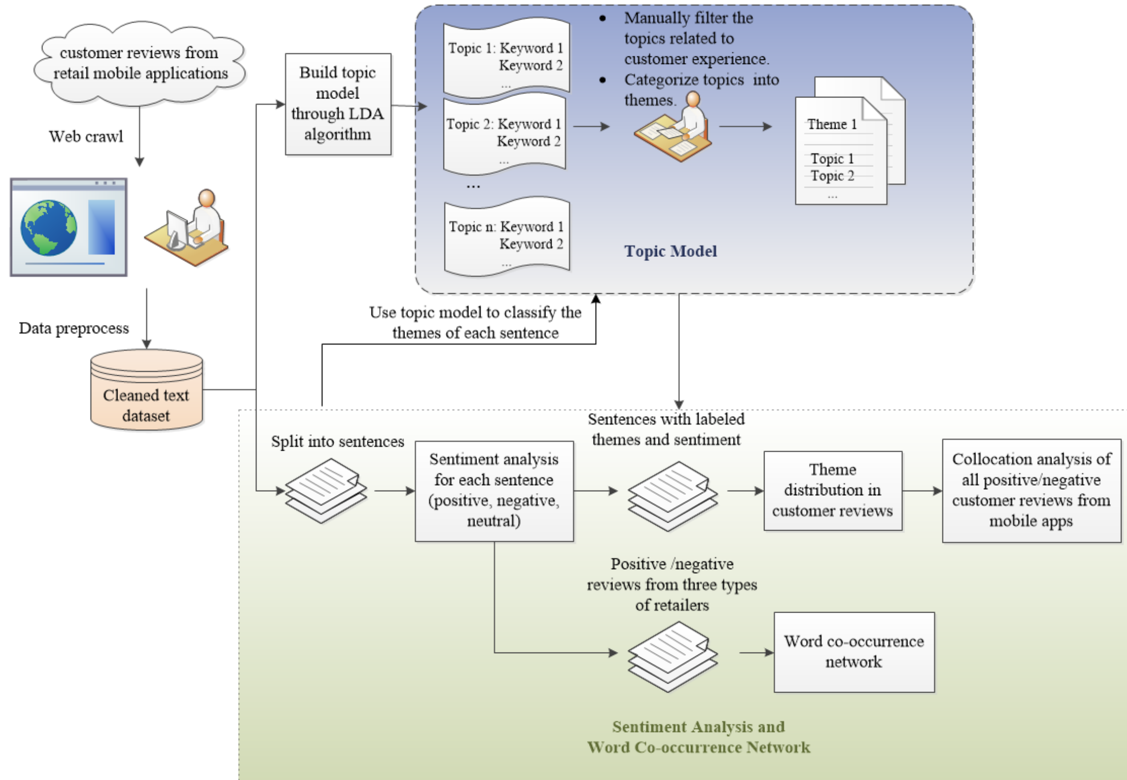

Figure 8. Text-mining Research Flow

Data Analysis Method

Data Pre-processing

The actions involved in data pre-processing are language detection, tokenization, natural language specific stop-word elimination, and lemmatization, which significantly reduces the size of the input text documents. The data pre-processing procedures were conducted as follows:

Langdetect was utilized to determine that all of the reviews were in English. Langdetect is a Language detection library in Python. Given a piece of text, this tool will provide the probabilities of that text belonging to each language. In this research, all of the probabilities of customer reviews belonging to English are above 90%, which determined that all of the customer reviews are written in English.

Generally, textual data is a collection of characters. All processes in text analysis rely on the words in the data set. As a result, tokenization of documents is required for a parser. Tokenization aids in the division of textual information into individual words. There are numerous open-source tools available for performing the tokenization process. In this research, NLTK in python was implemented. NLTK stands for Natural Language Tool Kit, which is a popular platform for developing Python programs that interact with human language data. It offers simple interfaces to over 50 corpora and lexical resources, as well as a set of text processing libraries for tokenization, classification, tagging, parsing, and other tasks. All customer reviews were tokenized and converted to words, the smallest unit of meaning in a language. The entire text corpus was then converted to lowercase to ensure consistency ("Clothes" and "clothes" should not be treated as two distinct words). Figure 9 provides an example of tokenization result. One pieces of customer reviews is "Can shop easily online with the app". After the tokenization, this customer review was transferred to lowercase words and the frequency of each word was also recorded.

Can shop easily online with the app
{'can': 1, 'shop': 1, 'easily': 1, 'online': 1, 'with': 1, 'the': 1, 'app': 1}

Would like better sales
{'would': 1, 'like': 1, 'better': 1, 'sales': 1 }

Love all fabulous sales and great merchandise!
{'love': 1, 'all': 1, 'fabulous': 1, 'sales': 1, 'and': 1, 'great':1, 'merchandise': 1}

The app scanner is not working properly and not scanning anything.
{'the': 1, 'app': 1, 'scanner': 1, 'is': 1, 'not': 2, 'working': 1, 'properly': 1, 'and': 1, 'scanning': 1, 'anything': 1}

I needed a Apple Watch and by surprise you sell them. Thank you
{'i': 1, 'needed': 1, 'a': 1, 'apple': 1, 'watch': 1, 'and': 1, 'by': 1, 'surprise': 1, 'you': 2, 'sell': 1, 'them': 1, 'thank': 1}

Figure 9. Example Tokenization of Customer Reviews

High-frequency words with less importance (referred to as stop words), such as articles and pronouns, were removed. In this research, the retailers' names and nicknames, such as "jcpenney", "jcp", "tjx", "saks", etc., were also removed, since these names occurred many times but could not provide much information in the further text analysis. Any special characters (@, #, $), punctuations (e.g., !, ?), HTML tags, and extra white spaces were all removed.

Lemmatization is the process of grouping together the various inflected forms of a word so that they can be analyzed as a single item. For example, the lemmatization algorithm should understand that the word *better* is derived from the word *good*, and thus, the lemme is *good*. In this study, NLTK toolkit in Python was utilized to conduct lemmatization. NLTK is designed to handle large text collections using data streaming. In NLTK, lemmatization is the algorithmic process of determining a word's lemma based on its meaning and context. The NLTK Lemmatization method is based on WorldNet's built-in morph function. It was able to use the English lemmatizer to extract tokens in their base form. In this research we only consider nouns, verbs, adjectives, and adverbs. Figure 10 provides the example result after removing the stop words and lemmatization. For example, one piece of customer review is "The app scanner is not working properly and not scanning anything". The stop words, "the", "it", "is", "as", are all removed. The retailer's name "KOHLS" is also removed. The words "opens", "causes", "wearing", "brands", "paying" are transferred to "open", "cause", "wear", "brand", and "pay", the base verb forms and noun forms.

The new update causes the app to crash before it opens.
[['new', 'update', 'cause', 'app', 'crash', 'open']]

I love the find stuff on sale especially name brands
[['love', 'find', 'stuff', 'sale', 'especially', 'name', 'brand']]

Love how they will not the actual size the model is wearing
[['love', 'note', 'actual', 'size', 'model', 'wear']]

I have never had as much trouble paying a bill through an App as I do with KOHLS.
[['never', 'much', 'trouble', 'pay', 'bill', 'app']]

The first person was rude and I asked to speak with a supervisor and he disconnected the call.
[['first', 'person', 'rude', 'ask', 'speak', 'supervisor', 'disconnect', 'call']]

Figure 10. Example Result of Lemmatization

Exploratory Analysis

The lengths of the customer reviews were calculated by counting the word numbers of each customer reviews. For example, customer review "The new update causes the app to crash before it opens" has 11 words, then the length of this customer review is 11. The length distribution of customer reviews was then shown and compared in a bar chart. Basically, longer customer reviews carry more information. Customers tend to convey much information and express different attitudes in one piece of review.

In the further analysis, to accurately classify the topics and explore the underlying causes of praises and complaints, each review was split into sentences. For example, customer could comment like "*I got really excited to get 25% off through using the mobile app. BUT they didn't put shoprunner option for the delivery methods. I called customer support, got transferred three times and no one were able to help me to solve the problem. I didn't want to pay extra $20 for shipping if I can get it for free. Very disappointing and time-consuming purchase.*" This piece of customer review could be split into five sentences, which are "*I got really excited to get 25% off through using the mobile app.*", "*BUT they didn't put shoprunner option for the delivery methods.*", "*I called customer support, got transferred three times and no one were able to help me to solve the problem.*" , "*I didn't want to pay extra $20 for shipping if I can get it for free*". "*Very disappointing and time- consuming purchase*". These five sentences reflected different topics and sentiments. The first sentence shows a positive attitude to discount; the second sentence focus on the delivery service; and the third sentence provides a negative feedback on customer support service. Therefore, in the research, it provides more detailed information to split the customer review into sentences to conduct further topic classification and sentiment analysis. In total, we obtained 18,225 sentences from the whole textual dataset.

The ratings of the customer reviews from each mobile application were also compared. In the iOS system, users could rate the mobile application from one to five stars. Individual ratings inform customers' overall evaluation to the mobile application. To understand customers' evaluation towards these retail mobile applications, the proportion of different rating of customer reviews from different mobile application were calculated and compared.

Latent Topic and Theme Identification from OCRs

Next, the Latent Dirichlet Allocation (LDA) algorithm (Blei et al., 2003) was utilized to extract topics of OCRs from each mobile application by Python. In LDA algorithm, we assume a total of *N* words constitute an OCR (*d*), with the word sequence denoted by $w = (w_1,\ w_2, \ldots\ w_n)$. We also assume that all OCRs (d= 1, 2, …, D) are combined to form a corpus *M*, containing words $\{w_1,\ w_2, \ldots\ w_D\}$. The topic generation process in LDA is as follows:

1. Choose $N \sim Poisson(\xi)$
2. Choose $\theta \sim Dir(\alpha)$
3. For each word w_n, choose a topic $t_n \sim Multinomial(\theta)$, choose a word w_n from $p(w_n|t_n, \beta)$.

where α and β are the hyper-parameters of the Dirichlet prior based on the topic distribution and word distribution in OCR.

The probability density function of θ conditioned on α is:

$$p(\theta|\alpha) = \frac{\Gamma(\sum_{k=1}^{K} \alpha_k)}{\prod_{k=1}^{K} \Gamma(\alpha_k)} \theta_1^{\alpha_1 - 1}, \ldots \theta_K^{\alpha_K - 1}$$

(1)

The joint distribution of θ, a set of topics t, and a set of words w is

$$p(\theta, t, w|\alpha, \beta) = p(\theta|\alpha) \prod_{n=1}^{N} p(t_n|\theta) p(w_n|t_n, \beta)$$

(2)

The marginal distribution of a review can be derived by integrating over θ is

$$p(w|\alpha, \beta) = \int p(\theta|\alpha) \left(\prod_{n=1}^{N} \sum_{t_n} p(t_n|\theta)\, p(w_n|t_n, \beta)\right) d\theta$$

(3)

The probability of a corpus is obtained by taking the marginal probabilities of all reviews.

$$p\big((C|\alpha, \beta)\big) = \prod_{m=1}^{D} \int p(\theta_m|\alpha) \left(\prod_{n=1}^{N_m} \sum_{t_{mn}} p(t_n|\theta_m)\, p(w_{mn}|t_{mn}, \beta)\right) d\theta_m$$

(4)

The optimal number of topics for customer reviews from mobile application was determined based on coherence value, a metric that measures the degree of semantic similarity between high-probability keywords in the topic. The coherence for topic *k* containing *n* words $(w_1,\ w_2, \ldots\ w_n)$ is given by Equation (5). $P(w_i)$ represents the likelihood of w_i in a random review, while $P(w_i, w_j)$ represents the likelihood of w_i and w_j in a review. The optimal number of topics was chosen when the smallest k reached the highest coherence value.

$$Coherence_k = \frac{\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} log\frac{P(w_i,w_j)}{P(w_i)P(w_j)}}{\binom{n}{2}} \qquad (5)$$

The output of LDA includes topics represented by a list of keywords, in which the keywords are ordered in a decreasing probability.

In this study, Gensim toolkit in Python was utilized to implement LDA algorithm. According to the coherence value, we choose 18 as the optimal number of topics. The eight keywords with the highest probabilities were chosen to indicate each topic. Two researchers then manually reviewed the extracted topics of the customer reviews; the summarized topics reflected customer experience. These topics were grouped into general themes based on user experience theory and customer value theory.

Figure 11 shows an example process of topic name summarization and theme identification. The raw result that Gensim toolkit shows are lists of words. The first list of topic keywords include “update, fix, website, open, slow, load, crash, freeze, late, constantly, bug, function, recent, developer, stop, awful, break”, and the second list of topic keywords include “time, work, download, terrible, multiple, reason, useless, error_message, fine, literally, worth, past, completely, every_single, leave, simply, smooth, interface, apple_pay”. The first eight keywords with the highest probabilities were selected to represent the topic. Therefore, the topic keywords of the first topic are, “update, fix, website, open, slow, load, crash, freeze” and the topic keywords of the second topic are, “time, work, download, terrible, multiple, reason, useless, error_message”. Then researchers manually summarized the topic name of the first topic as “App update”, and the topic name of the second topic as “App download”, based on the content of the keywords. These two topics then could be categorized into the same theme, “App use”, which reflected the user experience in application usage according to the Components of User Experience model.

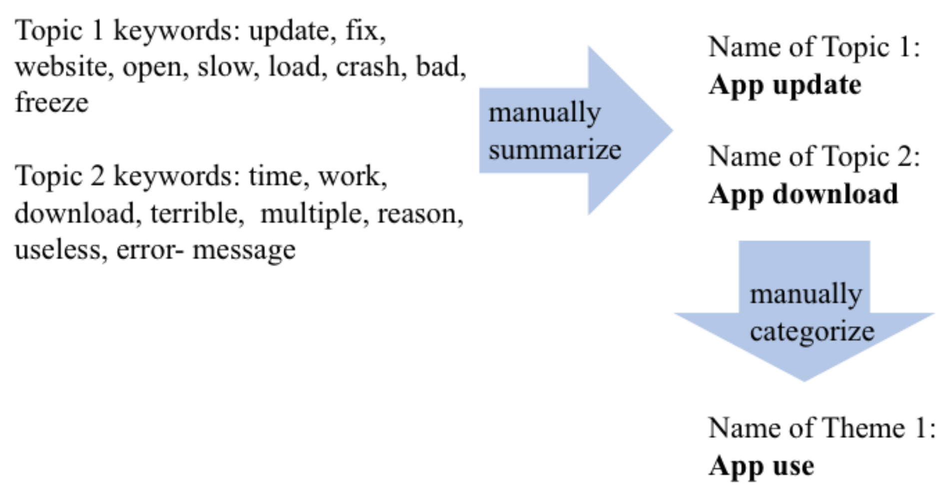

Figure 11. Example Process of Topic Name Summarization and Theme Identification

After the theme identification process, the LDA model could be utilized to calculate the possibilities of the occurrence of each topic in each document. Since a piece of customer review usually contains multiple topics, to accurately measure the dominant topic, each review was split into several sentences and the dominant topic in each sentence was determined through the LDA topic model and labeled in the sentences as well as the corresponding themes (Srinivas & Ramachandiran, 2020). Table 2 lists some example reviews and the corresponding dominant topics as well as the probability of the dominant topic in the review. The topics are represented via keywords in this table. For example, the probability of the dominant topic “update, fix, website, open, slow, load, crash, freeze” occurs in the customer review “The new update causes the app to crash before it opens” is 0.5038. Since this is the highest probabilities among all topics, we consider that the dominant topic of this customer review is “update, fix, website, open, slow, load, crash, freeze”. Even though not all of the topic keywords have occurred in this customer review, researchers could also understand that this review is related to app update and app crash which is consistent with the topic.

Table 2. Example Reviews and the Dominant Topics

Customer Review	Dominant topic (represented via keywords)	Probability
The new update causes the app to crash before it opens.	update, fix, website, open, slow, load, crash, freeze	0.5038
I love the find stuff on sale especially name brands	find, price, online, sale, store, brand, stuff, shop	0.6182
Love how they will note the actual size the model is wearing	good, size, shoe, nice, clothes, quality, pair, fit, dress	0.5631
I have never had as much trouble paying a bill through an App as I do with KOHLS.	card, payment, credit, bill, charge, month, mail, balance	0.4244
The first person was rude, and I asked to speak with a supervisor, and he disconnected the call.	customer, service, call, receive, wait, minute, hold, system	0.4498

Sentiment Analysis and Collocation Analysis

Sentiment analysis (also known as opinion mining) is a type of natural language processing (NLP) technique that determines whether data is positive, negative, or neutral.

Sentiment analysis focuses on the polarity of a text. In this research, consumers may mention different topics in one piece of review and express different sentiments. To accurately understand their experience, differentiate their praise/complaints toward different themes, and further investigate strengths/weakness of retail mobile applications, customer reviews were split into sentences, and sentiment analysis of each sentence was conducted using the Valence Aware Dictionary and sEntiment Reasoner (VADER) toolkit in Python. It is a lexicon and rule-based sentiment analysis tool that is tuned in to sentiments expressed on social media and in customer reviews. It is completely open-sourced. For a given sentence, VADER could calculate a polarity score, which is calcluated by adding the valence scores of all words in the lexicon, adjusting them according to the rules, and then normalizing them to be between -1 (most extreme negative) and +1 (most extreme positive). Therefore, this tool provides a single unidimensional measure of sentiment for a given sentence. To keep the result robust, we set standardized thresholds for classifying sentences. In this research, the sentences with polarity scores smaller than -0.1 were classified as "negative." And the sentences with polarity scores larger than 0.1 were considered as "positive." Table 3 shows some example reviews and the corresponding sentiment. For example, the customer review "Love how they will not the actual size the model is wearing" has the polarity score of 0.6369, which is larger than 0.1, and is considered as a "positive" review. While the review "The first person was rude and I asked to speak with a supervisor and he disconnected the call" has the polarity score of -0.4588, which is smaller than -0.1, and should be considered as a "negative" review.

Table 3. Example Reviews and the Sentiments

Customer Review	Sentiment	Polarity Score
The new update causes the app to crash before it opens.	Negative	-0.4939

I love the find stuff on sale especially name brands	Positive	0.6784
Love how they will note the actual size the model is wearing	Positive	0.6369
I have never had as much trouble paying a bill through an App as I do with KOHLS.	Negative	-0.4019
The first person was rude, and I asked to speak with a supervisor and he disconnected the call.	Negative	-0.4588

The distribution of positive, neutral, and negative sentences in each theme were compared and discussed. The proportion of positive, neutral, and negative sentences in each theme were calculated and presented in a bar chart to compare.

A collocation analysis was conducted on all the positive/negative customer review sentences. Collocations are words that occur together frequently. It traces the appearance of words that commonly appear next to each other in a text. A collocation analysis allows researchers to identify contiguous collocations of words, and in this research, could further indicate the underlying causes of praise and complaints from customer reviews to explore the strengths and weakness of the mobile applications (Srinivas & Rajendran, 2019). Specifically, the frequently occurring bigrams were obtained by analyzing positive/negative review sentences in each theme. And the twenty most frequently occurred bigrams were analyzed to understand the root cause of praise and complaints and to gather insights on customer perception.

Figure 12 provides the most frequently occurring bigrams from all review sentences expressing a negative opinion about the theme “Search & Navigation”. The bigrams (“hard”, “navigation”) indicated that consumers complaints because the mobile is hard to navigate. It could be observed that the bigrams such as (“scroll”, “page”), (“scroll”, “screen”), and (“difficult”, “scroll”) indicated that the scrolling problems could be an underlying cause of poor search & navigation performance. Likewise, other causes of dissatisfaction related to search & navigation can be identified as messy screen design and awful filter function.

(“hard”, “navigate”), (“search”, “experience”),

(“frustrating”, “experience”), (“scroll”, “page”), (“filter”, “function”),

(“awful”, “filter”), (“messy”, “screen”), (“search”, “results”),

(“scroll”, “screen”), (“difficult”, “scroll”)

Figure 12. Frequent Bigrams from Review Sentences Expressing Negative Sentiment towards “Search & Navigation” Theme

Comparative Analysis

To gain a better understanding of consumers’ benefits and costs associated with various types of retailer mobile applications, a comparative analysis was conducted. Among the retailer mobile applications chosen in this study, Bloomingdale’s, Nordstrom, Saks Fifth Avenue, and Net-A-Porter could be categorized as high-end fashion department store. According to the introductions of their mobile applications, Nordstrom “has been a leading fashion retailer from 1901” and “offers customers one of the most extensive selections of clothing, shoes and accessories for men, women, kids and the home.” Likewise, Bloomingdales, Saks Fifth Avenue and Net-A-Porter all focus on the merchandising of designer styles, providing luxury clothing, handbags and accessories.

Macy's, JCPenney and Kohl's are considered as mid-tier retailers since they offer products for sale in a broad assortment of unrelated product categories, including apparel, jewelry, electronics, furniture, etc. Nordstrom Rack and TJMaxx are categorized as off-price department stores, since they provide consumers with branded or designer items at significantly lower prices than full-price stores.

Word co-occurrence network was utilized here to visualize the comparison. Word co-occurrence refers to the co-occurrence of two words in one sentence. In this study, word co-occurrence frequencies in positive and negative sentences of high-end fashion retailer mobile applications, mid-tier general retailer mobile applications, and off-price retailer mobile applications were counted separately in R, using the widyr package. The network of these co-occurring words was visualized to show the importance and relationships of words in data sets. The network was composed of a set of nodes and links. The nodes were the words and a link between two words indicated that the words had co-occurred in the same review (Choudhury et al., 2010). The thickness of the link represented the frequency of co-occurrence. The stronger the connection, the more frequently the two words appeared together. The node has many links that connect it directly to other nodes, indicating that it is the central node and plays an important role in the network. (Zhao and Min, 2019).

CHAPTER IV. RESULTS AND ANALYSIS

The purpose of this chapter is to present the analysis procedures conducted in this study, and their subsequent results. The chapter is divided into three major sections: (a) exploratory analysis, (b) topic modeling results, (c) sentimental analysis and collocation analysis, (d) comparative analysis.

Exploratory Analysis

The lengths of customer reviews (represented by the number of words) are shown in Figure 7. Most customer reviews contain more than 20 words, and some reviews could be as long as more than 100 words. These customer reviews usually contain several sentences. According to previous research, longer reviews, as compared to shorter reviews tend to contain more information, demand more cognitive recourses to process, and maybe perceived as more helpful (Pan & Zhang, 2011). Meanwhile, the length of the review reflected the level of reviewers' involvement. For utilitarian products, longer reviews may include more concrete, product attribute information, conducive to others' evaluation of the product (Pan & Zhang, 2011). Therefore, in this research, most customer reviews include more than one sentences, and might convey information related to different topics. To better classify the topics and sentiments, these customer reviews were split into sentences. According to Figure 13, there are also more than 1,200 customer reviews only contains several words, for example, "*Great service*", or "*Excellent store, Excellent reputation*". Those customer review do not carry very detailed information and feedback, but usually have strong sentiment in praises or complaints.

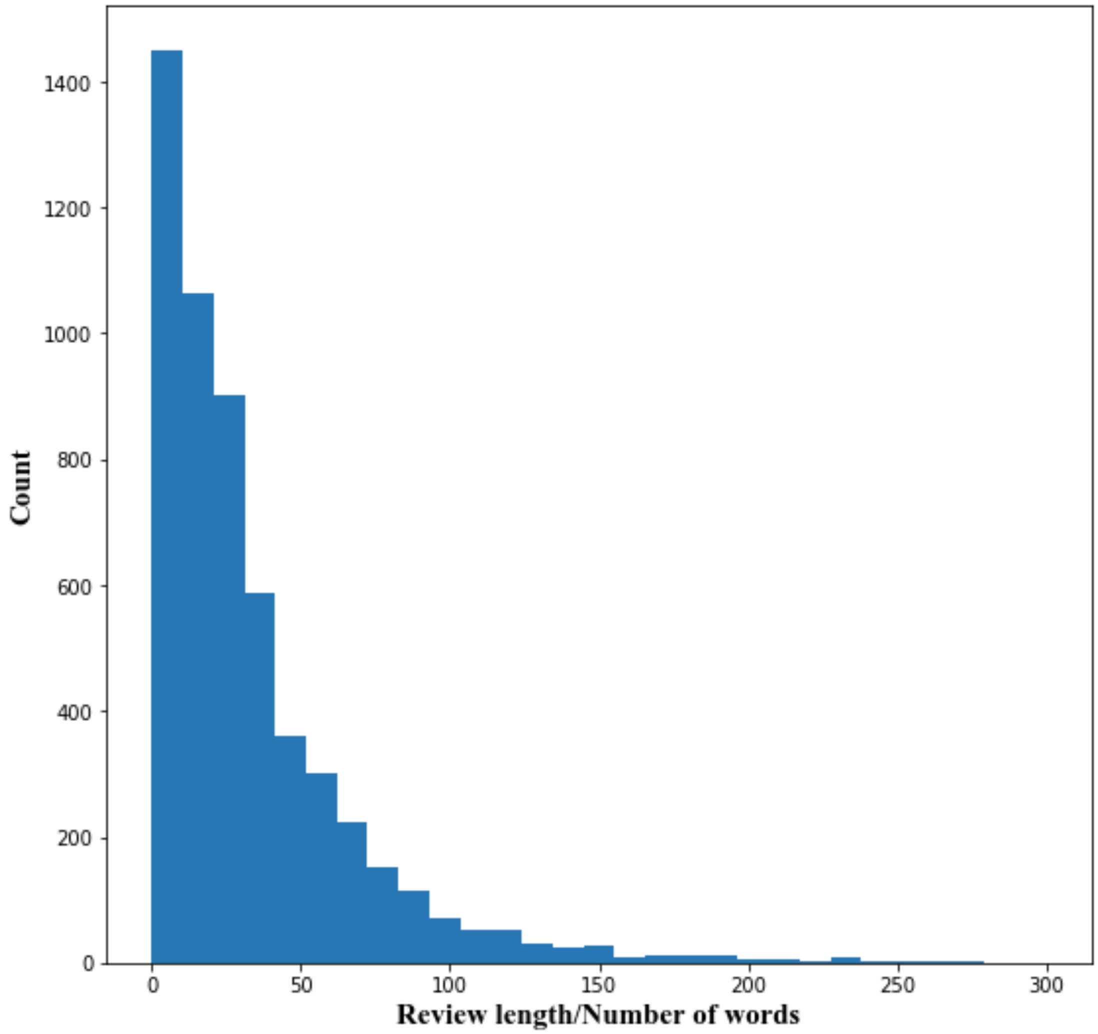

Figure 13. Review Length Distribution of Customer Reviews

In iOS system, customers could rate the mobile application from 1 to 5. Figure 14 shows the rating distribution of each mobile application. Most customers tend to leave strong attitude feedback and ratings. Among these mobile applications, Macy's, Net-a-Porter and Saks Fifth Avenue have the most 5 ratings, while TJMaxx, Kohl's, and JCPenney have the most 1 rating. For example, customers comment on Macy's like "*With Macy's app, it's so easy to shop online as well as in store, I don't have to look for price check, can use store mode on app to check prices and availability of a particular item , also don't have to worry about carrying my coupons anymore, I can access it anywhere* *anytime* ." And customers criticize Kohl's "*I am disappointed in this app. I found a item of clothing that I scanned on the app and was ready to purchase. At check-out it as double the price on those scanners*". This varying distribution allow us to deeply explore both strength and weakness of mobile application, and to explore various user/customer experience when using mobile application. There are only a few customers giving 2, 3 or 4 in feedback towards mobile applications. Some customers rated 3 to show their neutral attitude, for instance, customers suggest "*Would love to receive sale notification of the items that I liked or on my wish list.*" While some customer leave ratings of 3 because they feel both positive and negative attitudes, for example, "*I love the selection and prices at Bloomingdale's. Just a little disappointed I wasn't offered the 15% my first in-app purchase*."

Overall, the ratings of customer reviews indicated the different performance of mobile application from customers' perspectives. Macy's, Net-A-Porter and Saks Fifth Avenue provide satisfactory mobile applications, which meet most customers' needs, while the mobile applications of Kohl's, TJMaxx and JCPenney still have lots of improvement space. Reviews with ratings of 1 or 5 infer strong sentiments, while reviews with ratings of 3 may convey mixed attitudes, which are also valuable to understand user experience and customer value.

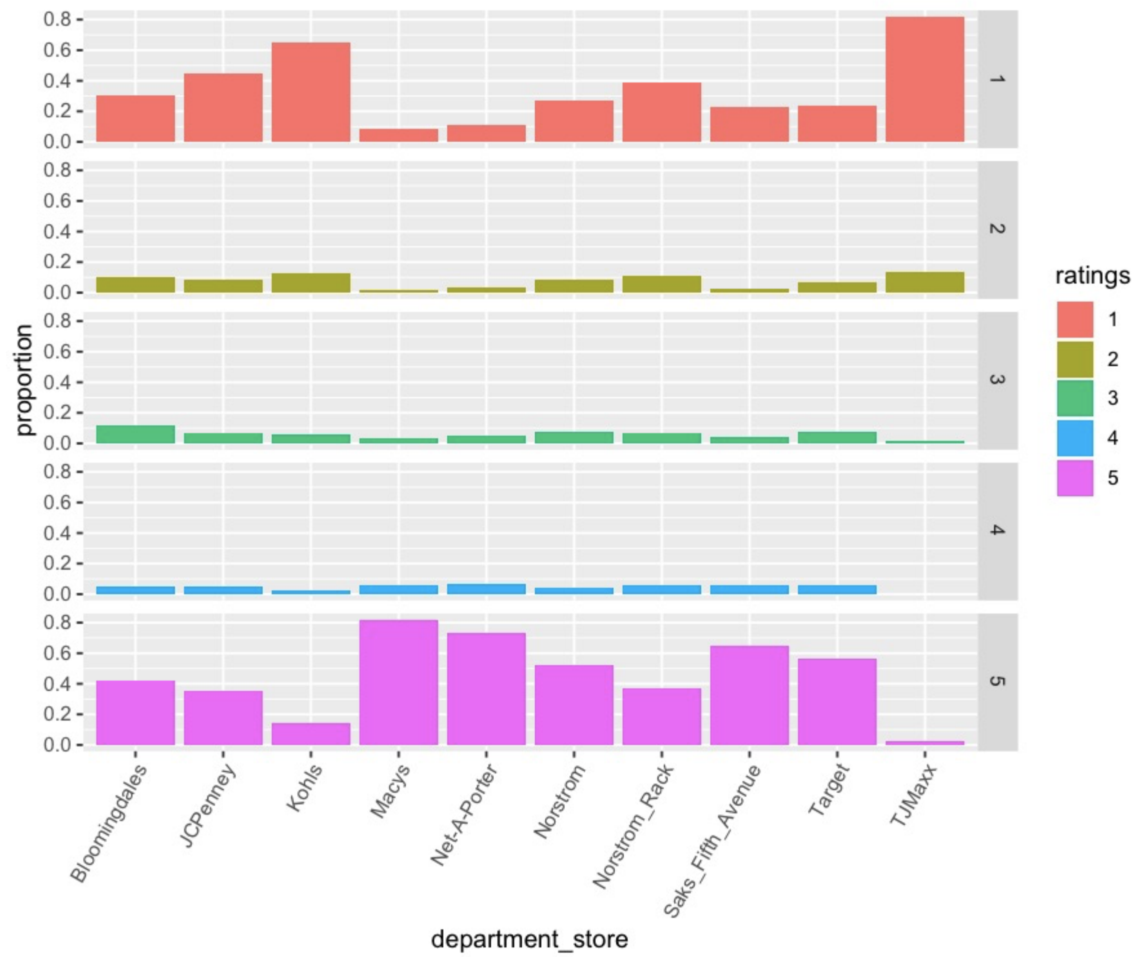

Figure 14. Customer Review Rating Proportions of Different Retail Mobile Applications

Topic Modeling Results

PyLDAvis, a Python tool for implementing the LDA algorithm, uses bubble plots to visualize and interpret the topics in a topic model, like Figure 15. Each bubble in a bubble plot represents a different topic. The larger the bubble, the greater the percentage of keywords in the corpus that are about that topic. The further apart the bubbles are, the more dissimilar they are. Figure 9 shows a bubble plot that includes 24 topics. It shows that topic 19, topic 20, topic 23 and topic 24 are all small topics and overlapped, which means these topics only cover small amount of content and have high similarity. A good topic model will have bubbles that are similar in size and do not overlap. To achieve this, we need to determine the optimal number of topics, so that each topic could cover same amount of content and does not have high similarity.

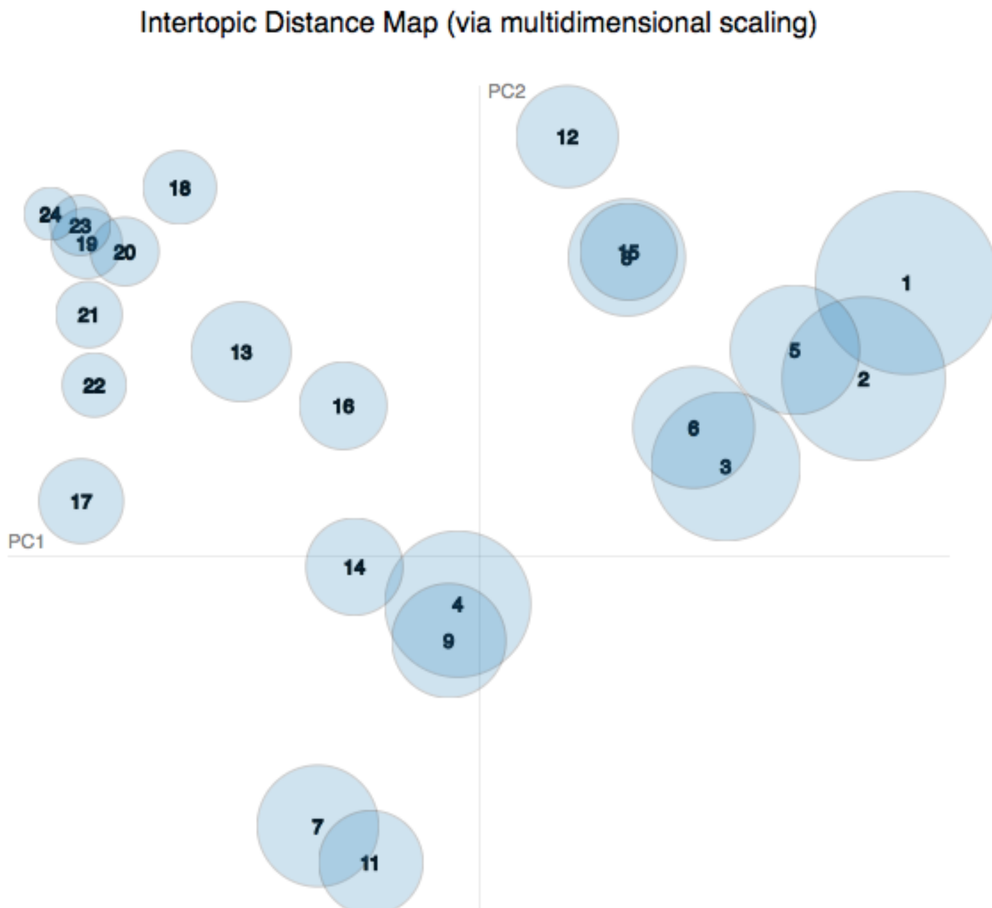

Figure 15. Example of Unsatisfying Distance Map of LDA Topic Modeling

Topic coherence evaluates a single topic by measuring the degree of semantic similarity between high scoring words in the topic. Coherence score increases with the increase in the number of topics. A good model will generate topics with high topic coherence scores. Figure 16 presents the coherence scores of LDA models with different number of topics. Apparently, when number of topics increases from 4 to 18, the coherence scores increase. When the number of topics is larger than 20, the coherence score tends to be flat. Therefore, we choose to extract 18 topics from our dataset.

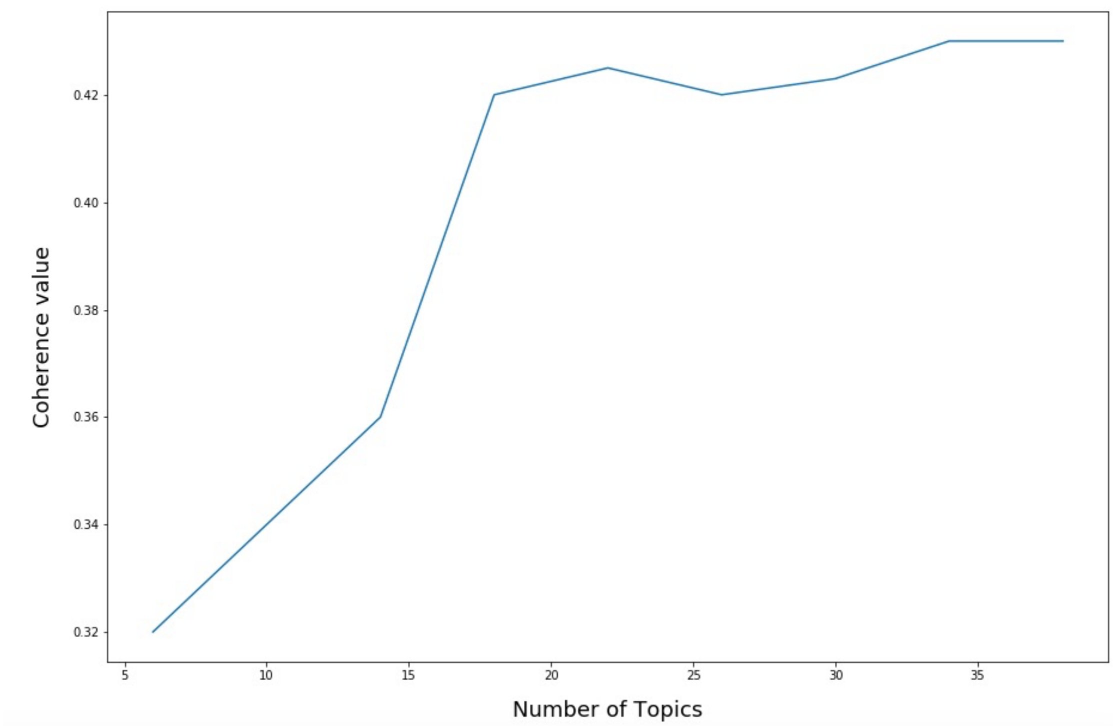

Figure 16. Coherence Score of Models with Different Number of Topics

Figure 17 presents the intertopic distance map of topic modeling, which contains 18 topics. All of the bubbles have the similar size, which means each topic covers similar amount of content. All four quadrants have at least one topic, which indicated that the topics cover the content of all four quadrants. Only topic 1 & 2, and topic 12 & 15 have overlapped. Overall, this is a good model with optimal number of topics that cover most of the content from textual dataset. For those overlapped topics, researchers could manually summarize and categorize them.

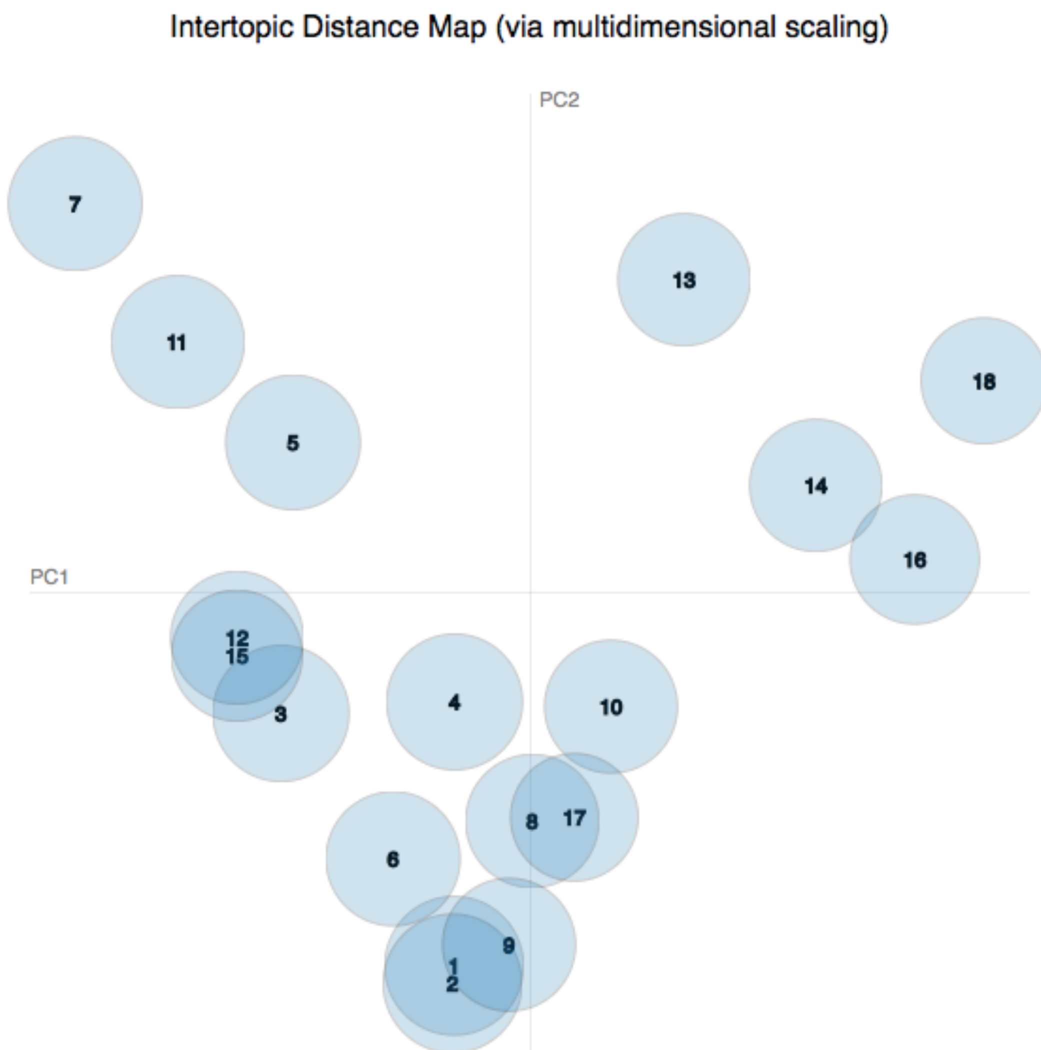

Figure 17. Distance Map of LDA Topic Modeling

In the case of topic modeling with LDA, the best coherence value was achieved with 18 topics from application reviews. Upon manual inspection, the topics irrelevant to user/consumer experience and overlapped with other topics were discarded, and the remaining topics with similar keywords/meaning were grouped together. Overall, 14 topics are related to user/consumer experience and categorized into seven themes: app use, search & navigation, place order, product quality, customer service, financial value, and utilitarian motivation. The eight most important keywords of each topic and the corresponding themes of user/consumer experience using retail mobile applications are shown in Table 4.

These topics and themes reflect the conceptual model, especially the three components of user experience and omnichannel customer value in more details.

Three themes, app use, search & navigation, and place order, mainly reflect user experience in retail mobile applications. The theme **App Use** mainly includes two topics, app update and app download, and reflected the **usability**. The topic keywords reveal that users are very concerned about the speed and frequency of app download and update. If the app crashes/freezes and sends error messages during use, it will dramatically influence the instrumental qualities of user experience. For example, *"Run too slow keep on freezing."* and *"I have to constantly reopen the app and it keeps happening."* Meanwhile, it is interesting to see that users also evaluate the website using experience as well as mobile application using experience in their mobile application reviews. For example, "*Update your website/app to fix this*." And some related comments show the inconvenience that the inconsistence of information leads in the omnichannel shopping context. For instance, "*I stopped using the app and today I logged onto the website outside of the app and realized that now I could see my wish list but nothing I had been saving in the app had actually saved*." These reviews show how the retail mobile application play an important role in bridging different channels. Whenever retailers update information of mobile applications, they are supposed to keep everything consistent with other channels so that customers could transform to the updated version smoothly, enjoying the new features without losing any previous information.

The theme **Search & Navigation** mainly focuses on the users' searching experience using mobile application, and mainly reflects **ease of use**. With a relatively smaller screen than computer, mobile app design tends to be tighter and leaner, with only the necessary useful features to fully utilize the constricted space. In the retailer mobile applications, it is important for customers to be able to navigate and search their desired product easily and quickly. According to the keywords, a scrollable layout and a filter panel is the prevailing design template among retailer mobile applications, and easy for customers to use. Some comments also mention the function of the "back button," for instance, "*Don't like when you go back to search results after viewing an item it takes you to the top of the page search results instead of back to the item you just viewed*." Either back to the top of the page or back to the item just viewed is a slight difference that will also influence customers' experience, so the designers must think about the functions/features from the customers' perspective.

The theme **Place Order** consists of four topics, login, add to cart, payment and order processing, making up a series of procedures during order placement. In the login process, it is important to keep high **fluency**. Most customers hope that the applications could remember the account and password so that they need not type it in every time, and it would be more satisfying if the account information could be consistent with the website. For example, customers said "*No idea how the app and the Rewards website are not linked*." and "I *tried using their website to do the same but it doesn't accept my credentials there*." To most customers, adding items into the cart is not a hard process, but what if there is an out of stock item? Besides saving the items in the wish list, customers also need restock notification to keep track of the desired products. Like account information, credit/reward card information is also expected to be saved in the apps and keep consistent with the website. Customers mention in their reviews, *"Entering a credit card is miserable."* and *"So frustrating to put credit card information in."*, which shows their dissatisfaction when having to repeatedly type in credit card information.

Since some customers may still be concerned about data privacy, a “Save this information” button might be a good choice to meet the needs of different people. The last process includes checkout/ship/cancel/pick up the orders, which involves **usability** and **utilitarian value** in the shopping experience. Customers prefer quick delivery within several days and cheap shipping fees at checkout. Order pick-up is a huge advantage that mobile app provides in omnichannel retailing context, enabling customers to get orders quickly without paying shipping fee. Customer offer high praise for this process, such as “*Also, The fact that I can now pick up at store without paying shipping is great*.” and “*I am so glad that I can place orders at Macy’s and pick up the same day within few hours, they never let me down!*” However, some barriers and issues are also occurring in this process, indicating the improving opportunities for retailers to achieve a more seamless customer experience. For example, customer complaints include, “*I placed an order using curbside pickup. When I got there, I got no response from Bloomingdale's and there was nowhere to park. Do not offer a service that you do not have*” and “*The curbside pick-up was very poor and staff was rude on the phone*.” To provide high-quality order pick-up service, only information consistency between app and brick-mortar stores is not enough. Well-trained staff and well-run physical facilities such as enough and convenient parking lots and prominent direction signs are both necessary to offer this service.

Product quality, customer service, financial value, and utilitarian motivation indicate customers’ shopping and consumption experience, reflecting major **customer value** in omnichannel experience. Like website online shopping, customers still cannot touch and try on the fashion goods via mobile apps, thus their experience related to

Product Quality still focus on the size issues. Some customers would praise the fit size, "*The dress fits true to size and is extremely elegant!",* while some customers seem not so satisfied and provide suggestions, "*There should be size chart available on app*." Compared with other channels, mobile app consumers need their problems to be solved more quickly. With their mobile phones, customer could choose many real-time communication channels, such as live chat, phone calls, etc., to ask customer service to solve technical issues within "hours" or even "minutes." For example, "*I spent over 2 hours trying to make a purchase, even called customer service twice, but the app refused to take my gift cards.*"

According to Kamali and Loker (2002), when consumers shop online, they are not only looking for detailed information about the product but also comparing prices, which is consistent with the theme **Financial Value** in this study. Customers' feedback also indicated that one reason that they choose to use the mobile app is to use the discount coupons and promotion codes. When these promotion codes are effective and customers can enjoy the free shipping or discount, they gain financial value and are more willing to use this channel. For instance, customers comment, "*Love the app, and the discounts*." Otherwise, if the promotion code does not work, customers are very likely to give up the fashion department store's mobile app because of the disappointment, for example, "*It took me nearly 2 hours to check out and I never received the 10 percent discount offered if you have never ordered*."

Utilitarian Motivation refers to rewards acquired from the degree of match between product characteristics and individual preferences (Merle et al., 2010). These rewards are linked to the use of these products that the consumers received. In consumers' comments, the motivation to buy products for certain events such as Christmas gifts or anniversary gifts was the main perspective of utilitarian motivation, which indicated some parts of their shopping tasks. Customers praised the mobile application, "*This has made Christmas shopping so much easier.*" If the orders cannot be delivered on time, customers would complain, "*I ordered gifts for Christmas on November 30, it is now February 1 and I still have not received them.*"

Table 4. Topics and Themes of Customer Experience Using Mobile Applications

Themes	Topic	Topic Keywords
App use	app update	update, fix, website, open, slow, load, crash, freeze
	work condition	time, work, download, terrible, multiple, reason, useless, error-message
Search & Navigation	search & filter	back, search, filter, page, click, review, screen, scroll
	easy & quick navigation	easy, shopping, navigate, love, convenient, quick, simple, efficient
Place Order	login	password, account, login, sign, email, reset, website, access
	add to cart	item, cart, add, stock, empty, save, wish-list, inventory
	place payment	card, payment, credit, bill, charge, month, mail, balance
	order processing	order, place, cancel, ship, day, pick, up, checkout
Product Quality	fit & quality	good, size, shoe, nice, clothes, quality, pair, fit, dress

Customer Service	quick response	customer, service, call, receive, wait, minute, hold, system
	solve tech issue	issue, change, phone, problem, delete, error, support, user
Financial value	discounted offer	discount, offer, coupon, return, happy, code, free, ship
	sale price	find, price, online, sale, store, brand, stuff, shop
Utilitarian motivation	purchase gift	gift, purchase, Christmas, anniversary, hard, track, feel, matter

Figure 18 presents the theme distribution of mobile application customer reviews. Overall, the topics of 25.5% of the sentences are related to *place order*, which are mentioned most by customers. Placing an order in a mobile application consists of several steps, including login into the account, add the items into account, check out and finish payment, and the potential subsequent cancellation/pick-up steps. These experiences are different when compared with offline shopping or website shopping. And customers are more eager to share these experiences in their app reviews. Customers are also concerned about the *product quality* and *customer service* quality, which is consistent with general online shopping references. Among these seven themes, customers mentioned utilitarian motivation least in their reviews. These customers are already familiar with online shopping for different purposes and seldom mention the utilitarian motivation in their reviews, except for some special circumstances, such as Christmas deals or birthday gift cards.

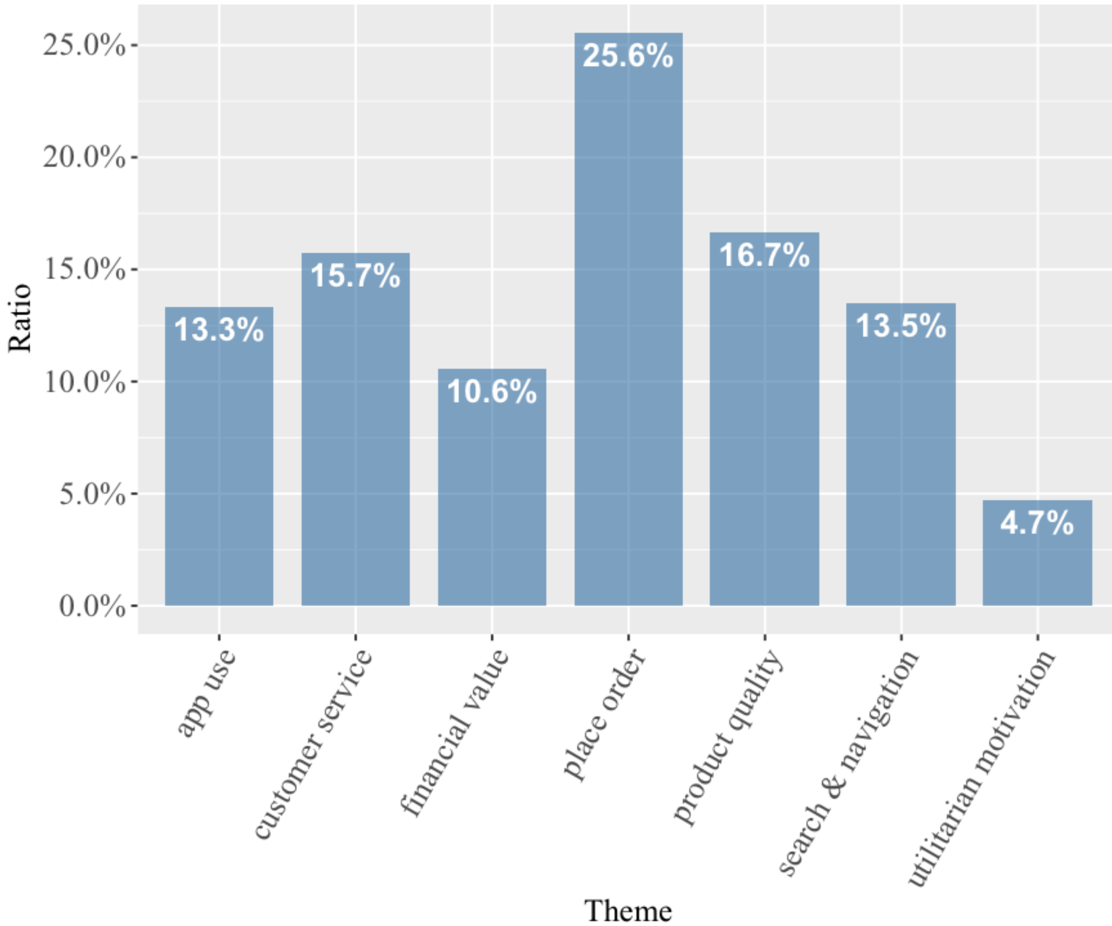

Figure 18. Theme Distribution in Customer Reviews of Mobile Applications

Sentimental Analysis and Collocation Analysis

Figure 19 presents the distribution of seven themes in the positive and negative mobile application reviews. Over 50% of the mobile application customer reviews provided positive feedback in the search & navigation theme, which suggests the overall satisfaction toward the search/filter function and the web navigation design of the mobile applications. However, a majority of customers did not comment positively about the customer service, app use and place order themes. When it comes to customer service, it does not only mean mobile app customer service, but may also include website and offline store customer service. for example, customer mentioned *"Love the customer* *service in store but hates the app!"* and *"I've called and gone to a nearby JC Penny store to check on status and still no answer."* It is still necessary to improve the whole customer service system to better communicate with customers through different channels. The negative reviews related to app use theme are usually short to indicate the strong disappointment, for example, *"Updates is horrible."* or *"It freezes."* These technical issues dramatically influence the customer experience and quite likely to lose customers.

It is also important to optimize the functions in order placement processes, reducing unnecessary scrolling and typing, automating the entering of codes and numbers through "remember the number" and "scan the code" functions. Most customers are satisfied with product quality, which shows the advantage of these retailers. Usually customers choose to use the mobile application after they are familiar with the specific retailer and have a general understanding of the products the retailer provides. Even though they cannot touch/try on the products, they could make a relatively accurate estimation of the size and have a reasonable expectation of the quality.

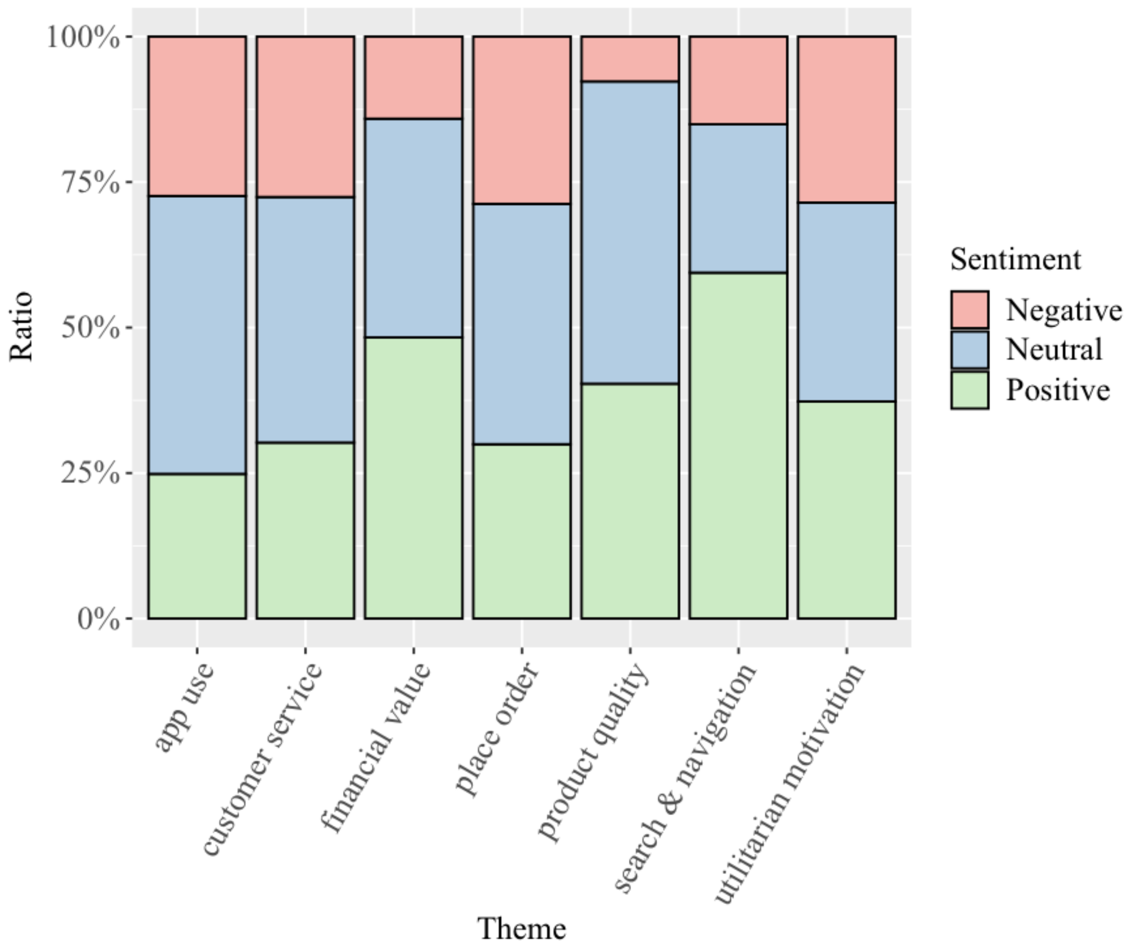

Figure 19. Sentiment Analysis of Customer Review Themes

Figure 20 and Figure 21 further indicate the underlying causes for praise/complaints of each theme from the bigram analysis in Appendix A . These insights are obtained by analyzing the most frequently co-occurring words in positive/negative customer reviews. In terms of the negative feedback, in the user experience of mobile applications, users are disappointed by the **usability**, for example, the frequent error messages, freezing screen, messy design of the screen, stuck in scrolling, awful filter function, etc. Customers also comment negatively because of the wrong password and the unavailability of Apple Pay, which reduce the **fluency** and **ease of use**. It may be not the application's fault when it shows "wrong password," but it would provide a smooth experience if the password could be “remembered” and “typed in automatically” by the mobile application. Apple Pay, as a contactless payment method, transforms mobile payments with an easy, secure, and convenient way to pay. To retain more customers, it is important to provide more payment options, for example, integrate applications with Apple Pay, Alipay, and Google Pay. When users switch from other channels to retail mobile application, they are supposed to easily find the recent shopping information, including account information, password, wish list, payment, etc.

In the omnichannel shopping experience, major complaints focus on the limited size/color and wrong size in the theme of product quality. A rude attitude and slow service speed are the major problems in customer service, for example, one customer said that “*The customer service guy was so incredibly rude!*”, which shows the importance of improving the staff training program for customer service system. The problems in the theme of financial value are mainly caused by the operation and functions of the mobile application system: as one customer said, “*It said a really good sale price when added but reflected full price when checking out, I’m not good!*” Marketers need to double-check how these system errors happen, increase the information consistency, and solve the technical issues. To promote the mobile applications, retailers might provide mobile coupons and discounts to drive consumers to download and use their mobile applications. However, when consumers cannot find a place to add discount code, it reduces the financial value, leading consumers giving up the mobile application at the very beginning. According to topics analysis, customers were motivated to shop when they need to purchase a holiday gift or an anniversary gift, and they require the gifts to be delivered on time. If the item were lost or could not be tracked, customers feel unsatisfied with the purchase experience. Overall, omnichannel customer value when using mobile application mainly focus on utilitarian value, including product quality, financial value, and customer service. To increase the customer benefit gained in omnichannel shopping experience, it is necessary to provide accurate size charts, keep products in stock, push notifications. Meanwhile, mobile application shoppers need quick and high-quality customer service responses.

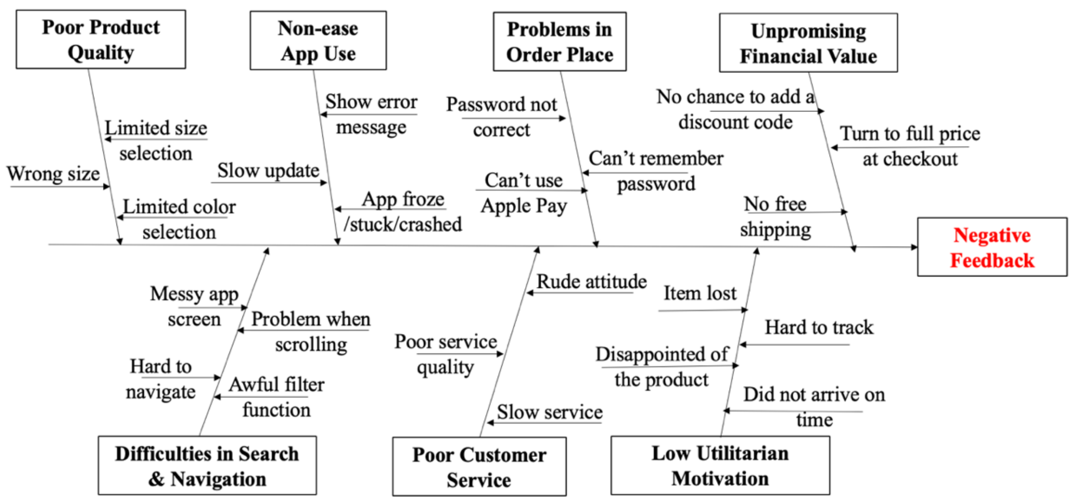

Figure 20. Underlying Prominent Causes for Negative Feedback

When it comes to the strengths, in application using experience, even though some customers complain about the slow speed of a version update, other customers praise the updated version if it really meet more needs and have high **usability**, for example, "*After the recent update the look and accessibility improved greatly, I wish I could explore it more.*" The key factor to keep a seamless order placement experience is information consistency, including consistent login information, consistent payment information, and consistent cart information, which shows the importance of **fluency**. When customer search products, a user-friendly interface helps a lot to quickly find the right products. A user-friendly interface does not only need **easy-to-use** navigation and useful functions, but also need design with high perceived aesthetics. What's more, the **personalized** size/product recommendation is also helpful to target the desired items. When customers attempt to place orders, it would be more convenient for them if the account information, credit card/mobile wallet information, and the items in the cart were all kept same in the website channel.

In terms of the customer value gained in omnichannel shopping experience, it seems that customers love products sold by mobile applications if they have perfect quality and true sizes. They enjoy the free shipping deals and promotion coupons. For customers who care a lot about financial value, free shipping is an important factor affecting their purchase behaviors. Mobile application customers tend to make phone calls instead of sending emails when contacting customer service for support. To satisfy these customers, the service system must be quick response and helpful, with high efficiency. In terms of the application use experience, to help consumers better finish their specific shopping tasks, the holiday events and sales must be highlighted. In addition, a more personalized recommendation, such as anniversary gift recommendation, would increase **personalization** and finally enhance the customer value.

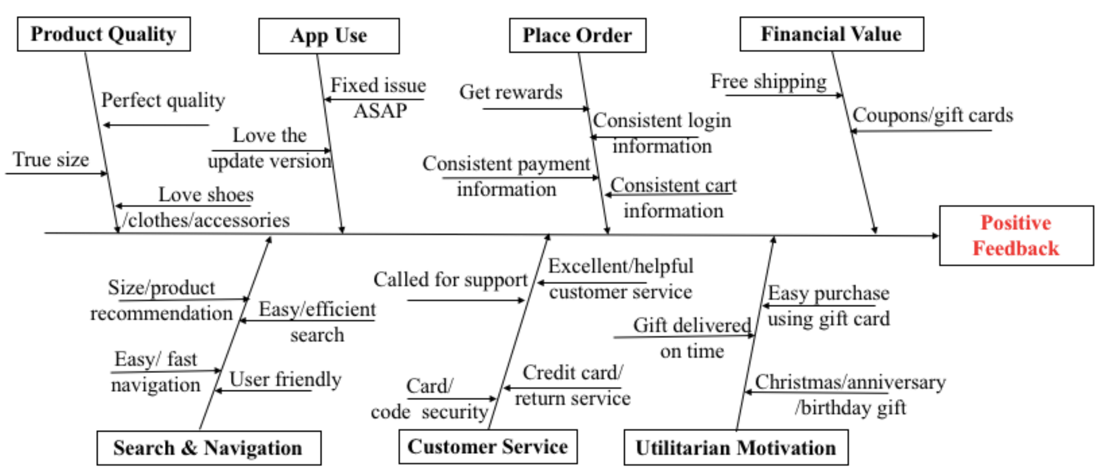

Figure 21. Underlying Prominent Causes for Positive Feedback

Comparative Analysis

To further understand the user/consumer experience in mobile applications of different types of retailers, a comparative analysis was conducted. Figure 22, 23, and 24 shows the word-occurrence network of positive reviews from the mobile applications. In all of the positive word-occurrence networks, “love”, “app”, “shopping”, and “easy” were in the center part of the network with the thickest links, which indicate the most important role of these words in customer reviews. These words appeared pair-wise in one review most frequently and had links with most other words, indicating customers’ positive attitude toward app shopping and showing that ease of use were mentioned most in all customer reviews. The linking words of “love” indicated what customers value in the whole experience. The linking words of “app” mainly infer user experience in mobile application usage. And the linking words of “shopping” focus more on the omnichannel shopping experience. All of the networks present words “quality”, “shipping”, “navigate”, “price”, “user”, “friendly” which means product quality, financial value, screen navigation, shipping service, user-friendly design are the main praises from customers of all types of retailers’ mobile applications.

Figure 22 presents the word co-occurrence network of positive reviews from high-end fashion retailers’ mobile applications, including Nordstrom, Bloomingdale’s, Saks Fifth Avenue, and Net-A-Porter. Around four center words, there were many linking words, reflecting user/consumer experience in more details. Customers “love” “price” and “sales” in the mobile applications, which reflect that they are eager to gain financial value when purchase high-end products, and sales events are effective strategy for high-end fashion retailers to promote mobile applications. Customers also “love” “brands”, “selection” and “beautiful” “fashion products”, which is consistent with what high-end fashion retailers offer. When they are able to search and purchase their favorite designer clothing or other high-end fashion products in mobile application efficiently, they enjoy an easy and convenient using experience and they gain utilitarian value in omnichannel shopping experience. High-end fashion retailers emphasize a lot on customer hedonic value and emotional experience. The words “happy”, “enjoy”, “amazing” linking to “app”, reflected the **emotional components** in user experience and **hedonic value** in luxury consumption experience, which were consistent with the overall positive attitudes. Meanwhile, words “customer” and “service” also has a thick link, which means that customers mentioned heavily about customer service in their reviews. The term “customer service” also connects to “excellent” and “experience” in the network. The in-person experience is an important part of in-store experience offered by high-end fashion retailers in physical stores. In mobile applications, high-end fashion retailers insist to provide excellent customer service to keep conveying this customer value. For example, customers mentioned “*I received excellent speedy service. Bloomingdales has excellent customer service as well*.”

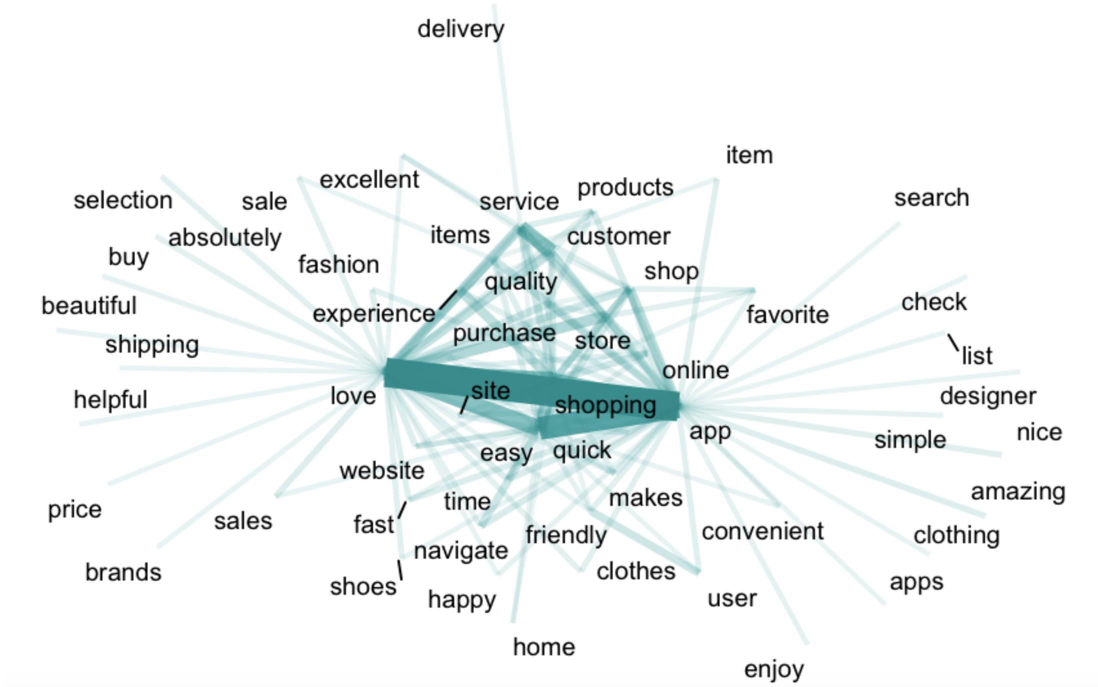

Figure 22. Word Co-occurrence Network of Positive Reviews from High-end Fashion Retail Mobile Applications

Note: The word co-occurrence frequency could be found in Appendix B.

Mid-tier retailers in this study include Macy's, Kohl's and JCPenney. Figure 23 presents the word co-occurrence network of positive reviews from mid-tier retailers' mobile applications. Similar with high-end retailers, customers from mid-tier retailers also love the easy-to-use mobile applications, where "easy" reflects the **instrumental qualities** and "love" reflects the **emotional components** in user experience of mobile applications. Besides fashion clothing, customers also purchase housewares for the whole "family". For example, customers mentioned "*Macy's always provides me with a happy shopping experience whether is for a family member or mysel*f." This word-occurrence network mainly shows the utilitarian value in omnichannel shopping experience. Customer from these retailers focus more on financial value and customer service through the words “coupons”, “deals”, “sales”, “free”, “shipping”, “return”. For customers of mid-tier retailers, it is satisfactory if the retailers provide free shipping/return and different deals. Meanwhile, the words “convenient”, “purchase”, and “enjoy” are connecting, indicating that customers enjoy the convenience of the mobile applications, which is also a key value that mid-tier retailers aim to provide. For example, “*Easy and convenient! Thoroughly enjoying this shopping experience.*”

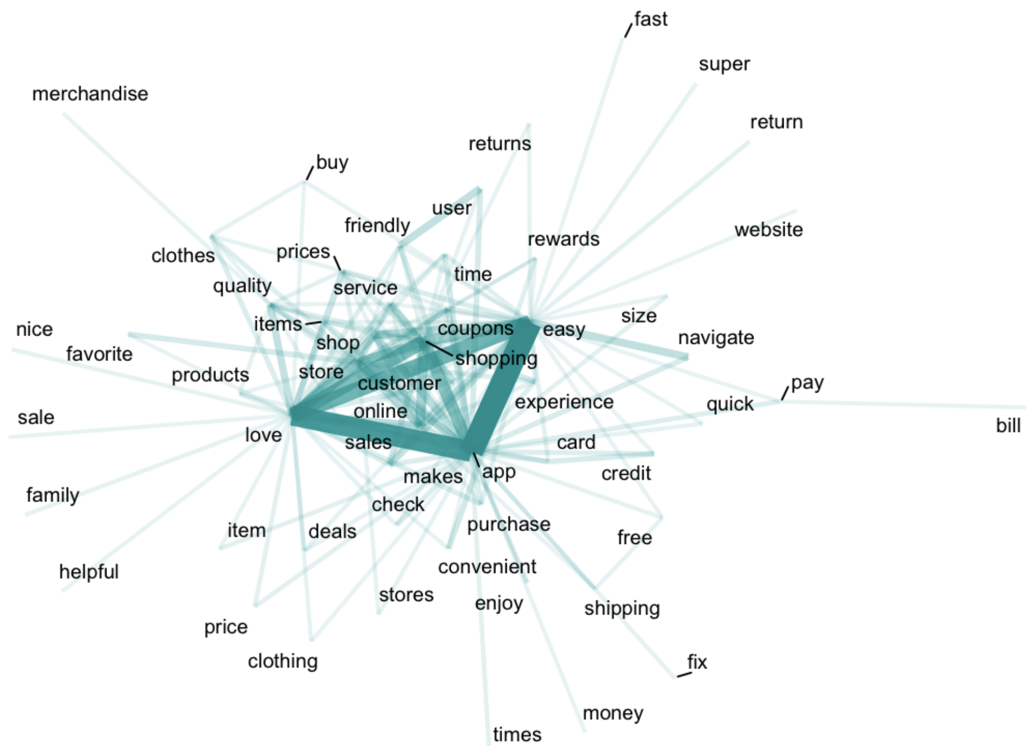

Figure 23. Word Co-occurrence Network of Positive Reviews from Mid-tier Retail Mobile Applications

Note: The word co-occurrence frequency could be found in Appendix B.

Figure 24 presents the word co-occurrence network of positive reviews from off-price retailers’ mobile applications, including Nordstrom Rack and TJMaxx. According to the linking words of “love”, it is apparent that customers “love” “deals”, “sales” and “free shipping”, showing that customers gain **financial value** in this shopping experience. Meanwhile, they commented positively to the "clearance" in the mobile applications, for example, "*It's about the same as shopping at TJ Maxx or Ross stores like that. Had great clearance deals. Standard shipping takes about a week and a half. But love this app*!". Compared with high-end and mid-tier retailers, customers from off-price retailers seldomly mentioned "convenience", which might because customers need to type in much information, such as rewards cards, promotion codes, etc., to get the best deals. But as long as customers gain the financial benefit, they feel satisfied. Moreover, customers feel "happy" and gain hedonic value when they search and "found" desired products. For example, customers said "*I found so many nice pieces and saved a lot of money*."

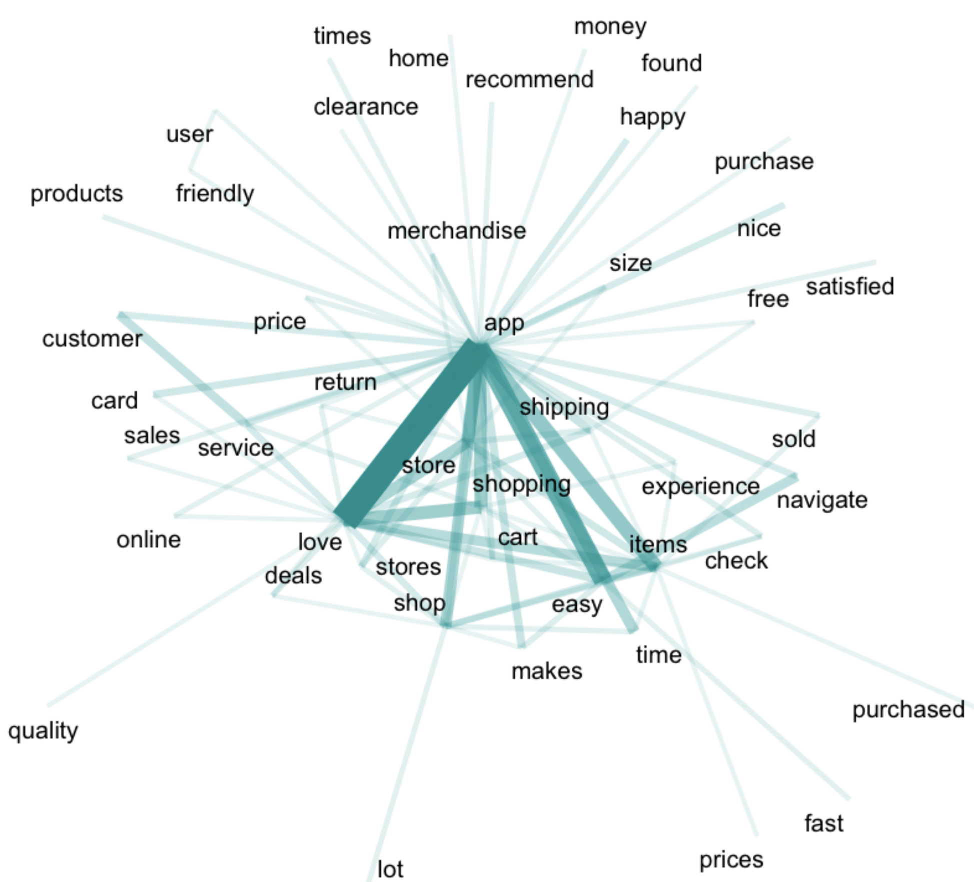

Figure 24. Word co-occurrence Network of Positive Reviews from Off-price Retail Mobile Applications

Note: The word co-occurrence frequency could be found in Appendix B.

Figure 25, 26, 27 present the word-occurrence network from negative mobile application reviews from different types of retailers. In three negative word-occurrence networks, there is only one center word “app”, which indicated that most negative words were related to mobile application using experience. The word “website” linking to “app”, infer that customers may feel low **fluency** between different channels, for example, the inconsistent information. For example, customers mention “*The Nordstrom Card website should be integrated in this app so a user with the Nordstrom credit card is able to see the current balances on their card and make payments within this app.*” The **emotional components** of user experience remain quite similar in negative experience. For example, the words “horrible”, “frustrating”, “ridiculous” all reflect the negative **emotional components** when users faced with issues in mobile application usage. Meanwhile, “customer” and “service” has a thick connection in all three networks, showing that the unsatisfying customer service, lower the **customer value**, is the major concern in omnichannel shopping experience when using mobile application.

In terms of the complaints toward mobile application using experience of high-end fashion retailers, even though “app” is in the center of the network, the co-occurred words with thickest link are “customer” and “service”. When customers are using mobile applications, they still need high-quality customer service just as in-store experience. However, customers mentioned “*Spoke with customer service representative Sam, located in the Philippines, he stated that he could not help me with placing an order online and* *could not apply the promo code*". For high-end fashion retailers, outsourcing customer service might lead to reducing the quality of customer service, which harm the major customer value they are supposed to provide. "update", "slow" and "fix" are three words that have thickest links with "app", which indicated that customers of high-end fashion mobile application are mainly disappointed about the **usability**, including the issues in application update and the slow fix. In the topic modeling analysis, one of the utilitarian motivations to purchase in mobile application is shopping for gifts. The word "gift" here shows that many people would choose high-end fashion retailer to finish this shopping task for Christmas gift or anniversary gift. However, some customer commented negatively, like "*You can't add the option of gift wrapping on the app."* Therefore, it is important to recognize customers' special shopping tasks and fulfill their needs.

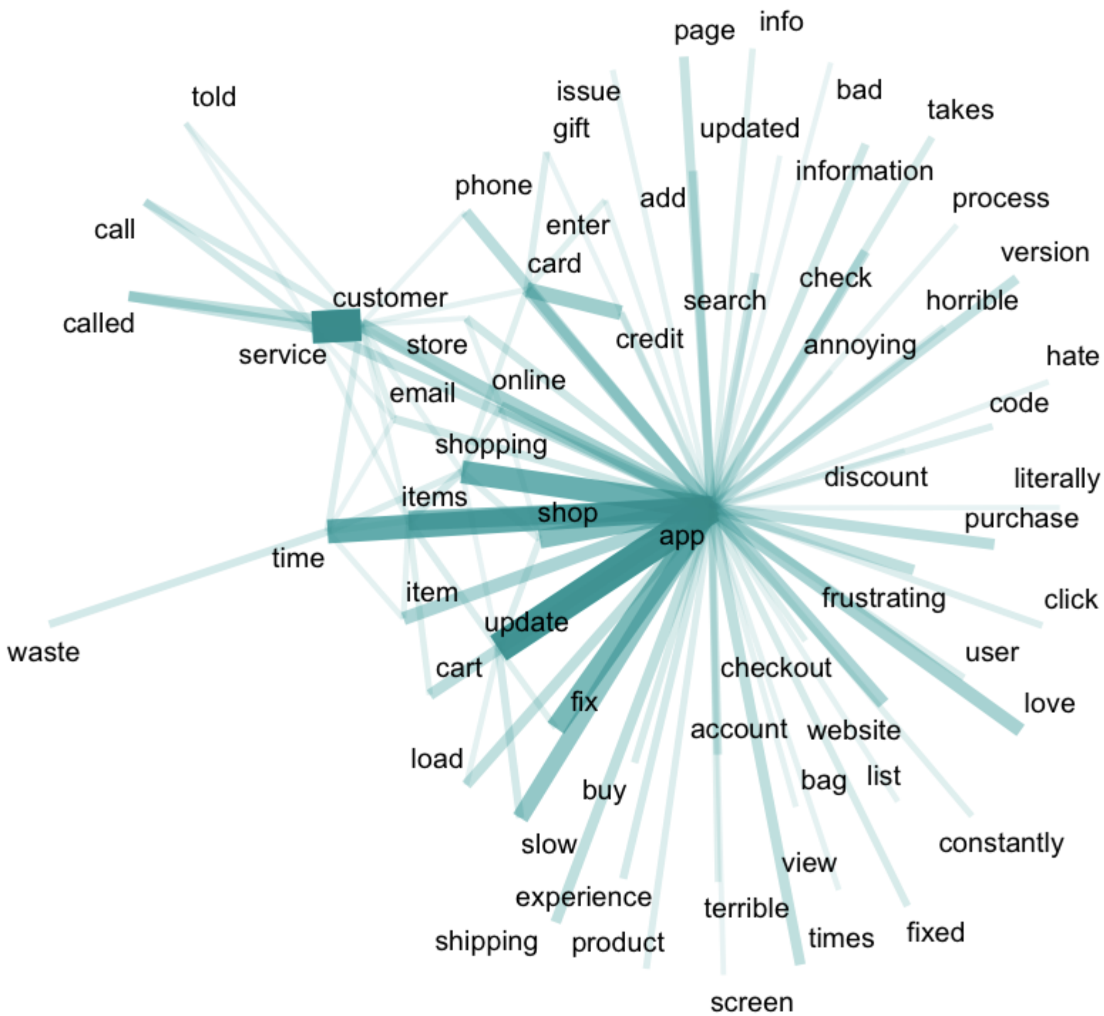

Figure 25. Word Co-occurrence Network of Negative Reviews from High-end Fashion Retail Mobile Applications

Note: The word co-occurrence frequency could be found in Appendix B.

When it comes to the complaints toward mobile application using experience of mid-tier retailers, the words “time”, “update”, “fix” have the thickest link with the center word “app”, showing that customers complained a lot about the issues in application update. Meanwhile, “customer” and “service” also have thick link. When there are any problems or issues, customers assume that they could get help from customer service.

Otherwise, if the customer service does not work well, for example, "I called customer service but according to Mariano there is no IT app support department", customers would feel disappointed. In addition, the words "app", "website", "phone", "store" are all linked together in this network. Mid-tier retailers, such as Macy's, JCPenney and Kohl's, all have much more brick-mortar store than other two types of retailer, which allow customers in mid-tier retailers have more opportunities to switch between different channels and require mid-tier retailers to have a higher fluency in their mobile application. Otherwise, customers would say "*can't get a customer service person on the phone*." Or "*The barcode scanner for in-store price checking has not worked a single time. I have the most updated version of the app. Useless."* The connected words "bill", "payment", "charge", "account" reflect another concern of customer using mid-tier retailer mobile applications. According to the result of positive word-networks, customers loves to purchase for themselves and also for family, since these mid-tier retailers offer a wide variety of products, thus many customers have the specific retailer store credit card. When the retailer store credit card is not available to use in mobile applications, customers would feel low **fluency** and low **usability** of this mobile application and feel very disappointed. For example, "*Trying to place on and use and use my JCPenney card as payment, site keeps asking for credit card number, very frustrating*". Since these retailers have more physical stores and websites available, customers may choose "delete" the mobile applications which reduces their omnichannel shopping intentions using mobile applications, if they have an overall negative using/shopping experience and choose other channels instead. For example, customers describe their experience, "*As soon as app was used, scam emails started coming in. Nothing secure about their apps. Delete it ASAP*"

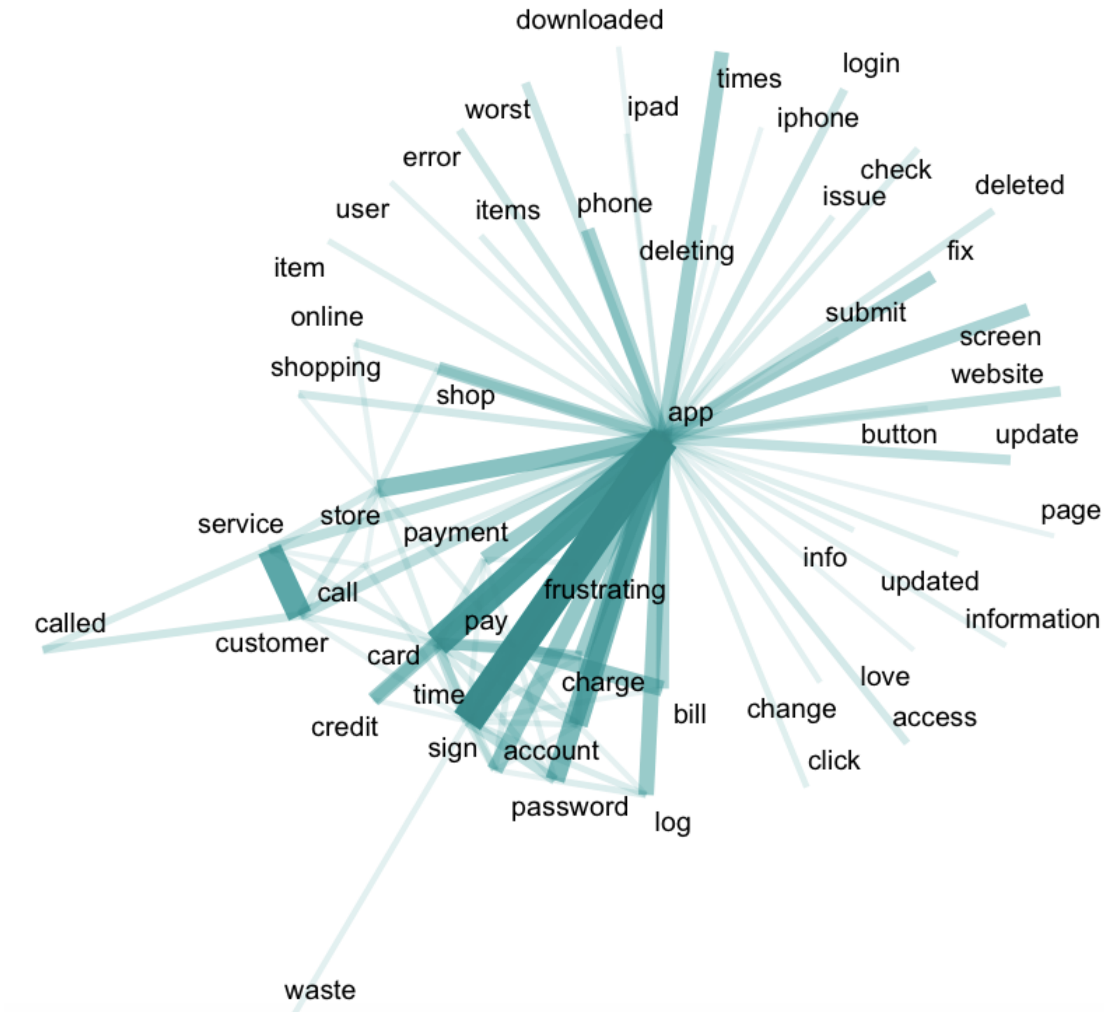

Figure 26. Word Co-occurrence Network of Negative Reviews from Mid-tier Retail Mobile Applications

Note: The word co-occurrence frequency could be found in Appendix B.

Regards to the negative feedback toward mobile application using experience of off-price retailers, customers also complain a lot about the payment process. The words “password”, “pay”, “rewards”, “bill”, “credit” linked together, showing that some customers have issues when check-out, and it would be disappointed if the customers could not get rewards in payment. The word “link” presents that customer have difficulty in linking the payment methods, email address, rewards to the mobile application. This **low fluency** and **usability** lead customers unable to login successfully and gain financial value in the omnichannel shopping experience. For example, customers said “*Keep saying I have login and it’s sending link to email address. Several attempts, no email.*” Or “*I have NEVER been able to link my card to use my phone for payment in-store*.”

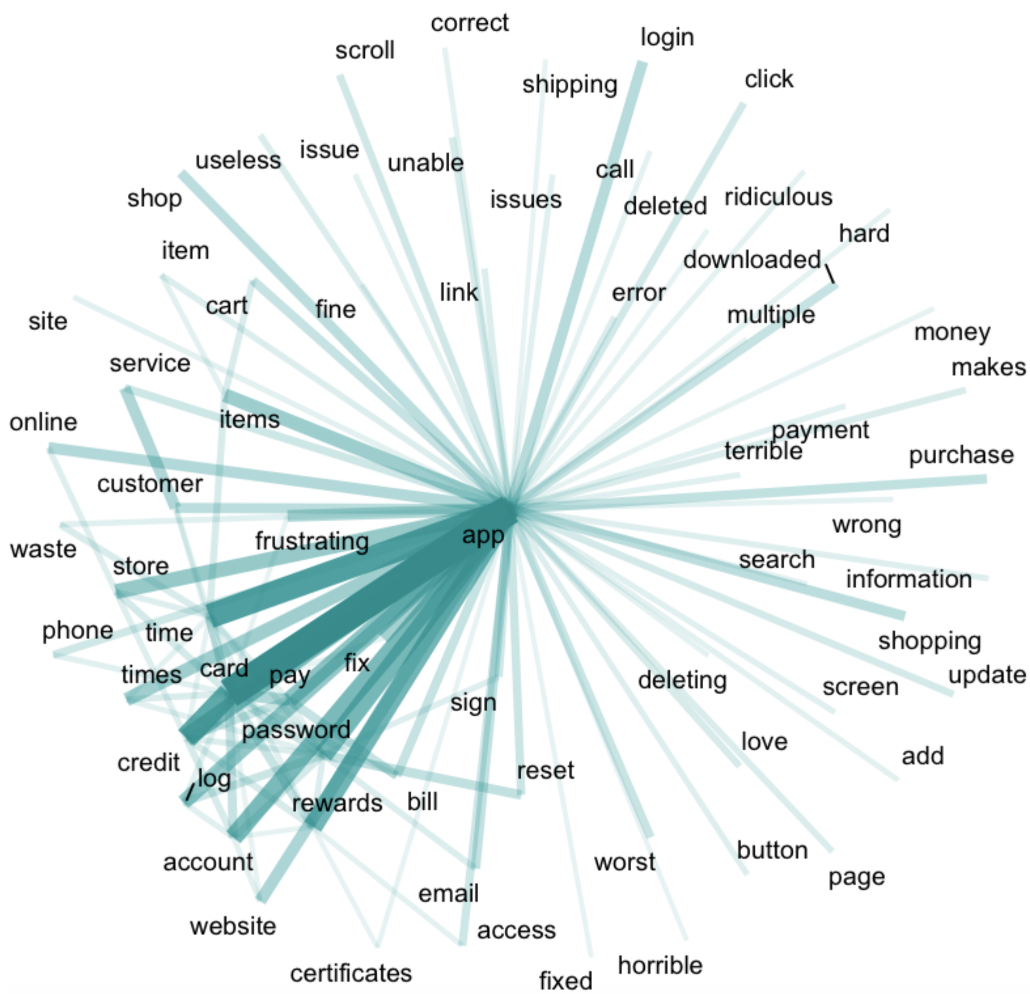

Figure 27. Word co-occurrence Network of Negative Reviews from Off-price Retail Mobile Applications

Note: The word co-occurrence frequency could be found in Appendix B.

CHAPTER V. CONCLUSIONS

Chapter V contains the following sections: (a) overview of the study, (b) contributions and implications, and (c) study limitations and future research opportunities.

Overview of the Study

The advantages of the omnichannel strategy have led many retailers to adopt an omnichannel approach to increase sales and build customer relationships (Sopadjieva et al., 2017). For customers, omnichannel retailing offers a seamless, convenient, and comfortable shopping experience (Brynjolfsson et al., 2013). In an omnichannel shopping experience, consumers interact with multiple touchpoints/human-machine interfaces to get the best deals and access optimal support (Broekhuizen et al., 2021). Retail mobile applications, as the key human-machine interface, bridge the online and offline channels and play an important role in omnichannel shopping. To better understand and improve customers' omnichannel experiences, it is necessary to examine their experiences when using retail mobile applications and analyze the underlying causes of their positive/negative experiences.

This research was designed to explore the human-machine user/consumer experience and omnichannel shopping experience when a customer uses retail mobile applications. Based on the customer value theory and components of the user experience model, this research specifically investigated the three components of user experience in mobile application usage, and the reflected customer value, thus to holistically understand the customer omnichannel shopping experience using mobile applications, which is critical to the success of a retailer's omnichannel strategy.

To achieve this goal, 10 iOS mobile applications for retailers were chosen and the 500 most recent iOS application customer reviews from each retailer were crawled using Python. To glean knowledge from those customer reviews, a text-mining research schema was developed using textual data pre-processing, LDA topic modeling, sentiment analysis, and word co-occurrence networking. Through this schema, the topics and themes of the customer reviews were summarized and categorized. Meanwhile, the underlying causes of praises/complaints of the customer reviews were investigated, and the similarities and differences of user/consumer experience using mobile applications in different types of retailers were also identified. There were several major findings, which are highlighted below.

First, 14 topics related to customer experience were identified and categorized into 7 themes: App Use, Search & Navigation, Place Order, Product Quality, Customer Service, Financial Value, and Utilitarian Motivation. Note that 3 themes, App Use, Search & Navigation, and Place Order, mainly focus on human-machine user experience in mobile applications. The topics belonging to these themes mainly reflect ease of use, fluency, and usability. The Product Quality, Customer Service, Financial Value, and Utilitarian Motivation themes mainly indicate customers' shopping and consumption experience when using a mobile application. The topics belonging to these themes mainly describe the utilitarian value in an omnichannel experience.

Second, underlying causes for praise/complaints related to each theme were further indicated. The sentiment analysis provides more details about positive/negative feedback. In the human-machine user experience of mobile applications, users are satisfied with or disappointed by the perceived usability, perceived fluency, and perceived ease of use. The mobile application could be improved by providing more payment options, fixing issues in application updates, optimizing filter function, designing a clear layout, etc. In the omnichannel shopping experience, major complaints focus on the utilitarian value, including product quality, customer service, and financial value. In positive feedback, the perceived personalization helps customers to target the desired items efficiently.

Third, the user/consumer experiences on the mobile applications of different types of retailers were analyzed through a comparative analysis. Consumers using mobile applications from high-end fashion retailers gained utilitarian value when there was a wide selection of brands and they could purchase designer clothing. Mid-tier retailers with many brick-and-mortar stores allow customers more opportunities to switch between different channels. Therefore, those customers have a higher requirement for perceived fluency in the mobile application. Otherwise, they may choose to delete the mobile application, which reduces omnichannel shopping intentions using mobile applications. Consumers using mobile applications from off-price retailers need high perceived fluency and usability so that they are able to log in smoothly and gain financial value in the omnichannel shopping experience. Meanwhile, the word co-occurrence network presents the emotional components of the user experience and the hedonic value from positive/negative customer reviews.

Discussion

Nowadays, many retailers have launched their mobile applications to stimulate and encourage consumers to shop in the omnichannel context. However, the features of these applications vary considerably from retailer to retailer, thus leading to different user/consumer experiences.

The initial experience of using the mobile application is to download/update the app. Much of the negative feedback of the retail mobile applications is about the technical issues when downloading or updating, including crashes, freezes, long wait times, etc. Some retailers might not have very mature and talented teams dedicated to software development to quickly solve these issues, thus leading to low customer retention or adoption of their mobile applications. To take advantage of digital world capabilities and improve the usability of mobile applications, retailers need to seek more efficient strategies to collaborate with technical teams to deliver a smooth user/consumer experience.

To increase brand awareness and build better relationships with customers, retailers would also benefit from enhancing the perceived personalization of the mobile applications. The personalized interaction, for example, personalization of size/style recommendations, personalized reminders of special days, and personalized deal notifications, would strengthen the relationship between the consumer and the brand. Especially for high-end fashion retailer mobile applications, it is necessary to provide a unique experience for each user/consumer. For example, the mobile application of Nordstrom would provide free personalized advice on fashion, beauty, and gifts, and would announce the new arrival of the user's favorite brands (Gyoshev, 2018).

Many empirical studies suggest that the perceived aesthetics of a human-machine interface act in an important role in shaping users' attitudes and experiences (Schenkman & Jönsson, 2000; Van der Heijden, 2003). However, in this study, customers seldomly mention their perceived visual attractiveness of mobile applications. Instead, consumers mainly focus on the evaluation of ease-to-use of the design features. That might be because the likes or dislikes of visual features of those mobile applications are not strong enough to urge users to leave comments, which is also consistent with the result of rating proportions. According to the result of rating proportions of mobile applications, most comments are rated as either 1 or 5, expressing a strong positive or strong negative attitude.

In this study, perceived ease of use is mainly attached to the themes Search & Navigation and Place Order. The layout of the screen, the filter functions, and the return process all influence the user experience. Particularly, the mid-tier retailers provide a wide variety of products, and their customers need efficient search functions to quickly target the products. For example, Macy's mobile application includes high-quality product filters, access to lists and favorites, and a frictionless in-store return process. Customers can virtually see their preferred furniture and home furnishings in a custom-built room created to mirror their exact living space using Macy's 3D room planning service. (Grill-Goodman, 2021). Those user-friendly designs lead to an overall positive evaluation from customers.

In the omnichannel context, mobile applications are a key channel to bridge many other channels. High perceived fluency allows users/consumers to freely switch between channels. Especially in the pandemic context, the “order online, pick up in-store” shopping pattern has seen tremendous growth. However, much of the convenience factor is lost if customers are unable to get their items quickly after arriving at the store. Target's app is a market leader in curbside pickup. Customers can use the app to notify the store that they are on their way to the store and will be automatically checked in when they arrive. The app notifies employees to bring the order to the car for contactless delivery, ensuring a smooth and quick pick-up (Morgan, 2020).

Meanwhile, information consistency and process consistency are related to perceived financial value. Customers place a high financial value on the off-price retailers. When customers use these mobile applications, they expect to get deals, discounts, rewards, etc. For example, one customer of T.J. Maxx complained, "*I wasn't even able to register my reward credit card on the app.*" Therefore, any discount links in emails, the rewards through the loyalty program, and the website coupons should all be consistent with the mobile applications. To achieve this, it is necessary to develop strategies to ensure communication and coordination between departments of different channels and the software talent teams.

Table 5 and 6 lists the key concepts in user experience model and customer value, and the related themes/co-occurred words as well as the example customer reviews. All of the concepts of instrumental qualities are all reflected in themes emerged from customer reviews. The emotional components could be extracted from word co-occurrence networks of positive/negative reviews. In positive reviews, customers have positive emotions, including happiness and satisfaction; while in negative reviews, customers' emotions contain disappointment and frustration. These two tables indicate that the user experience model and customer value theory is attached tightly with themes and the analysis of customer reviews. Meanwhile, the tables shed light on the improvement of user experience and enhancement of customer value. For example, to increase personalization of the mobile applications, retailers might first focus on the refinement of search & navigation part. More customized search and filter functions would provide customers a more personalized experience.

Table 5. Concepts Reflected in Themes and Example Customer Reviews

Key Concepts	Themes	Examples
Ease of use	Search & Navigation Place Order	"*Convenient, easy to navigate, makes shopping a breeze, Absolutely fabulous.*" *"I get quality merchandise delivered in a timely manner and so easy to return if needed."*
Usability	App use Place Order	"*Run too slow keep on freezing.*" "*I've been waiting for my orders to come in few days , then when i check it was cancelled without informing me.*"
Fluency	Place Order	"*No idea how the app and the Rewards website are not linked.*"
Personalization	Search & Navigation	*"excellent recommendations to help me find my items."*
Utilitarian value	Product Quality Customer Service Financial value Utilitarian motivation	*"The dress fits true to size and is extremely elegant!",* *"I spent over 2 hours trying to make a purchase, even called customer service twice, but the app refused to take my gift cards."* "*It took me nearly 2 hours to check out and I never received the 10 percent discount offered if you have never ordered.*" *"I ordered gifts for Christmas on November 30, it is now February 1 and I still have not received*

		them."

Table 6. Concepts Reflected in Word Co-occurrence Network and Example Customer Reviews

Key Concepts	Co-occurred words	Example
Emotional components	Annoying - Cart Happy – App	*"Super annoying as once you put something in the cart you can't click on it to review it."* *"Extremely happy with this user-friendly app."*
Hedonic value	Enjoy – Purchase	*"This app is such a great place to enjoy and purchase."*

Contributions and Implications

Theoretical Contributions and Implications

First, this is the first attempt to integrate the human-machine user experience model to understand the omnichannel shopping experience. Under the omnichannel context, consumers switch between different channels and human-machine interfaces to achieve a seamless shopping experience. The findings of this study show the importance of the user experience in human-machine interfaces when adopting omnichannel shopping, through the combination of human-machine user experience model and the customer value theory. The customer value theory indicates the benefit and cost in the context of omnichannel shopping, mainly including product quality, customer service, and financial value. And the human-machine user experience model provides three components of the experience of the user, which are instrumental qualities, non-instrumental qualities, and emotional components. Based on these two theories, the findings provide a rich body of knowledge concerning user/consumer experience in omnichannel shopping, pointing out the major instrumental qualities and customer value by analyzing meaningful topics and themes using text-mining techniques.

Second, this study provides empirical support for adopting the human-machine user experience model to explore the retail mobile application experience. Because there are so many kinds of human-machine interfaces in omnichannel retailing, this study chose to focus on mobile applications, the key connectors of the online and offline activity, to empirically demonstrate the three components of the user experience as well as customer value in omnichannel shopping. The findings suggest that the instrumental qualities are an important component in the user experience, and these include the ease of use, usability, personalization and fluency in the omnichannel context. The findings also suggest that the major customer benefit gained in omnichannel shopping is utilitarian value, while hedonic value is also indicated in customer reviews. When using mobile applications, besides product qualities and financial value, customer service is also an important dimension. These findings, therefore, contribute to the human-machine user experience model and customer value theory in the omnichannel retail field.

Third, this is the first attempt to thoroughly investigate the user/consumer experience using text-mining methods n omnichannel shopping. This research schema provides an in-depth text analysis of mobile application customer reviews through the use of LDA topic modeling, sentiment analysis, and word co-occurrence networks. The findings demonstrate that this new research schema developed from our research could be an novel and efficient method of discovering knowledge from textual data sources. Researchers were able to extract key topics, categorize and classify themes, and compare and analyze the user/consumer experience efficiently and accurately from a large text dataset, using these computer-aided text analysis methods. Researchers are also encouraged to feed more textual data from other mobile applications and websites using this research schema and glean knowledge related to the omnichannel shopping experience.

Contributions and Implications for the Industry

First, online customer reviews provide insight into the customer's experience throughout the purchase process (Xu, 2019). Many studies have utilized online reviews to investigate consumers' needs (Jia, 2018), product features (Guo et al., 2009), core attributes in relation to customer experience (Xu, 2019), etc. This study is one of the few studies to analyze mobile application reviews to extract knowledge related to user/consumer behavior patterns, which shed light on the business intelligence explored from the customer reviews. It is necessary for retailers to further understand the mobile application customer reviews and differentiate the topics related to the user experience and shopping/consumption experience, to develop practical strategies to improve the performance of the mobile application itself, and also satisfy consumers' needs.

Second, to achieve a seamless omnichannel shopping experience, it is necessary to keep optimizing the mobile applications. Mobile applications play an important role in bridging different channels. The findings suggest that mobile application customer reviews also contain much information related to experience in other channels. Given that customers tend to read customer review before purchase, the positive reviews of other channels, such as the praises of friendly salesperson, might attract others to visit the physical stores; while the negative reviews of other channels, such as no parking lot when pick-up, might reduce the traffic of physical stores and mobile application usage. Meanwhile, the customer reviews related to omnichannel experience also indicate the improvement direction of omnichannel strategy adoption. For example, customers complained that they could not see the web-saved items in mobile applications. To address this concern, retailers might keep connection with different software teams and strengthen the communication of different channel departments.

Third, human-machine interaction user experience plays an important role in successful omnichannel shopping. This study suggests that ease of use, usability, fluency and personalization are four important factors in instrumental qualities involved in the user experience. Therefore, the developer teams of retail mobile applications need to launch, test and perform maintenance on the applications, making sure the technical issues are always solved quickly. The user interface of the mobile application needs to have a user-friendly design so that users are able to navigate and search in the mobile application easily. It would be useful to collect the users' searching data and provide them with personalized recommendations of styles/sizes. Additionally, it would be convenient for users if the departments of different retailer channels could share and keep information consistent to increase the perceived fluency.

Fourth, customer value is composed of multiple value dimensions that make different contributions in different situations. The findings indicated that the major customer value of omnichannel shopping focus on utilitarian value. To improve the omnichannel shopping experience, retailers should make an effort to help consumers finish their shopping tasks, including keeping high product quality, providing coupons/rewards/discounts, and providing quick customer service.

Fifth, the findings imply that consumers have slightly different expectations of mobile applications of different types of retailers, depending on their positioning and business features. High-end fashion retailers offer designer clothes, shoes and handbags, which customers like to purchase as gifts for anniversaries, birthdays and Christmas. Therefore, it is important for those retailers to have quick delivery service to make sure the high-quality products are shipped on time. Mid-tier retailers already have many physical stores and have built what are now mature online website systems. Consumers pursue a seamless omnichannel shopping experience, which requires high perceived fluency in every channel, especially in a mobile application. If the mobile application channel is not able to bring them more convenience, consumers will give up the channel. For off-price retailers, consumers mainly seek financial value, which not only requires sales, deals, and discounts, but also needs high fluency in the checkout process.

Education Contribution and Implications

First, this study shows the importance of retail mobile applications and human-machine interactions in the omnichannel shopping experience. It is suggested that educators need to incorporate related content into their curricula. The typical omnichannel shopping class does not teach enough about the mobile application user experience and human-machine interaction for significant, meaningful use or discourse. In this digital world, the understanding of the human-machine user experience will help students to better design and utilize multiple user-friendly digital devices to fulfill user/consumer needs in the retail field.

Second, text mining is a powerful tool in real-world marketing. This technology leverages artificial intelligence to power natural language processing. Students can discover deeper insights about their comments and reviews without resource-intensive manual processing. It also provides a clear vision to the organization on how users or customers are behaving. With more and more retailing companies adopting text-mining practices to analyze data, it would be helpful for students to have these vital skills and become more cross-functional in order to succeed in the job market and in their careers in this ever-growing digital world.

Third, the research methods adopted in this study provide innovative digital visualization. For example, the word co-occurrence networks provide an intuitive data visualization to show the word relationships in texts, thus allowing exploration of the business intelligence from a new perspective. By utilizing these methods, students have more ways to innovatively present their works.

Limitations and Future Research

Several limitations are identified in this study, accordingly, leading to future research opportunities. First, the sample focused on department store retail mobile applications, not including fashion brand mobile applications. Thus, further research is suggested to expand the scope of this study to explore user/consumer experiences in more types of retail mobile applications under the omnichannel context.

Second, this research only focused on the omnichannel shopping experience when using mobile applications. There are many omni shoppers utilizing other channels, such as in-store, websites, social media, etc. Therefore, future research might cover more channels, including customers from both online and offline channels in order to deeply understand the benefits/costs in the omnichannel shopping journey.

Third, certain limitations existed due to the research design. This study utilized topic-modeling methods, sentiment analysis methods, and word co-occurrence networking to explore knowledge. But these techniques are unable to investigate the relationships between the user experience and customer value. Therefore, further research could examine the effect of user/consumer experiences on customer omnichannel shopping behaviors.

Fourth, the results of topic modeling methods rely on the customer review content, and topic modeling methods only cover the most heavily mentioned opinions. Therefore, some less-mentioned content might be neglected. For example, customers seldomly mentioned non-instrumental qualities of the human-machine interface, such as aesthetics. Future research may also want to examine these less-mentioned constructs in the theoretical model.

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APPENDIX A.

Bigrams Frequency

Bigrams of positive customer reviews in App Use

item1	item2	Frequency
app	love	16
app	fix	15
app	fine	14
app	update	12
app	screen	10
user	friendly	7

Bigrams of positive customer reviews in Customer Service

item1	item2	Frequency
customer	service	140
customer	called	19
excellent	service	17
customer	love	15
customer	call	14
called	support	13
credit	card	10
app	security	9
return	service	8

Bigrams of positive customer reviews in Financial Value

item1	item2	Frequency
free	shipping	25
online	store	24
shop	online	22
app	amazing	21
app	love	16
love	coupons	11
gift	card	10

Bigrams of positive customer reviews in Place Order

item1	item2	Frequency
credit	card	194
app	card	86
app	rewards	54
card	pay	45
credit	pay	37

app	account	32
pay	bill	29
card	account	28
card	rewards	27
card	gift	25
app	log	22
credit	rewards	21
cart	access	21

Bigrams of positive customer reviews in Product Quality

item1	item2	Frequency
app	nice	22
app	love	9
highly	recommend	9
high	quality	8
beautiful	clothes	8
shopping	app	7
store	clothing	7
true	size	7
love	shoes	7
love	clothing	7
love	store	7
clothing	accessories	7
love	accessories	6

Bigrams of positive customer reviews in Search & Navigation

item1	item2	Frequency
app	easy	142
easy	navigate	78
love	shopping	70
easy	shopping	68
efficient	app	52
convenient	easy	42
love	app	41
fast	navigation	41
shopping	experience	35
recommend	size	34
recommend	styles	33
shop	easy	30

Bigrams of positive customer reviews in Utilitarian Motivation

item1	item2	Frequency
gift	app	18
gift	card	17
purchase	app	13
purchase	gift	11
love	purchase	8
easy	purchase	7
love	app	7
gift	delivered	6
anniversary	gift	6
Christmas	gift	6

Bigrams of negative customer reviews in Non-ease App Use

item1	item2	Frequency
worst	app	32
app	update	28
terrible	app	22
app	time	14
error	message	14
app	useless	13
website	app	12
app	freezes	9
app	crash	9
times	multiple	8

Bigrams of negative customer reviews in Poor Customer Service

item1	item2	Frequency
customer	service	98
waste	time	48
service	horrible	16
service	poor	14
app	service	13
customer	called	13
rude	attitude	13
app	time	12
slow	service	12

Bigrams of negative customer reviews in Unpromising Financial Value

item1	item2	Frequency
app	online	8
shop	online	6
app	shop	5
free	shipping	4
full	price	4
add	code	4
discount	code	4
promotion	code	4
items	sale	4
item	price	4
pay	price	4

Bigrams of negative customer reviews in Problems in Order Place

item1	item2	Frequency
pay	bill	80
app	pay	49
pay	card	39
app	card	33
app	bill	33
card	credit	30
Can't	pay	21
apple	pay	19
reset	password	19
forget	password	18
wrong	password	18
pay	account	17

Bigrams of negative customer reviews in Poor Product Quality

item1	item2	Frequency
pair	shoes	4
wrong	size	4
annoying	size	3
size	selection	3
black	color	2

color	selection	2

Bigrams of negative customer reviews in Difficulty in Search & Navigation

item1	item2	Frequency
app	shopping	15
hard	navigate	10
frustrating	experience	9
search	experience	8
scroll	page	7
filter	function	7
annoying	app	6
awful	filter	6
messy	screen	6
search	results	6
scroll	screen	5
difficult	scroll	5

Bigrams of negative customer reviews in Low Utilitarian Motivation

item1	item2	Frequency
horrible	app	19
hard	app	9
horrible	experience	5
items	purchase	5
highly	disappointed	5
lost	items	4
hard	makes	4
purchase	frustrating	4
arrive	time	4
hard	track	4

APPENDIX B.

Word Co-occurrence Frequency

Word co-occurrence frequency of positive customer reviews from high-end fashion retailers

Term 1	Term 2	Frequency
app	love	149
app	easy	113
shopping	love	80
love	easy	75
app	shopping	69
customer	service	65
shopping	easy	51
store	love	46
love	service	41
app	shop	38
shopping	experience	37
love	customer	34
app	items	29
app	store	28
easy	navigate	28
shopping	service	28
user	friendly	27
love	shop	26
love	quality	26
easy	shop	25
shopping	store	24
shopping	online	24
items	love	23
shopping	shop	22
store	service	22
app	online	21
app	service	21
app	products	20
app	navigate	20
store	shop	20
app	time	20
quality	service	20
love	time	19
shopping	customer	19
store	customer	19
app	makes	19

easy	makes	19
sales	love	18
love	website	18
app	fast	18
app	customer	18
shopping	items	17
store	online	17
experience	love	17
items	easy	17
app	amazing	17
products	quality	17
products	service	17
products	love	16
app	item	16
love	fashion	16
app	nice	16
online	shop	16
app	website	16
shopping	time	16
shopping	quality	16
love	fast	16
shop	service	16
app	experience	15
selection	love	15
online	love	15
love	shoes	15
app	fashion	15
love	purchase	15
easy	site	15
app	quality	15
app	clothes	15
store	favorite	15
shopping	makes	15
app	user	15
app	friendly	15
sale	love	14
easy	quick	14
app	site	14
store	quality	14
love	clothes	14

shop	favorite	14
love	absolutely	14
service	excellent	14
store	easy	13
love	navigate	13
love	quick	13
app	purchase	13
app	favorite	13
love	makes	13
online	easy	12
app	happy	12
easy	time	12
love	buy	12
app	enjoy	12
credit	card	12
app	simple	12
easy	fast	12
products	customer	12
quality	customer	12
app	convenient	12
easy	friendly	12
return	policy	12

Word co-occurrence frequency of positive customer reviews from mid-tier retailers

Term 1	Term 2	Frequency
app	easy	89
app	love	77
love	easy	56
love	shopping	49
app	shopping	41
store	love	39
easy	shopping	36
online	shopping	32
store	shopping	31
store	online	26
shop	easy	25
shop	app	24
online	love	24
store	app	23

shop	love	23
easy	navigate	23
user	friendly	22
customer	service	22
love	quality	21
online	easy	20
easy	makes	20
shop	online	19
app	coupons	19
online	app	18
love	sales	18
love	prices	18
shop	shopping	16
shopping	makes	16
store	shop	15
easy	convenient	15
shopping	experience	15
items	app	14
app	user	14
app	friendly	14
app	time	14
store	favorite	14
store	quality	13
love	coupons	13
easy	coupons	13
love	service	13
credit	card	13
app	navigate	13
items	love	12
app	purchase	12
love	purchase	12
store	easy	12
store	coupons	12
love	customer	12
app	check	12
app	card	12
app	makes	12
love	clothes	12
easy	prices	12
shopping	prices	12

Word co-occurrence frequency of positive customer reviews from off-price retailers

Term 1	Term 2	Frequency
love	app	38
easy	app	24
app	items	18
love	shopping	16
app	shopping	16
app	store	16
app	shop	14
love	store	14
app	time	13
love	items	12
easy	navigate	11
customer	service	10
love	easy	9
app	makes	9
app	shipping	9
store	items	8
app	card	8
app	nice	7
love	shop	7
easy	shop	7
app	customer	7
love	shipping	7
easy	items	7
app	stores	7
love	service	7
app	service	7
app	happy	7
app	navigate	7
app	cart	6
app	sold	6
app	check	6
easy	makes	6
app	experience	6
shop	store	6
store	shipping	6
shop	items	6

store	stores	6
love	deals	6
easy	check	5
time	shop	5
app	merchandise	5
easy	shopping	5
app	sales	5
easy	store	5
sold	items	5
shop	stores	5
app	online	5
app	size	5
app	recommend	5
app	times	5
shop	lot	5
love	return	5
shopping	service	5
app	satisfied	5
app	price	5
easy	fast	5
app	products	5
love	cart	4
shop	makes	4
cart	shopping	4
shop	shopping	4
shopping	experience	4
love	sales	4
app	purchase	4
merchandise	store	4
shopping	store	4
app	free	4
shipping	free	4
cart	items	4
check	items	4
time	items	4
shopping	items	4
experience	items	4
shipping	items	4
purchased	items	4
app	user	4

app	friendly	4
user	friendly	4
items	prices	4
love	stores	4
love	online	4
store	size	4
app	found	4

Word co-occurrence frequency of negative customer reviews from high-end fashion retailers

Term 1	Term 2	Frequency
service	customer	62
app	update	57
app	slow	46
app	fix	44
app	shopping	39
app	items	38
app	shop	36
app	time	32
credit	card	29
app	customer	27
app	love	27
app	item	26
app	website	26
app	card	24
app	online	23
app	cart	22
app	purchase	22
app	phone	22
app	shipping	21
app	times	21
app	frustrating	21
customer	called	21
app	load	21
app	check	20
app	service	20
app	version	20
service	called	20

app	page	19
app	add	18
app	search	18
app	account	17
app	information	17
app	store	17
app	email	17
service	call	16
customer	call	16
shopping	items	16
app	experience	16
time	waste	16
slow	update	16
app	buy	15
app	credit	15
app	fixed	15
app	takes	15
app	code	14
customer	time	14
shopping	time	14
shopping	shop	14
app	horrible	14
card	gift	14
app	product	14
shop	update	14
items	update	14
app	user	14
app	click	14
app	checkout	13
online	shopping	13
card	shopping	13
app	info	13
card	enter	13
cart	items	13
time	items	13
app	terrible	13
app	constantly	13
customer	email	13
update	fix	13
app	bag	12

customer	card	12
customer	shopping	12
app	view	12
app	process	12
item	time	12
app	enter	12
service	items	12
customer	items	12
item	items	12
app	list	12
app	hate	12
app	issue	12
online	store	12
update	load	12
customer	told	12

Word co-occurrence frequency of negative customer reviews from mid-tier retailers

Term 1	Term 2	Frequency
time	app	91
app	card	80
customer	service	70
app	pay	60
app	password	56
app	account	56
app	store	51
app	sign	47
pay	bill	46
app	log	45
card	credit	44
app	charge	43
app	payment	43
app	times	42
app	phone	40
app	frustrating	40
app	shop	39
app	fix	39
app	screen	38
app	bill	37
pay	card	34

app	customer	32
app	website	31
app	service	31
app	credit	31
app	update	30
time	password	30
time	card	30
charge	card	30
app	worst	27
time	pay	26
account	card	26
app	login	26
app	error	25
app	online	25
customer	called	25
app	shopping	24
store	customer	24
app	deleted	23
pay	charge	23
store	service	23
app	access	23
card	payment	23
time	sign	22
service	called	22
sign	card	22
app	check	21
password	card	21
customer	card	21
customer	call	21
app	items	20
time	log	20
password	log	20
sign	pay	20
app	issue	20
service	card	20
app	updated	19
app	click	19
app	item	19
store	card	19
store	shop	18

time	account	18
app	info	18
password	pay	18
account	pay	18
app	user	18
app	change	18
app	information	18
app	call	18
time	waste	18
app	ipad	17
sign	password	17
account	log	17
store	pay	17
account	charge	17
store	online	17
time	customer	17
time	frustrating	17
time	payment	17
time	call	17
app	iphone	16
app	deleting	16
app	downloaded	16
sign	account	16
app	love	16
store	shopping	16
time	charge	16
time	credit	16
pay	payment	16
frustrating	payment	16
store	call	16
service	call	16
app	page	16
time	bill	16
app	button	16
app	submit	16

Word co-occurrence frequency of negative customer reviews from off-price retailers

Term 1	Term 2	Frequency
app	card	127

app	time	104
card	credit	95
app	rewards	82
app	password	80
account	app	77
app	credit	75
app	pay	67
app	log	63
app	store	62
app	items	57
app	times	56
app	fix	53
app	website	49
app	frustrating	48
service	customer	47
pay	card	47
app	online	46
app	login	44
app	customer	41
app	shopping	41
app	shop	41
app	purchase	38
card	time	38
password	reset	38
email	app	37
account	card	36
app	cart	36
app	downloaded	36
app	bill	36
pay	bill	36
card	rewards	35
app	worst	34
pay	credit	33
log	password	33
card	password	33
app	reset	33
app	service	32
app	access	32
app	sign	32
app	phone	31

app	scroll	30
app	click	29
store	card	28
app	update	28
account	password	28
app	unable	27
items	time	27
account	credit	27
app	love	27
credit	rewards	27
waste	time	26
items	cart	26
app	makes	26
app	error	25
app	useless	25
card	times	25
app	page	25
time	password	25
app	item	24
app	link	24
email	password	24
credit	password	24
card	bill	24
password	rewards	24
store	online	23
store	time	23
store	credit	23
app	information	23
app	button	23
password	sign	23
issues	app	22
account	log	22
app	waste	22
app	payment	22
log	card	22
phone	card	22
app	screen	22
app	terrible	22
time	rewards	22
items	item	21

customer	time	21
pay	time	21
account	website	21
app	add	21
app	site	21
app	issue	21
pay	password	21
times	password	21
time	times	20
app	deleting	20
app	hard	20
app	ridiculous	20
app	wrong	20
app	call	20
app	search	20
app	correct	20
access	rewards	20

VITA

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