Demographic-Related Purchase Behaviours of Consumers: The Evolving Tension between Exploration and Exploitation in Frequently Purchased Consumer Goods Markets

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ABSTRACT

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Consumers make trade-offs in their purchase decision making between extending market knowledge from exploring a product market and maximizing purchase value based on exploiting their current knowledge. The value of these strategies can be enhanced opportunistically by taking advantage of promotions. In this research, a new and unique data-mining model was developed to process store scanner data for quantifying the brand selection behaviour of an individual consumer in reaction to promotions. Selected consumers in each of Pittsfield's salty snack, yogurt, and toilet tissue markets were then segmented into four behavioural segments using clustering analysis based on their Prevalence of Promotion and their Value of Information from Purchases. The behavioural segmentation was valid, as the four generated behavioural segments in each product market could be differentiated by using demographic variables.

In a product market, the demographic profiles of behavioural segments can be generated and used for improving the performance in targeting consumers. The generated demographic profiles of a behavioural segment explain how consumers in the segment react to promotions, which can be used for predicting how consumers will react in the future. Complementing demographic profiles, dynamic behavioural evolvements in consumer purchase lifecycles can also help to predict the purchase behaviours of consumers in the future from the purchases that the consumers have made. The evolvements enable people to understand how consumers with a given amount of market experiences make their purchase decisions via making trade-offs between market knowledge extension and immediate purchase value maximization.

Product markets differ in their available number of brands for selection. The findings generated in a product market, however, cannot be generalized to a different product market. Consumers have different demographic-related purchase behaviours across frequently purchased consumer goods markets.

Based on the findings in the research, the dissertation discusses and provides suggestions for retail businesses to improve their performances for achieving a competitive edge.

DECLARATION

No portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

COPYRIGHT STATEMENT

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PUBLICATIONS TO DATE

A number of academic articles have been (and are being) crafted out of the work done for this dissertation. These are:

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Luo, C & Chen, Y-W. (2016). Self-assessment of Adapted EFQM's Criterion 'People' in Chinese Textile Enterprises. In 2016 International Conference on Innovation, Management and Industrial Engineering (IMIE 2016), Kurume, Fukuoka, Japan on August 05-07.

CHAPTER 1: INTRODUCTION

1.1 Background

Promotional mix is widely used by retailers to reach their marketing goals, such as stimulating sales, winning new consumers, increasing expenditures by existing customers, developing the store image, and gaining competitive advantages (McGoldrick, 2002; Keegan and Green, 2008). Retailers flexibly use tools of the promotional mix such as advertising, public relations, sales promotions, direct marketing, publicity, and personal selling to communicate with consumers and thus influence consumers' purchase decisions for achieving organizational objectives (Keegan and Green, 2008; The Chartered Institute of Marketing, 2009; Mangold and Faulds, 2009). In late 2012, marketing expenditures accounted for 11% of a firm's total revenues (MarketingCharts, 2012). In 2013, they accounted for an average of 10.6% of firm budgets and presented a growing trend at a rate of 6.1% (CMO Council, 2013). According to Sebastian (2015), $540 billion was expected to be spent by marketers on global advertising in 2015, which represented a 4.6% of the increase in advertising expenditures compared to those in 2014.

However, the application of marketing weapons may not always enable marketers to reach their expected performances in sales due to a low response rate to promotions (Gilbert and Jackaria, 2002). Consumers are inclined to accept promotions that are attractive to them, rather than those that bother them. Understanding consumers for the purpose of providing tailored promotions is the key to making attractive promotions. To understand consumers, at least 80% of chief marketing officers use traditional sources of information, such as market research and competitive benchmarking, to make marketing strategies (IBM, 2011). These traditional sources of information enable marketers to generate aggregate insights about consumers (IBM, 2011). The needs and wants of individual consumers are still under-discovered by using traditional information sources.

In response to the increased desire for understanding individual consumers, data-driven marketing has emerged to enable marketers to generate insights about how individual consumers think and behave. It refers to identifying and satisfying consumers' needs and wants via analysing data about or from consumers for generating profits (McGoldrick, 2002; Financial Times, 2015). In 2011, around 74% of chief marketing officers used customer analytics as an information source to influence marketing strategy decisions (IBM, 2011). In the next three to five years, around 81% of chief marketing officers plan to focus on and more extensively use customer analytics and customer relationship management solutions in supporting strategy making (IBM, 2011). Around 71% of chief marketing officers regard the data explosion as the most prominent challenge in influencing marketing functions over the next three to five years (IBM, 2011).

In a fiercely competitive market, marketers are motivated to invest in data-driven marketing. This is mainly due to the desire of maximizing marketing investment efficiency and understanding current and prospective consumers, the demand in delivering more-relevant communications to consumers, and the growing availability of consumer data for analysis (Global DMA LLC and Winterberry Group LLC, 2014). In the U.S., 65% of marketers think that data plays a critical role in their current marketing and advertising efforts. In total, 70.9% of American marketers also believe that the importance of data is growing substantially in their marketing and advertising efforts. In view of this, 67.6% of American marketers increased their investment in data-driven marketing from 2013 to 2014, and 69.6% of American marketers intended to invest more in data-driven marketing from 2014 to 2015 (Global DMA LLC and Winterberry Group LLC, 2014). The increased investments in data-driven marketing indicate that data-driven marketing will be a popular trend in marketing in the future.

Marketers are using consumer data to segment consumers based on their understandings for better targeting unique consumer segments. In 2011, 61% of chief marketing officers extensively used customer data to segment and target consumers (IBM, 2011). According to IBM (2011), chief marketing officers in high-performing organizations invest more efforts into capturing and using data in customer segmentation and targeting. Effectively segmenting consumers enables marketers to identify and categorize groups of consumers according to their common characteristics for the purpose of follow-up targeting (Keegan and Green, 2008). To capture the most selling opportunities with limited resources, marketers need to identify, evaluate, and invest in those consumers who have significant potential to respond to their marketing activities. The segment evaluation and the investment in a targeted segment are part of the process of targeting (Keegan and Green, 2008). To optimize the performances of marketing efforts, tailoring marketing activities to optimize consumers' value from purchases in a target segment is required (Keegan and Green, 2008).

In a frequently purchased consumer goods market, new brands and/or new characteristics of existing brands are frequently introduced to the turbulent market. Particularly, in a highly competitive turbulent consumer goods market, like salty snacks, a large number of product brands are available for selection. The introduction of new brands and the presence of a large number of brands make consumers perceive that the product market is full of uncertainties and risks (Erdem and Keane, 1996). For the purpose of learning, consumers are either sampling different brands to extend their market knowledge (i.e. exploring) or continuously purchasing a subset of their preferred brands to avoid risks (i.e. exploiting) (Luo *et al.*, 2015). Their exploration and exploitation activities enable them to learn information about the brands in the product market (Erdem and Keane, 1996). Exploitation behaviour is defined as maximizing the decision's utility according to what is known about the market. Exploration behaviour is defined as sampling different brands of a product to extend knowledge about the product market. Under uncertainties, consumers' past experiences in brand selection, possibly associated with promotional mix elements, affect their current choices due to the change of their information set from market learning (Luo *et al.*, 2015; Yang *et al.*, 2015; Erdem and Keane, 1996; Heilman *et al.*, 2000). This decision-making problem is a typical dynamic choice problem, as identified in the marketing literature (Yang *et al.*, 2015). Prior research suggests that consumers' exploration and exploitation behaviours are motivated by the available promotional mix (Bucklin *et al.*, 1998; Alvarez and Casielles, 2005; Bucklin *et al.*, 1995). Understanding the trade-offs between exploration and exploitation in relation to the promotional mix is regarded by many researchers as important and valuable in understanding consumers (Audibert *et al.*, 2008; Erdem and Keane, 1996; Luo *et al.*, 2015). It enables marketers to understand how consumers make trade-offs between extending their market knowledge and buying earlier than planned to maximize their utility from purchases based on what is known about the market.

1.2 Research Questions and Objectives

This research is a piece of quantitative research about data-driven marketing. The purpose of the research is to facilitate the understanding of consumer brand selection behaviours in relation to promotions in order to enable marketers to tailor their marketing strategies for enhancing the attractiveness of promotions. Segmenting consumers based on their brand selection behaviours in relation to promotions enables marketers to better understand the behaviour of consumers in a behavioural segment. In order to support marketers in better understanding consumers and developing tailored marketing strategies to capture the most selling opportunities in turbulent product markets, this research is engaged in answering the following research questions:

1) *How can we measure a consumer's brand selection behaviour in relation to promotions?*

2) *Are consumer purchase behaviours in relation to promotions dependent on the type of promotion?*

3) *How do consumers differ in their brand selection behaviours in relation to promotions?*

4) *Can demographics be used to target a group of consumers with expected brand selection behaviours in relation to promotions?*

5) *How do the brand selection behaviours in relation to promotions evolve in consumer purchase lifecycle?*

6) *How do the purchase behaviours of consumers differ across product markets?*

The objective related to the first research question is to develop a data-mining model for analysing consumers' brand selection behaviours in relation to promotions in frequently purchased consumer goods markets. Transactional data of consumers is easy for retailers to obtain (IBM, 2011) and can reflect consumers' real purchase behaviours. This research thus quantifies consumers' purchase behaviours via processing their transactional data. The developed behavioural measurement model enables marketers to understand the brand selection behaviours in relation to promotions from the purchase records of consumers.

In a product market, retailers use various types of promotions to achieve their business objectives. The objective of the second research question is to find out the reactions of consumers in response to different types of promotions. This enables marketers to understand whether the type of promotion is a factor in influencing the promotional responsiveness of a consumer.

To answer the third research question, the research aims to identify the typical behavioural segments in a product market. This research typifies a type of brand selection behaviour in relation to promotions with a typical behavioural segment. The identification of the typical brand selection behaviours in relation to promotions enables marketers to understand how consumers in a behavioural segment will behave in their purchase decision making.

To implement the developed data-mining model in this research, a large number of purchase records are required for each consumer. However, it might be impossible for a retailer to obtain transactional records of all consumers in a product market. A retailer cannot access the transactional data of consumers with other retailers. For the purpose of targeting and positioning, profiling behavioural segments using widely accessible behavioural data is essential. In prior research, it has been suggested that consumers' purchase behaviours can be identified by using their demographic characteristics (Lichtenstein *et al.*, 1997; Bawa and Ghosh, 1999; Teunter, 2002; Kwon and Kwon, 2007; Urbany *et al.*, 1996; Bell *et al.*, 1999; Blattberg *et al.*, 1978; Gilbert and Jackaria, 2002). In practice, retailers can and do obtain demographic information of their customers from the customers' bank accounts (when customers use debit or credit cards to make payments, the retailers can then access the customers' personal information from the bank). Retailers also have access to the demographic information of the whole population from government census bureaus (United States Census Bureau, n.d.). Demographic data thus is the most widely accessible behavioural data for profiling behavioural segments. The fourth research question aims to find out the capability of demographic variables in targeting consumers in a behavioural segment.

As a dynamic choice problem, consumers' past experiences in brand selection in relation to promotions influence their current purchase behaviours (Luo *et al.,* 2015; Yang *et al.,* 2015; Erdem and Keane, 1996; Heilman *et al.,* 2000). To answer the fifth research question, the researcher therefore proposes to find out how consumers behave in purchase decision making with the increase in market experiences over time. To accomplish this, the research aims to identify the behavioural evolvement patterns, routes, and approaches in consumer purchase lifecycles. This identification enables retailers to predict consumers' purchase behaviours in the future based on the past purchase experiences of those consumers.

To answer the sixth research question, the researcher aims to find out whether the findings concerning the brand selection behaviours in relation to promotions differ across product markets. The comparison of the findings across product markets enables marketers to understand how the purchase behaviours of consumers differ across product markets and thus to predict the potential purchase behaviours of consumers in a product market.

1.3 Overview of Research Design and Outcome

In order to achieve those objectives, this quantitative-based research uses the IRI marketing dataset to perform the analysis. The IRI marketing dataset was constructed primarily for marketing purposes. It contains the real transactional data of American consumers across 11 years. The use of the IRI marketing dataset for analysis in this research is due to its high accessibility and the rich information on household demographics (Perloff and Denbaly, 2007; Bronnenberg *et al.*, 2008). Since the IRI marketing dataset is available to academic researchers for studying research topics in marketing and economics (Bronnenberg *et al.*, 2008), it can be obtained from the library at the University of Manchester. Descriptions of the IRI marketing dataset are presented in Chapter 4.

To compare brand selection behaviours in relation to promotions across product markets, three out of 31 product markets in the IRI market dataset are selected for analysis. The brand selection conditions, the typical behavioural segments, the demographic profiles, and the dynamic behavioural evolvements in those selected product markets are compared to identify the similarities and differences of consumer purchase behaviours in those product markets. Descriptions of the selected product markets are provided in Chapter 4. The research design is illustrated in Figure 1.1.

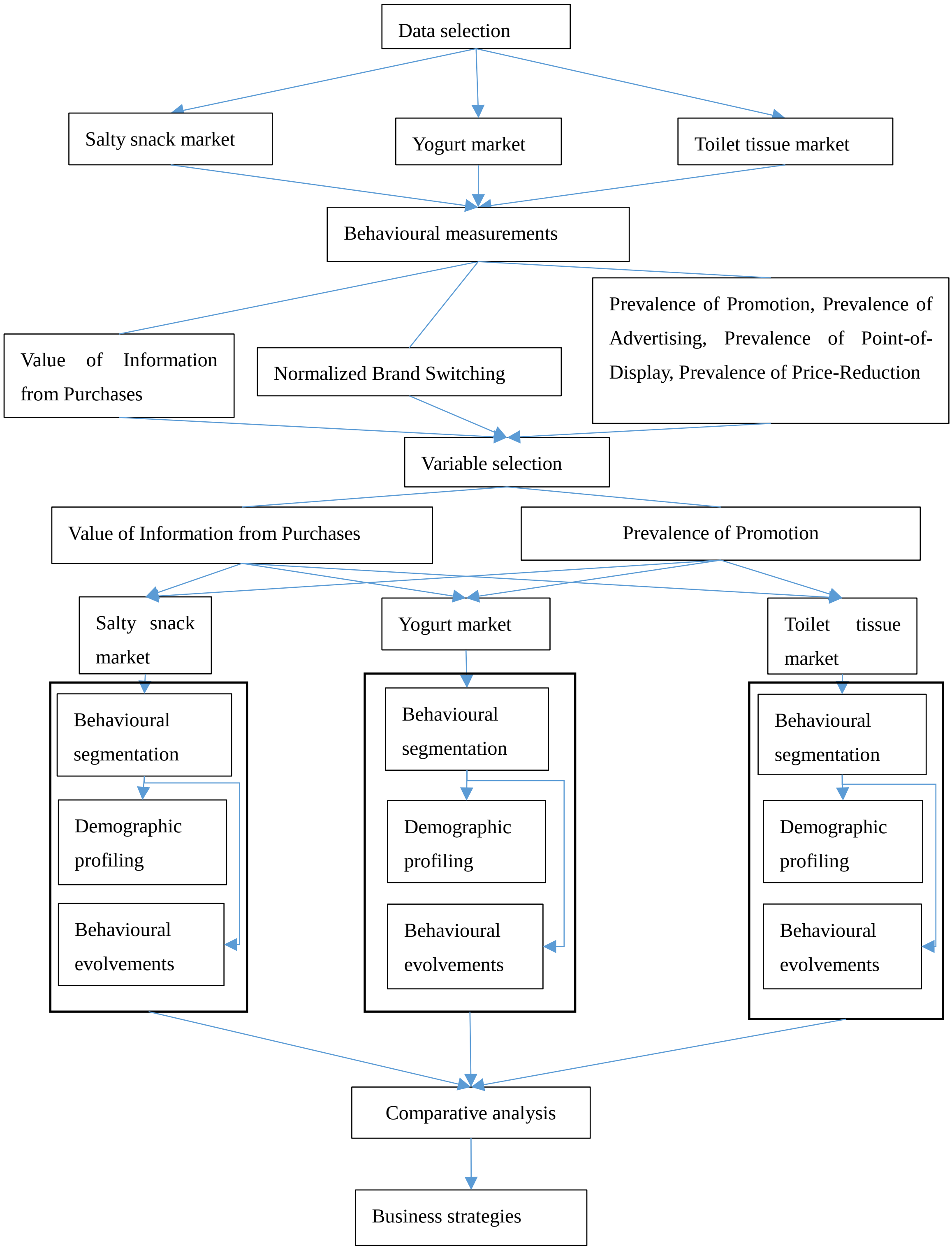

Figure 1.1: Research design

In this research, the Prevalence of Promotion, the Prevalence of Advertising, the Prevalence of Point-of-Display, the Prevalence of Price-Reduction, the Value of Information from Purchases, and the Normalized Brand Switching are proposed to measure promotion proneness, proneness to advertising, proneness to point-of-display, proneness to price-reduction, dynamic choice behaviour, and brand-switching behaviour, respectively. In clustering analysis, strongly correlated variables provide redundant information, which may result in a problem in identifying clusters (Fraiman *et al.*, 2008). As the Value of Information from Purchases and the Normalized Brand Switching are highly correlated and used to measure consumers' brand selection behaviours, one variable needs to be selected from these two variables. Compared with the Normalized Brand Switching, the Value of Information from Purchases is easier to use when processing a large amount of data and has stronger theoretical support. The Value of Information from Purchases therefore is selected for conducting the clustering analysis. By the same token, as the Prevalence of Promotion can represent and reflect consumers' reactions to all types of promotional mix and significantly correlates with the Prevalence of Advertising, the Prevalence of Point-of-Display, and the Prevalence of Price-Reduction, it is selected as the other variable in the clustering analysis. In this study, the selected consumers in each of three product markets are segmented based on their Value of Information from Purchases and Prevalence of Promotion. The behavioural segments in each product market are defined based on their characteristics in these two behavioural variables.

In order to support retailers to target consumers with given purchase behaviours without measuring the past purchase experiences of those consumers, consumers' demographic characteristics are used to profile behavioural segments in each product market. The common demographic characteristics that are associated with a behavioural segment across years are identified as the demographic profile of the behavioural segment for the purpose of targeting. In prior research, consumers' current purchase behaviours have been found to be influenced by their purchase experiences (Luo *et al.,* 2015; Yang *et al.,* 2015; Erdem and Keane, 1996; Heilman *et al.,* 2000). Consumers' purchase behaviours thus are supposed to evolve over the years in their purchase lifecycles. In order to find out whether consumers' purchase behaviours evolve over the years and how the behaviours evolve, the segment memberships of consumers in four continuous years are compared. Behavioural evolvement patterns and routes are identified based on dynamic changes in the segment membership of consumers.

In order to find out how these findings differ across product markets in this research, the findings in one product market are compared with the corresponding findings in another product market. The findings of the comparative analysis may allow marketers to predict and understand the brand selection conditions of consumers, the typical brand selection behaviours in relation to promotions, the predictive capability of demographics, and the dynamic behavioural evolvements of consumers in a given product market.

In general, this research uses inductive reasoning approach to reach the conclusions from analysing the transactional data of selected consumers in three product markets. The patterns and regularities are detected from the data analysis in each product market for developing general conclusions about consumer brand selection behaviours in relation to promotions in a product market.

1.4 Significance of the Research

In an era of information, data-driven marketing is an inevitable trend in retailing. Retailers use data from consumers to simulate and predict consumers' purchase behaviours. Understanding consumers plays a vital role in segmenting consumers and designing specific promotions to meet the specific needs of consumers. It is a weapon for retailers in achieving competitive advantages and increasing market share. For example, Tesco devotes itself to understanding consumers through analysing mass consumer data collected from Clubcard holders (Davis, 2007). The understanding of consumers allows Tesco to construct complicated marketing strategies and promotional campaigns. Nevertheless, the data explosion is a big challenge that needs to be tackled by retailers to improve performances in marketing (IBM, 2011). To tackle the problem, a user-friendly data-mining model that is designed for handling large amounts of data is required to quantify consumers' purchase behaviours.

This research provides a new and unique behavioural segmentation approach for retailers to support the development of marketing strategies for improving the response rate of promotions. It developed six behavioural measurements for quantifying consumers' purchase behaviours in brand selection in relation to promotions. None of those behavioural measurements involves complicated calculations in quantifying behaviours. It may allow retailers to process big data by using given programming in this research. The quantified behaviours are then used in clustering analysis for identifying the typical purchase behaviours of consumers in a product market.

In prior research, the dynamic choice processes have long been recognized and have been widely modelled using a series of predictive choice models (Erdem and Keane, 1996; Heilman *et al.*, 2000; Narayanan *et al.*, 2005; Hauser and Wisniewski, 1982; Meyer, 1982; Hagerty and Aaker, 1984; Ratchford, 1980; Che *et al.*, 2015; Stüttgen *et al.*, 2012; Ching *et al.*, 2012; Gönül and Srinivasan, 1996; Bucklin *et al.*, 1995, 1998). However, recent predictive choice models have not explicitly captured the dynamic trade-offs between market knowledge extension and immediate value maximization. The clustering analysis in this research examines the evolvements of brand selection behaviours in relation to promotions by considering the trade-off between market knowledge extension and immediate value maximization in the consumer purchase lifecycle. It extends prior research on consumer choice to uniquely clarify how consumers make their purchase decisions to optimize their expected utility from extending market knowledge and taking advantage of promotions.

As for retailers, the key to capturing the most selling opportunities with limited resources is to target the right consumers by providing tailored promotions based on the predicted purchase behaviours of consumers. The demographic profiling in this research allows retailers to easily target consumers and predict the purchase behaviours of those consumers by simply looking at the demographic characteristics of the targets. It complements dynamic behavioural evolvements in predicting consumers' purchase behaviours in their purchase lifecycles.

1.5 Overview of Chapters

This doctoral thesis consists of eight chapters, the structure of which is presented in Figure 1.2.

Chapter 1: Introduction

- Background
- Research questions and objectives
- Overview of research design and outcome
- Significance of the research
- Overview of chapters

Chapter 2: Literature Review

- Consumer purchase behaviour applied to promotional mix
- Exploration and Exploitation
- Behavioural segmentation
- Household characteristics related to consumer purchase behaviour

Methodology

Chapter 3: Methodological and Analytical Research Design

- Measuring the consumer's response to promotions in retail purchase data
- Measuring the consumer's response to advertising, point-of-display, and price-reduction in retail purchase data
- Measuring consumer's dynamic choice behaviours
- Measuring consumer's brand switching behaviours
- Analysis process of the research

Chapter4: Numerical Studies

- IRI Marketing data
- Brand selection conditions across product markets
- Algorithm implementation for processing transactional data
- Variable selection

Results

Chapter 5: Analysis of Behavioural Segments

- Salty snack market
- Yogurt market
- Toilet tissue market
- Market comparison

Chapter 6: Analysis of Demographic Profiling

- Salty snack market
- Yogurt market
- Toilet tissue market
- Market comparison

Chapter 7: Analysis of Dynamic Behavioural Evolvements

- Salty snack market
- Yogurt market
- Toilet tissue market
- Market comparison

Chapter 8: Conclusion

- Summary and discussions of findings
- Contributions
- Limitations and future research

Figure 1.2: Thesis structure

Following the chapter of introduction, Chapter 2 reviews the relevant literature and encapsulates the gaps in the literature. This multi-disciplined research focuses on the overlap of the multi-armed bandit problem, consumer behaviour, and marketing. To create a successful marketing campaign, marketers need to have a good understanding and estimation of how consumers will react to a campaign. Promotional approaches in the retail market are reviewed to provide background knowledge about what an approach is and how it works to influence consumers' purchase decisions. In response to promotions, consumers' experiences influence their attitudes to promotions. Consumers' attitudes to promotions play a critical role in determining their proneness to promotions. The promotion proneness, which is a criterion in behavioural segmentation, is then reviewed and clarified. Consumers who are prone to take advantage of promotions may have different purposes and may be attracted by different promotional approaches. Their reactions to the promotional mix are discussed via explaining the implied purpose of their reactions to the promotions.

As the other criterion for behavioural segmentation, the concept of exploration and exploitation is originally from the multi-armed bandit problem. Consumer buying requires consumers to select one or a few brands from a set of brands at each time of purchase in seeking maximum expected utility from purchases. It is a version of the multi-armed bandit problem (Ishikida and Varaiya, 1994). This research reviews the application of exploration and exploitation in consumer behaviour for clarifying consumers' dynamic choice processes under uncertainties in purchases. The conceptual background and measurement models of the dynamic choice process are presented to explain how consumers make their brand selection decisions. This research aims to identify the trade-offs between extending market knowledge and maximizing immediate purchase value. To understand the principles of the implied trade-offs, the influences of the promotional mix on dynamic choice process are discussed. To identify the literature gaps in brand choice models, this study also reviews the brand choice models proposed in prior research. The literature on behavioural segmentation is reviewed to introduce the segmentation approaches used in prior research. The findings regarding the relationships between demographics and consumers' purchase behaviours in prior research are reviewed and presented to provide background knowledge about demographic profiles.

Chapter 3 and Chapter 4 are the methodology chapters of this thesis. Chapter 3 introduces the behavioural measurements developed and used in this research as well as the analysis process of the research. This chapter aims to provide answers to the first research question. Section 3.2 introduces the measurement of promotion proneness. Section 3.3 presents the measurements of proneness to advertising, point of display, and price reduction. In Section 3.4, the behavioural measurement for quantifying a consumer's dynamic choice behaviour is presented. Section 3.5 then introduces the measurement of brand-switching behaviour. Section 3.6 presents the steps in the analysis process.

Chapter 4 describes the application of the data-mining model in the numerical studies. Section 4.2 reviews the IRI marketing data used in this research and explains the data-preparation processes in selected product markets. Section 4.3 discusses the comparative analysis of the brand selection conditions across product markets, answering the sixth research question. Section 4.4 presents the implementation of the data-mining model in dealing with transactional data. To conduct the behavioural segmentation, the behavioural variables for the clustering analysis are selected. Section 4.5 presents the process and results of the variable selection. The results provide answers as to whether consumer purchase behaviour in relation to promotions is dependent on the type of promotion (i.e. the second research question).

Following the methodology chapters, Chapter 5, Chapter 6, and Chapter 7 present and discuss the results generated in this research. Chapter 5 discusses the results of the behavioural segmentation. This chapter aims to answer the third and sixth research questions in terms of the typical brand selection behaviours in relation to promotions. Sections 5.2, 5.3, and 5.4 describe typical brand selection behaviours in relation to promotions in the salty snack, yogurt, and toilet tissue markets, respectively. The comparative analysis of the typical purchase behaviours of consumers across product markets is discussed in Section 5.5.

Following the same structure as Chapter 5, Chapter 6 and Chapter 7 present the results of the demographic profiling and dynamic behavioural evolvements in those three product markets, respectively. In Chapter 6, the validity of behavioural segmentation in each product market is assessed and presented in a sub-section. Then, the demographic variables that can be used to target consumers are identified. The improved performances of targeting using demographic profiles are quantified in each product market. The results presented in Chapter 6 provide an answer as to whether demographics can be used to target a group of consumers with expected brand selection behaviours in relation to promotions (i.e. the fourth research question). The findings of the comparative analysis, which are presented in Section 6.5, provide an answer to the sixth research question in terms of the demographic profiles of behavioural segments across product markets.

Chapter 7 discusses the dynamic behavioural evolvements in those three product markets. The behavioural evolvement routes presented in this chapter clarify how the brand selection behaviours in relation to promotions evolve in the consumer purchase lifecycle. The trade-offs between the maximization of immediate purchase value and the extension of market knowledge in consumer decision making are discussed to explain the behavioural evolvement routes of consumers. This chapter answers the fifth and sixth research questions in terms of the dynamic behavioural evolvements across product markets.

Chapter 8 is the conclusion chapter of this thesis. The findings generated in this research are summarized and discussed in relation to the research questions. This research is evaluated, and the theoretical and practical contributions are discussed in Section 8.3. Finally, this thesis concludes with the provision of research limitations and future research work.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Chapter 2 reviews the literature relevant to this research, aiming to provide background knowledge about the research. This multi-disciplined research focuses on the application of the multi-armed bandit problem in consumer purchase behaviours responding to marketing campaigns. The underlying areas and the structure of this research are demonstrated in Figure 2.1.

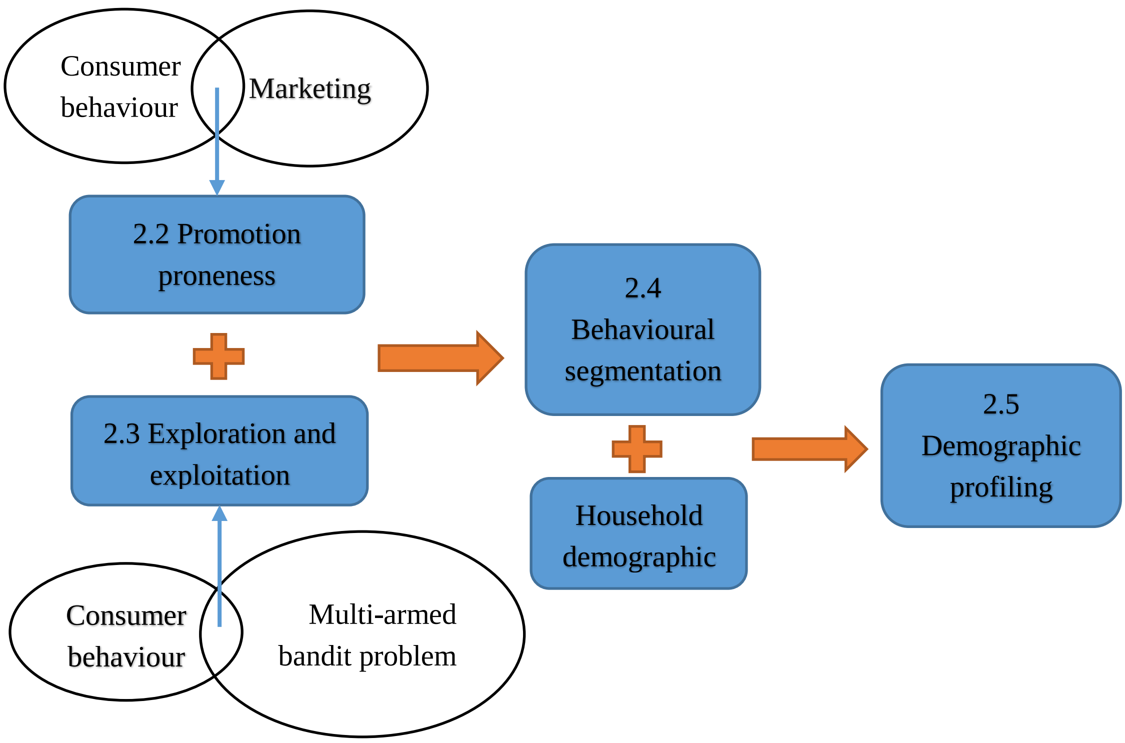

Figure 2.1: Underlying areas and the structure of the research

This research studies the promotion proneness of consumers and their exploration and exploitation behaviours in brand selection. Promotion proneness reflects the general psychological propensity of a consumer to react to the promotional mix (Anic and Radas, 2006; Danziger *et al.*, 2014; Teunter, 2002). Exploration and exploitation are the key concepts in the multi-armed bandit problem. In this research, the focus is on the application of exploration and exploitation in consumer behaviour, which is represented as the overlap area of consumer behaviour and the multi-armed bandit problem. Consumers in this research are segmented based on their proneness to promotions and their exploration and exploitation behaviours in brand selection. Thus, the behavioural segmentation is reviewed in this chapter to provide an understanding of customer segmentation. In order to profile behavioural segments to support marketers to easily target the right consumers, the household characteristics associated with promotion proneness and exploration and exploitation behaviours are reviewed.

This chapter consists of six sections. In this section, a general review of the chapter is provided. Figure 2.1 shows the main topics reviewed in this chapter.

In Section 2.2, consumer purchase behaviour as applied to the promotional mix is discussed. Two sub-sections are included in Section 2.2. The first sub-section discusses the tools of the promotional mix that are commonly used by marketers to increase and stimulate consumer demands and to retain and attract consumers. Advertising and sales promotions, including money-based; product-based; gift-, prize-, or merchandise-based; store-based; and co-operative promotions are discussed. In total, 17 sales promotion techniques are discussed in this sub-section. They are reduced price offers, coupons, rebates, extra products, samples, product warranties, self-liquidating, free mail-in, free inside or on pack, free with product, customer loyalty schemes, contests and sweepstakes, point-of-sale displays, demonstrations, bundling, tie-in promotions, and cross-promotions. These techniques are discussed in terms of their associated definitions and descriptions, purposes and benefits, technique formats, how and when to use the technique, and the limitations of the technique.

After reviewing the tools of the promotional mix, the second sub-section of Section 2.2 reviews the promotion proneness discussed in prior research. Firstly, the definition of promotion proneness provided in prior research is presented and reviewed. Then, the classification of promotion proneness is summarized and the types of promotion proneness discussed in prior research are presented and compared in terms of different classification criteria. Thirdly, this sub-section reviews studies about the promotion proneness of a consumer across different types of promotions. The findings about promotion proneness across promotion types are summarized and presented with the explanations of the findings. Fourthly, a review about whether the promotion proneness of a consumer is the same across different product categories is presented and discussed by summarizing findings in prior studies. Then, the measurements of promotion proneness proposed in prior research are discussed and reviewed by pointing out the associated advantages and disadvantages. Finally, the purposes of taking advantage of promotions are summarized from prior research.

Section 2.3 discusses the exploration and exploitation in brand selection. It consists of four sub-sections. In the first sub-section, the multi-armed bandit problem is introduced and the concepts of exploration and exploitation in the problem are provided. In the second sub-section, consumers' dynamic choice process is discussed and explained in terms of their exploration and exploitation behaviours in brand selection. The consumer's learning journey is presented and reviewed in terms of exploration and exploitation behaviours with an increase in market experiences. In this research, consumers are segmented based on their promotion proneness and exploration and exploitation behaviours. In the third sub-section, the relationship between promotion proneness and exploration and exploitation behaviours in brand selection is reviewed. In the dynamic choice process, consumers' past purchase experiences influence their current purchase decisions. Thus, the third sub-section discusses the relationships among market knowledge, promotion proneness, and exploration and exploitation behaviours. In the last sub-section of Section 2.3, the proposed models used for measuring brand choice behaviours in prior studies are reviewed. The measurement models are evaluated, and the advantages and limitations of each measurement model are discussed after presenting the model.

After reviewing consumer purchase behaviours, Section 2.4 summarizes and discusses the literature about behavioural segmentation in four main aspects. Firstly, the concept of customer segmentation is introduced and briefly reviewed in terms of its definition, functions and purposes, and the segmentation types. Then, behavioural segmentation is focused on and its necessity in achieving competitive advantages is presented and exemplified by using the case of Tesco. Thirdly, the studies that discuss behavioural segmentation in terms of promotion proneness and/or exploration and exploitation behaviours are summarized based on the data used in the behavioural segmentation. In this research, the studies that use real purchase data in behavioural segmentation are focused on and reviewed in detail. At the end of Section 2.4, four studies that segment consumers based on promotion proneness and/or exploration and exploitation behaviours are discussed in terms of the data used in the segmentation, the descriptions of the segmentation, and the potential limitations of the segmentation.

Section 2.5 aims to provide a general understanding of the household characteristics associated with consumer purchase behaviour. It consists of two sub-sections, and each has the same structure and discusses the same demographic variables associated with a type of consumer purchase behaviour. In the first sub-section, the relationships between promotion proneness and household income, education, age, employment situation and occupation, children status, family size, and marital status are reviewed. In the second sub-section, the relationship between exploration and exploitation behaviours and those demographic characteristics are discussed. The studies about those relationships are reviewed and the findings on the identified relationships in prior research are summarized. For each identified relationship, an explanation of the findings of the relationship is provided.

Section 2.6 is the conclusion of Chapter 2. It summarizes the key concepts and findings reviewed in the chapter.

In the next section, consumer purchase behaviours in response to the promotional mix are reviewed.

2.2 Consumer Purchase Behaviour Applied to the Promotional Mix

The marketing mix refers to the mixture of actions or tactics useful in promoting brands or products in a market for pursuing a certain market response (Waterschoot and Bulte, 1992). The typical marketing mix consists of the 4Ps: product, price, place, and promotional mix (Keegan and Green, 2008; Waterschoot and Bulte, 1992; Mangold and Faulds, 2009). The purpose of this research is to support marketers in effectively communicating with consumers, which can be achieved by using the promotional mix. As an important element of the marketing mix, the promotional mix is a set of communication tools that a company uses to carry out the promotion process and to effectively transfer messages about the benefits of its products or services to consumers (The Chartered Institute of Marketing, 2009; Karunanithy and Sivesan, 2013).

The promotional mix includes a blend of communication tools, such as advertising, support media, direct marketing and commerce, sales promotions, event sponsorships, public relations, product placement, and personal selling (Keegan and Green, 2008; Karunanithy and Sivesan, 2013). In this research, the focus is on the reactions of consumers to advertising and sales promotions. The advertising and sales promotions used in markets are discussed in the following sub-section. Consumers' purchase behaviours determine the success of the applied promotional mix. Consumers with high promotion proneness are more inclined to take advantage of promotions to meet their purchase demands. It is thus essential for marketers to target those consumers and make promotions to attract their attentions. Section 2.2.2 reviews promotion proneness to provide a general understanding of the concept.

2.2.1 Tools of promotional mix

2.2.1.1. Advertising

Advertising is defined as any sponsored, paid message that is communicated in a non-personal way to create and reinforce brand awareness and to persuade consumers to make purchases from a company (Keegan and Green, 2008; The Chartered Institute of Marketing, 2009). For most major retailers, advertising is an integral component of the overall marketing strategy for providing the main channel of communication to existing and potential customers (McGoldrick, 2002). As consumers make 75% of their purchase decisions in store, messages delivered at point of purchase are expected to have the best chance to influence consumers' purchase behaviours (Redbus, 2005; Babej and Pollak, 2007). In-store advertising, which provides a high level of consumer brand representation at or near the point of sale, is regarded as one of the most effective advertising tools and is widely used by retailers to influence consumers' purchase behaviours to achieve marketing objectives. Investment in in-store advertising is rapidly increasing, with compound annual growth of 21% through 2010 (Babej and Pollak, 2007). According to King (1975, cited in McGoldrick, 2002), advertising can be used to stimulate consumers to buy a product, to encourage consumers to find out more about a product, to increase their desire for a product, to remind them of previously satisfying products, and to modify negative attitudes and reinforce positive attitudes toward a product.

In a frequently purchased consumer goods market, heavy promotional support is required to provide psychological value to the product or brand (Keegan and Green, 2008). Advertising is designed to provide consumers with information about a product or brand to create and reinforce brand awareness (The Chartered Institute of Marketing, 2009; Keegan and Green, 2008). It thus plays a particularly important role in marketing in frequently purchased consumer goods markets.

2.2.1.2. Sales promotions

In recent years, the use of the promotional mix has shifted away from advertising toward sales promotions, and companies are increasingly investing in sales promotion activities to communicate with consumers (Gilbert and Jackaria, 2002; Martínez and Montaner, 2006; Shimp, 1990). Sales promotion, which is the offer of an incentive, plays an essential role in most retailers' communication mixes to induce desired sales results (McGoldrick, 2002; Gilbert and Jackaria, 2002). The large amount of money spent on sales promotions in frequently purchased consumer goods markets makes the effectiveness of sales promotions an important issue to marketers (Gázquez-Abad and Sánchez-Pérez, 2009; Raghubir *et al.*, 2004). Sales promotions include a range of tactical marketing techniques designed within a strategic marketing framework to affect consumers' purchase behaviours and achieve desired marketing objectives via adding value to a product or service (Brassington and Pettitt, 2006; Gilbert and Jackaria, 2002; McGoldrick, 2002; Teunter, 2002; The Chartered Institute of Marketing, 2009). Within the marketing mix, sales promotions as a communication tool have the strongest influence on short-term consumption behaviour and immediate effects on sales (Laroche *et al.,* 2003; Schultz *et al.*, 1998). In a highly competitive market, like the salty snack market, sales promotions work as an effective tool to stimulate consumers to select the promoted brands over those of competitors (Odunlami and Ogunsiji, 2011). In addition, the application of sales promotions tends to work best in frequently purchased consumer goods markets in which products are not expensive and the features of the products can be judged at the point of purchase.

Sales promotions consist of a diverse collection of incentive tools, which differ in their objectives (Alvarez and Casielles, 2005). Summarizing prior research, sales promotions can be classified into four categories: consumer promotions, trade/retailer promotions, business promotions, and sales force promotions, based on their objectives and targeted audience (Blythe, 2014; Kotler and Keller, 2012; Kotler *et al.*, 2008; Brassington and Pettitt, 2006). Consumer promotions are designed and used to shift the time of purchase, stimulate brand exploration, or encourage brand loyalty (Blythe, 2014; Kotler *et al.*, 2008). As the purpose of this research is to support marketers in designing an effective promotional mix to attract and retain consumers, consumer promotions, which aim at consumers, are the focus of this research.

According to Wilkinson *et al.* (1981, 1982, cited in McGoldrick, 2002), price reductions and changes in displays can result in a short-term increase in unit sales. Many researchers in retailing agree with this statement (McGoldrick, 2002; Gilbert and Jackaria, 2002). In particular, when both price reductions and display signs are applied, additional sales will greatly exceed the sum of those produced by each of them used independently (McGoldrick, 2002). In addition, sales promotions, especially price reductions, were found to be able to motivate consumers to try alternatives to extend their market knowledge or buy earlier than planned to maximize their decision’s utility according to what is known about the market (Bucklin *et al.*, 1995, 1998; Alvarez and Casielles, 2005).

Price reductions and displays are two examples of consumer promotion techniques. Gilbert and Jackaria (2002) classify consumer promotion techniques into value-increasing promotions and value-adding promotions, based on the promotion's objectives. In UK supermarkets, "*value increasing promotion, including coupons and price deals, and value adding promotion, including point of purchase display, demonstration, premiums, prizes and loyalty cards*" are widely used to obtain the desired response from customers (Gilbert and Jackaria, 2002, p.315). Based on the target audiences and objectives, Brassington and Pettit (2006) classify consumer promotion techniques into four categories: money-based; product-based; gift-, prize-, or merchandise-based; and store-based sales promotions. Besides these four categories, co-operative sales promotions have been identified as another type of sales promotion in prior research (Blythe, 2014; Kotler and Keller, 2012). In the rest of this section, the techniques of each category of consumer promotions are comprehensively reviewed.

2.2.1.2.1 Money-based sales promotions

Money-based sales promotions are a short-term measure that is widely used by manufacturers or intermediaries to attract price-sensitive brand switchers and/or to make a quick and easy response to a competitor's recent or imminent actions. Marketers use money-based sales promotions either to gain competitive advantages or to defend against competitive actions. The application of money-based promotion techniques should be temporary to avoid negative perceptions about the promoted product from consumers. A long-term money-based promotion may make consumers perceive the promotional price as the real price and make them adjust their perceptions of positioning and quality accordingly. Money-based sales promotions consist of a series of techniques, such as reduced price offers, coupons, and rebates (Brassington and Pettitt, 2006).

Reduced price offers

Reduced price offers, which offer consumers savings off the regular price of a product, are frequently implemented by retailers, by manufacturers, and through joint efforts of manufacturers and one particular retailer (Brassington and Pettitt, 2006; Kotler and Keller, 2012; Kotler *et al.*, 2008). Retailers normally use reduced price offers at the point of sale of the product to attract consumers' attention to the surrounding notices or leaflets advertising the offer (Brassington and Pettitt, 2006). To notify consumers outside of the store, retailers use local press advertising to publish promotional information to communicate with consumers and to motivate consumers to take advantage of the promotion immediately. Such advertising helps retailers to increase store traffic.

Unlike retailers, manufacturers themselves or with one of their retailers frequently implement reduced price offers on the product pack itself to stimulate short-term sales (Brassington and Pettitt, 2006; Kotler and Keller, 2012; Kotler *et al.,* 2008). The information of the reduced price is marked by the manufacturer directly on the label of the product package. Even though the implementation of a reduced price on a pack requires greater expenditure and a longer lead time, the effectiveness of the promotion in stimulating short-term sales still provokes manufacturers to frequently use this technique with or without the cooperation of their retailers.

Coupons

Coupons are a more complex type of money-based sales promotion compared to reduced price offers (Brassington and Pettitt, 2006). They are defined as "*the certificates that give buyers a saving when they purchase specified products*" (Kotler *et al.*, 2008, p.802). Different from reduced price offers, coupons are not price cuts open to all consumers, which avoids cheapening the brand (Brassington and Pettitt, 2006; Kotler *et al.,* 2008). The other advantages of coupons are their flexibility and direct application to the brand, which have made coupons become the main forms of sales promotions in both the US and the UK to promote the adoption of a new brand or to stimulate the purchase of a mature brand. The use of coupons enables consumers to reduce the risks from trying new brands to extend their market knowledge and to decrease costs from exploiting familiar brands (Brassington and Pettitt, 2006).

Manufacturers and retailers distribute coupons using various approaches, such as email, online media and text message systems, magazine and newspaper advertisements, within advertisements in leaflets delivered door to door, at the point of sale and the checkout, and on packs (Brassington and Pettitt, 2006; Kotler and Keller, 2012; Kotler *et al.*, 2008). However, the excessive distribution of coupons results in coupon clutter and a decline in redemption rates, which cannot help manufacturers and/or retailers to achieve the expected marketing results (Brassington and Pettitt, 2006; Kotler *et al.*, 2008). The purpose of implementing coupons is to induce favourable brand switching and attract new users (Brassington and Pettitt, 2006). The application of coupons to mature products and them being redeemed mainly by existing customers will make those consumers become sensitive to prices, which may result in a loss of profits in the long term. Consumer goods companies thus need to target consumers carefully to provide tailored attractive coupons (Kotler *et al.*, 2008).

Rebates

Rebates are cash refund offers occurring after the purchase. The use of rebates enables consumers to receive a refund for part of the purchase price of a product after they have sent a proof of purchase to the manufacturer (Kotler and Keller, 2012; Kotler *et al.*, 2008). The format of the refund can either be hard cash or a substantial coupon provided by manufacturers or retailers (Brassington and Pettitt, 2006). Manufacturers and retailers normally use rebates to increase the value and frequency of purchases via encouraging repeat purchases. However, a rebate scheme is only suitable for promoting big brands with well-known images and quality because the application of rebates may result in a negative perception about a brand that is new to consumers. In addition, from the perspective of consumers, claiming rebates may not be necessary and convenient, particularly when the amount of the cash refund is small.

2.2.1.2.2 Product-based sales promotions

Overcoming the limitations of money-based sales promotions, product-based sales promotions, which are centred on the product itself, rather than the selling price, are widely used by manufacturers and retailers (Brassington and Pettitt, 2006). Product-based sales promotions consist of three techniques: extra products, samples, and product warranties

(Brassington and Pettitt, 2006; Kotler and Keller, 2012).

<u>Extra products</u>

The extra product technique has two primary manifestations in promoting a product. One of the promotional approaches is providing ‘extra free’, for example ‘20% extra free’. Taking advantage of an extra free promotion, consumers can obtain a given extra product for free with the price paid for the product (Blythe, 2014; Brassington and Pettitt, 2006). From the perspectives of consumers, getting an extra product free is being given something in addition, which has higher perceived value than the value obtained from reduced prices (Brassington and Pettitt, 2006). Giving extra products free is especially suitable in responding to a competitor’s price attack because it can shape the value image of a product and avoid a direct price war (Brassington and Pettitt, 2006).

The other promotional approach is ‘buy one get one free’ or ‘two for one’. This offer centres on big rewards, which are equivalent to generous price discounts (Blythe, 2014; Brassington and Pettitt, 2006). Manufacturers and retailers use this promotional approach to dispose of excess stock and shut out competitors by loading up consumers. However, this promotional approach has two limitations. Firstly, the offer of providing an extra product free is costly and expensive for manufacturers and retailers (Brassington and Pettitt, 2006). Secondly, price-sensitive consumers may be attracted by a big reward to take advantage of a promotion to buy a product but then switch to another afterwards to make big savings (Blythe, 2014).

<u>Samples</u>

Samples are trial products offered to consumers for free or at a small charge, providing an opportunity for consumers to experience the product (Kotler and Keller, 2012; Kotler *et al.*, 2008; Brassington and Pettitt, 2006). Sampling thus enables consumers to extend their market knowledge with limited financial costs and encourages consumers to explore the product market. The use of samples is regarded as the most effective promotional tactic to introduce a new product or to create excitement for an existing one (Kotler *et al.*, 2008).

Sampling is particularly popular in the consumer packaged-goods market, as it enables consumers to experience the benefits from purchasing the product and thus make follow-up purchases.

Samples can be distributed using different approaches for different purposes. To inform existing customers of a new product, manufacturers can attach samples to existing products to allow consumers to try the new product (Brassington and Pettitt, 2006). This on-pack sample approach is suitable for manufacturers who are launching a new product in a range. However, as incentives to motivate consumers to explore a product, samples are expensive for marketers, as the marketers need to pay for the free samples. To tackle this limitation and offset the costs from using the most expensive promotional tactics, companies can charge a minimum price for each trial sample, where the cost is insignificant to consumers (Kotler *et al.*, 2008; Brassington and Pettitt, 2006). As trials target the whole audience instead of existing customers only, trials are suitable for manufacturers to introduce new products or new colours or flavours within an existing product line (Brassington and Pettitt, 2006). Distributing samples via print media can be an efficient way to reduce the costs of providing samples. Targeting potential consumers for providing samples enables manufacturers to achieve satisfactory promotional results with minimum cost. Small, light, and non-perishable samples can be distributed via direct mail. Other types of samples may need to be delivered door to door.

<u>Product warranties</u>

Product warranties are explicit or implicit promises made by sellers to consumers to indicate the expectations of greater product or service quality, less financial risk, increased value, and enhanced post-purchase service (Halstead *et al.,* 1993; Kotler and Keller, 2012). This promotional approach is frequently used by marketers in commodity markets as an alternative promotional weapon in price wars (Cooper and Ross, 1985; Kelley, 1988). Product warranties are used as a legal document designed to give consumers certain rights stated in the warranty, which might not directly influence a consumer’s purchase decision but will affect the consumer’s satisfaction with the complaint-handling process and outcome

(Kelley, 1988; Halstead *et al.*, 1993).

2.2.1.2.3 Gift-, prize- or merchandise-based sales promotion

Offering prizes, low-cost goods, or free gifts to complement the main product sale is also a widely used promotion technique for stimulating consumers' purchase behaviours (Brassington and Pettitt, 2006). This promotion technique can be implemented in many ways, which differ in their impacts and objectives as discussed below.

Self-liquidating

Self-liquidating goods are not necessarily directly related to the main product purchase, are offered at a low cost as an incentive to buy the product, and are usually obtained by submitting a specified proof of purchase (Brassington and Pettitt, 2006; Kotler *et al.,* 2008). The self-liquidating premium is sold below its normal retail price to consumers who request it (Brassington and Pettitt, 2006; Kotler *et al.,* 2008; Kotler and Keller, 2012). It is normally just sufficient to cover the costs of the promotion (i.e. including the cost of the premium itself, the postage, and the handling charges). The use of this promotional approach aims to reinforce the brand name and the identity of the product (Brassington and Pettitt, 2006). The low response rate of this offer type, which is because consumers need to pay extra money to benefit from the offer, is the main limitation of this promotional approach (Brassington and Pettitt, 2006).

Free mail-in

Free mail-in refers to a free gift received by a consumer in return for proof of purchase (Brassington and Pettitt, 2006). This promotional approach has become popular in recent years to accelerate and stimulate sales within a certain time period (Brassington and Pettitt, 2006). Unlike self-liquidating offers, free mail-ins have high response rates, as the attraction of free goods encourages consumers to respond to the promotions and make enough additional purchases to become eligible to take advantage of the promotions. This promotional approach is free for consumers but expensive for marketers, who need to cover the costs for providing the promotion. A good plan for the distribution of costs and the promotional period is essential for marketers to achieve desired sales performances.

Free inside or on pack

'Free inside or on pack' is an instant reward approach whereby consumers are offered free gifts contained inside or attached to the outside of a pack (Brassington and Pettitt, 2006). This promotion approach encourages brand switching and motivates consumers to try a different brand (Brassington and Pettitt, 2006; Blythe, 2014). In-pack free gifts are usually offered in child-orientated breakfast cereals to stimulate purchases, as children are not sensitive to prices nor loyal to their favourite brands. On-pack promotions are more attractive than in-pack promotions, as consumers can evaluate the free gifts in advance for making their purchase decisions (Brassington and Pettitt, 2006).

Free with product

'Free with product' offers require consumers to claim free gifts associated with a main product at the checkout (Brassington and Pettitt, 2006). It is a promotional approach similar to on-pack offers.

Customer loyalty scheme

A customer loyalty scheme is a reward programme offered by a manufacturer or retailer for retaining consumers who regularly make purchases with the same company (Brassington and Pettitt, 2006; Blythe, 2014; Kotler and Keller, 2012; Kotler *et al.*, 2008). The purpose of using a customer loyalty scheme is to encourage repeat purchases and to develop lasting customer relationships (Brassington and Pettitt, 2006; Kotler *et al.*, 2008). Alternative currencies, such as trading stamps, points, and tokens, are frequently used by manufacturers and retailers to translate into money-off vouchers for future purchases or gifts that are only available to customers who are loyal to the brand (Brassington and Pettitt, 2006; Blythe, 2014; Kotler and Keller, 2012; Kotler *et al.*, 2008).

Contests and sweepstakes

Contests and sweepstakes are promotions that offer consumers the chance to win very attractive and valuable prizes, such as cars, holidays, and large amounts of cash, by luck (Brassington and Pettitt, 2006; Kotler and Keller, 2012; Kotler *et al.*, 2008). Contests and sweepstakes are commonly used in petrol stations to encourage consumers to be loyal to the same petrol station (Blythe, 2014). Contests require consumers to demonstrate knowledge or analytic or creative skills about a jingle, slogan, guess, or suggestion, which are judged by a panel to select the winner (Brassington and Pettitt, 2006; Kotler *et al.*, 2008). Sweepstakes do not require consumers to demonstrate any knowledge or skills but do ask them to submit their names for the prize draw. For money-based, product-based, and gift-based sales promotions, the more successful the promotions are, the more products will be sold but the higher the costs that the marketers will need to pay (Brassington and Pettitt, 2006). By contrast, the costs for contests and sweepstakes are stable and will not be affected by the success of the promotion. The more successful the promotions are, the less possible it is that an individual consumer will benefit from the promotions. Consumers thus may have negative attitudes toward this type of promotion, especially if they think that the chance to win is very limited. At that point, money-based, product-based, or gift-based promotions may be more appropriate for providing those consumers with immediate benefits.

2.2.1.2.4 Store-based sales promotions

Store-based sales promotions are used in a retail store for marketing purposes, such as stimulating consumer purchases, attracting consumers' attention to promoted products, and encouraging product trials. Point-of-sale displays and demonstrations are two types of store-based sales promotions that occur at the point of purchase or sale (Brassington and Pettitt, 2006; Kotler *et al.*, 2008). As up to 55% of purchase decisions are made in store (Brassington and Pettitt, 2006), sales promotions at the point of purchase have significant influences on consumers' purchase decisions. Point-of-sale displays and demonstrations are essential when consumers enter a store undecided or are ready to switch brands.

Point-of-sale displays

Point-of-sale displays can be implemented by using a series of methods and materials, such as posters, dispensers, displays, dump bins, and other containers to display products, as well as attention-seeking display materials, like flashing signs, videos, and message screens (Brassington and Pettitt, 2006; Kotler *et al.*, 2008). Retailers use point-of-sale displays to inform consumers and to stimulate sales of a product by persuading consumers to try or repurchase a product (Brassington and Pettitt, 2006).

Demonstrations

Demonstrations are powerful in attracting consumers' attention and motivating consumers to try the demonstrated product (Brassington and Pettitt, 2006). Demonstrations are especially effective in promoting new and unusual products, which will benefit from exposure.

2.2.1.2.5 Co-operative sales promotions

Co-operative sales promotions are implemented by two or more companies via pooling their promotional resources to realize marketing objectives (Varadarajan, 1985, 1986). It enables marketers to capitalize on joint opportunities for increasing sales and profits, reducing promotional costs, and improving promotion effectiveness (Varadarajan, 1985, 1986). Co-operative sales promotions consist of bundling, tie-in promotions, and cross-promotions (Blythe, 2014; Kotler and Keller, 2012).

Bundling

Bundling is a pervasive promotional strategy used by manufacturers, wholesalers, and retailers to increase sales or profits; to reduce costs of production, carrying, or delivering; to introduce new products; or to compete with competitors by creating entry barriers (Knutsson, 2011; Richards, 2006; Sharpe and Staelin, 2010; Yang and Lai, 2006; Eppen *et al.*, 1991; Lee and O'Connor, 2003; Sarin *et al.*, 2003; Lawless, 1991; Bakos and Brynjolfsson, 1999). It is defined as the sale of two or more cross-category unrelated products or complementary and related products in a single package for a special reduced price (Knutsson, 2011; Khan and Dhar, 2010; Bae *et al.*, 2011; Guiltinan, 1987; Mulhern and Leone, 1991; Stremersch and Tellis, 2002). Bundling consists of several forms, such as mixed bundling, pure bundling, and brand alliances (Knutsson, 2011). Responding to bundling enables consumers to save money, reduce risks from purchasing a complex product bundle, and save efforts in searching for information (Harris and Blair, 2006; Aribag and Foutz, 2009; Andrews *et al.*, 2010; Sarin *et al.*, 2003; Knutsson, 2011).

Tie-in promotions

Tie-in promotions are a promotional technique implemented by two or more companies to increase pulling power via providing coupons, refunds, and contests to consumers (Kotler and Keller, 2012). It differs from bundling and cross-promotion in the way that the co-operating companies provide the promotions.

Cross-promotion

Cross-promotion is implemented via "*using one brand to advertise a noncompeting brand*" (Kotler and Keller, 2012, p.543).

2.2.2 Promotion proneness

The promotional mix is widely used by marketers to affect consumer decision making and achieve their desired marketing goals (Anic and Radas, 2006). The use of the promotional mix is very expensive for retailers and influences their profitability; the effectiveness of promotions is thus essential for them (Anic and Radas, 2006; Walters and MacKenzie, 1988). The effectiveness of promotions is determined by the redemption rate, which affects the profitability of promotions and the sales volume stimulated by the promotions (Rakesh and Khare, 2012). Consumers have different perspectives, preferences, and attitudes toward promotions and respond to promotions with different actions (Dickson and Sawyer, 1990; Lichtenstein *et al.,* 1993). In prior research, a promotion-prone consumer is more sensitive to promotions and is suggested to be more likely to buy promoted products (DelVecchio, 2005). Promotion proneness, which reflects the general psychological propensity of a consumer to react to the promotional mix, attracts the attention of retailers and is used as a criterion to examine the effectiveness of promotional tools (Anic and Radas, 2006; Danziger *et al.,* 2014; Teunter, 2002). The understanding of promotion proneness enables marketers to understand the influences of promotional mix on consumer purchase behaviours and to tailor promotional strategies to maximize the effectiveness of promotions (Anic and Radas, 2006; Teunter, 2002).

Promotion proneness has been extensively explored in prior research. However, there is no consistent definition of promotion proneness given by researchers (Anic and Radas, 2006). Webster (1965, p.186) defines promotion proneness as "*a function of both the consumer's buying behaviour and the frequency with which a given brand is sold on a deal basis*". Frank *et al.* (1972) describe promotion proneness as a psychological propensity to respond to promotions and define it as an increased propensity to respond to promotions because the form of the promotion positively affects purchase evaluation. Based on the finding that responding to a promotional mix substantially increases the level of purchases (Cotton and Babb, 1978), Hackleman and Duker (1980, p.333) define promotion proneness as "*the propensity of some consumers to purchase products when they are offered on a 'deal' basis*". Similar to the definition provided by Hackleman and Duker (1980), Lichtenstein *et al.* (1990, p.55) define promotion proneness as "*a general proneness to respond to promotions because they are in deal form*". Considering the measurement indicators of promotion sensitivity, Blattberg and Neslin (1990, p.66) propose the definition of promotion proneness as "*the degree to which a consumer is influenced by sales promotion, in terms of behaviors such as purchase timing, brand choice, purchase quantity, category consumption, store choice, or search behavior*". Building on the intrinsic conceptualization and interpretation of promotion proneness, Pechtl (2004) defines promotion proneness as an intrinsic propensity in terms of the emotions and motivations that a consumer may associate with the high–low strategy and the everyday-low-price strategy in retailing. Taking the decision-making process into account, Martínez and Montaner (2006, p.158) propose the definition of promotion proneness as "*the tendency to use promotional information as a reference to make purchase decisions*". Drawing from the literature about promotion proneness, Anic and Radas (2006, p.67) define it as "*consumers' tendency to refer to promotion when purchasing common household products, i.e. consumers' propensity to use, search and take advantage of promoted items*".

Prior research has suggested that promotion proneness refers to individual purchase behaviours in reaction to the promotional mix (Henderson, 1994; Lichtenstein *et al.,* 1995; Montgomery, 1971). It is inferred indirectly from actualized promotion response behaviours as a psychological propensity to buy promoted products and is conceptualized and measured at the psychological level as a construct that affects consumers' promotion responses (Danziger *et al.*, 2014; DelVecchio, 2005; Gupta and Denbleyker, 2015; Lichtenstein *et al.*, 1990; Teunter, 2002). In reactive purchase environments, consumers modify their purchase behaviours based on their past experiences with promotions in order to maximize immediate purchase value by taking advantage of the temporary incentives offered by a promotion (Wakefield and Barnes, 1996). Consumers' purchase decisions, however, are driven by their perceptions of the benefits obtained from purchases, which are subjective and susceptible to contextual influences (Alba *et al.*, 1999; Danziger *et al.*, 2014; Krishna, 1991; Krishna *et al.*, 2002). Drawing from the prior research presented above, this research defines promotion proneness as an individual consumer's psychological propensity to use, search for, and take advantage of promoted products to maximize the perceived immediate purchase value and the psychological benefits from buying a deal.

Summarizing the prior research, promotion proneness is distinguished in two approaches. Table 2.1 shows the classifications of promotion proneness in prior research.

Table 2.1: The classification of promotion proneness

Researcher	Classification Criteria	Type of Promotion Proneness
Gázquez-Abad and Sánchez-Pérez (2009); Pechtl (2004)	Indicators of promotion proneness	Overt promotion proneness
		Intrinsic promotion proneness
Ailawadi *et al.* (2001); Anic and Radas (2006); DelVecchio (2005); Gázquez-Abad and Sánchez-Pérez (2009); Gupta and Denbleyker (2015); Lichtenstein *et al.* (1995); Martínez and Montaner (2006); Rao (2009); Schneider and Currim (1991);	Promotional tools The efforts for information search	Active proneness
		Passive proneness

Pechtl (2004) classifies promotion proneness as overt and intrinsic promotion proneness, based on its indicators. Overt promotion proneness is based on the factors that measure how sensitively a consumer responds to promotions (Gázquez-Abad and Sánchez-Pérez, 2009; Pechtl, 2004). These factors, which are purchase time, brand choice, purchase quantity, category of consumption, store choice, and search behaviour concerning the articles being promoted, are based on consumers' overt behaviour toward promotions (Dickson and Sawyer, 1990; Gázquez-Abad and Sánchez-Pérez, 2009; Pechtl, 2004).

Intrinsic promotion proneness considers the intrinsic and psychological aspects of promotion proneness behaviours and is based on the emotional, motivational, and affective aspects of promotions in purchasing behaviours (Chandon *et al.*, 2000; Gázquez-Abad and Sánchez-Pérez, 2009; Laroche *et al.*, 2001; O'Neill and Lambert, 2001; Pechtl, 2004). For example, deal-prone consumers are found to commit to promotions and to be unable to resist a bargain (Hackleman and Duker, 1980; Henderson, 1994).

In prior research, researchers have also classified promotion proneness based on the required amount of information searching about promotions and the types of promotion tools that attract consumers. In this case, Schneider and Currim (1991) first distinguished active proneness from passive proneness by investigating consumers' reactions toward store features (i.e. advertisements in store flyers or local newspapers), coupons, and in-store displays. They define active promotion proneness as sensitivity to store features and coupons, which need to be located with relatively intensive searches prior to shopping. On the contrary, they define passive promotion proneness as sensitivity to in-store displays, which requires limited searches in the store environment. Building on the results of Schneider and Currim (1991) and Bucklin and Lattin (1991), Ailawadi *et al.* (2001) divide promotion proneness into proneness to out-of-store promotions and proneness to in-store promotions. Similar to the definition of active promotion proneness, proneness to out-of-store promotions requires some efforts from the consumer to locate the promotions outside of the stores. By the same token, proneness to in-store promotions is related to the passive promotion proneness proposed by Schneider and Currim (1991). This proneness requires limited effort from consumers, as in-store promotions are developed at the point of sale and can be easily recognized and located by consumers when shopping (Ailawadi *et al.,* 2001). In general, an active promotion-prone consumer is more likely to engage in intensive searches for locating out-of-store promotions than a passive promotion-prone consumer is. Active out-of-store promotion proneness and passive in-store promotion proneness are not mutually exclusive (Schneider and Currim, 1991). An active promotion-prone consumer may not invest time and efforts in searching for special offers before shopping but may react impulsively to a promotion where a brand is displayed/featured (Schneider and Currim, 1991).

The differentiation between active and passive promotion proneness suggests that promotion proneness varies across promotion classifications (Gázquez-Abad and Sánchez-Pérez, 2009). However, not all researchers agree with this argument. Some studies have found that consumers are likely to have the same purchase behaviours in response to any type of promotion, and promotion proneness is thus regarded as a generalized construct (Price *et al.*, 1988; Lichtenstein *et al.*, 1997; Shimp and Kavas, 1984). The generalized construct implies that targeting a segment of consumers who are prone to a type of promotion enables marketers to identify the consumers who are prone to all types of promotions (Lichtenstein *et al.*, 1997). Other studies have found that promotion proneness differs across consumers and the type of promotion (Blattberg and Neslin, 1990). Those studies insist that promotion proneness is domain specific, which implies that consumers may be sensitive and respond to a certain type of promotion but insensitive to others (Ailawadi *et al.*, 2001; Schneider and

Currim, 1991). Table 2.2 summarizes the studies with their supporting arguments regarding the promotion proneness of consumers to types of promotions.

Table 2.2: Promotion proneness across types of promotions

Argument	**Studies**
Generalized across type of promotions	Price *et al.* (1988); Lichtenstein *et al.* (1997); Shimp and Kavas (1984)
Varies across promotion classifications	Ailawadi *et al.* (2001); Gázquez-Abad and Sánchez-Pérez (2009); Schneider and Currim (1991)
Varies across each type of promotion	Bawa *et al.* (1997); Blattberg and Neslin (1990); Lichtenstein *et al.* (1995, 1997)

In prior research, promotion proneness has been widely regarded as a psychological propensity to buy promoted products (Danziger *et al.*, 2014; DelVecchio, 2005; Gupta and Denbleyker, 2015; Lichtenstein *et al.*, 1990; Teunter, 2002). If promotion proneness is a common consumer trait, consumers should have similar or the same sensitivity to promotions across product categories (Ainslie and Rossi, 1998). In other words, consumers who are prone to taking advantage of promotions to buy a product are expected to buy other products on promotion. However, prior studies have not achieved conclusive results about the promotion proneness of a consumer in different product markets. Some studies have found consistent promotion proneness of consumers across multiple product categories (Ainslie and Rossi, 1998; Bawa and Shoemaker, 1987; Blattberg *et al.*, 1978; Seetharaman *et al.*, 1999), but others have not found consistent results (Bell *et al.*, 1999; Manchanda *et al.*, 1999; Narasimhan *et al.*, 1996; Teunter, 2002). Teunter (2002) summarizes seven category characteristics that are related to and influence promotion proneness from prior research. These category characteristics are "*(1) the number of brands within a category, (2) the average price level within a category, (3) the average interpurchase time of a category, (4) storability, (5) perishability, (6) impulse sensitivity, and (7) category promotion frequency*" (Teunter, 2002, p.155). Categories with deeper, infrequent promotions; good storability; and high penetration with short purchase cycles receive higher promotional responses from consumers (Bell *et al.*, 1999; Narasimhan *et al.*, 1996; Raju, 1992).

Purchasing of promoted products and promotion proneness are positively correlated (Anic and Radas, 2006; Schneider and Currim, 1991; Umesh *et al.*, 1989). Umesh *et al.* (1989) found that promotion-prone consumers bought more products on promotion than those who were not promotion prone. Anic and Radas (2006) believe that consumers who engage in purchasing promoted products are more promotion prone. Even though there is little consensus in prior research on how promotion proneness must be measured, promotion proneness reflects and can be quantified as the percentage of purchases made on a promotion basis, according to conceptual findings (Hackleman and Duker, 1980; Henderson, 1994; Montgomery, 1971; Rao, 2009; Wierenga, 1974).

In prior research, consumers' promotion proneness has been measured by using different types of data, such as self-report data (Lichtenstein *et al.*, 1995) and redemption intention data (Bawa *et al.*, 1997) obtained from experiments, as well as actual transactional data (Hackleman and Duker, 1980; Henderson, 1994; Webster, 1965). Summarizing prior research, using actual transactional data to measure promotion proneness has three advantages over using experimental data. As mentioned above, consumers' promotion proneness is associated with and can be inferred from their observed purchase behaviours (Anic and Radas, 2006; Schneider and Currim, 1991; Umesh *et al.*, 1989). Using transactional data enables marketers to get insights from consumers' actual purchase behaviours, rather than their perceived and imaginary purchase behaviours (Teunter, 2002). Secondly, consumers' stated preferences might not correspond closely to their actual behaviours and thus are not reliable to be used to measure their actual purchase behaviours (Hensher *et al.*, 1988; Wardman, 1988). Thirdly, consumers' decision-making process is complicated and influenced by many unobservable and situational factors. Using consumers' transactional data over a long period to measure their purchase behaviours enables marketers to minimize the deficiency resulting from not considering the unobservable and situational factors (Teunter, 2002). In general, using transactional data to measure promotion proneness enables marketers to understand consumers' actual behaviours toward promotions, which can then be validated by using consumers' self-report data (Teunter, 2002).

Webster (1965) first proposed a measurement for quantifying promotion proneness by dealing with transactional data to reflect a household's propensity to promotions. Webster (1965, p.186) measured promotion proneness as a "*function of both the consumer's buying behaviour and the frequency with which a given brand is sold on a deal basis*". The proposed formula for calculating promotion proneness is presented in Formula 2.1.

Promotion proneness index =

$$\sum_{j=1}^{n}\left(\frac{\textbf{The total number of brand } j \textbf{ purchases on sale made by consumer } i}{\textbf{The total number of brand } j \textbf{ purchases made by consumer } i} - \frac{\textbf{The total number of brand } j \textbf{ purchases on sale in a sample}}{\textbf{The total number of brand } j \textbf{ purchases in a sample}}\right) * \left(\frac{\textbf{The total number of brand } j \textbf{ purchases by consumer } i}{\textbf{The total number o fpurchases of consumer } i}\right) \quad \textbf{(2.1)}$$

The proposed formula for measuring promotion proneness is relatively sophisticated (Blattberg and Neslin, 1990; Teunter, 2002) and is suitable for measuring a consumer's promotion proneness when the consumer makes all the purchases in a particular store. However, in practice, consumers freely choose to make purchases from a large number of retail stores in a city. As different retail stores may provide different promotions to consumers, the absence of promotions of a product in one store does not imply the absence of promotions of the same product in all stores. Consumers still have opportunities to take advantage of promotions to make purchases due to their shopping mobility across retail stores. To accurately measure the promotion proneness of a consumer, marketers need to have all the transactional records of the consumer and comprehensive promotion information across all retail stores. In practice, firstly, it is impossible for marketers to collect all the required data to measure promotion proneness based on the formula developed by Webster (1965). Secondly, even though the required data can be collected, handling and dealing with the large amount of data to generate insights into promotion proneness might be difficult to implement.

Cotton and Babb (1978) found that the availability of promotions results in a substantial increase in sales. They thus used the percentage increase in consumption during a promotion period to measure a consumer's response to promotions. Building on the findings of Cotton and Babb (1978), Hackleman and Duker (1980) defined promotion proneness and constructed three measurements of promotion proneness for individual consumers based on the principle of promotion proneness. The principle of promotion proneness refers to consumers' psychological propensity to purchase products when the products are on promotion (Cotton and Babb, 1978; Hackleman and Duker, 1980). The first proposed measurement was the percentage of promotion purchases relative to the total number of purchases. The second measurement took the price of purchases into account and quantified promotion proneness as a percentage of the expenditures on promotion purchases relative to the total expenditures on all purchases. The third measurement considered multiple unit purchases and quantified promotion proneness as the total number of units purchased on promotion out of the total number of units purchased. These three measurements of promotion proneness were also implemented by dealing with transactional data. Compared to the measurements provided by Webster (1965), these three measurements have relatively simple calculations and are easy to implement when dealing with a large amount of data.

Consumers are encouraged by and take advantage of promotions to switch brands, stockpile, accelerate purchases, seek and try new products, and/or spend larger amounts (Gázquez-Abad and Sánchez-Pérez, 2009; Gupta and Denbleyker, 2015; Pechtl, 2004; Teunter, 2002). They are not only induced by the immediate savings from purchasing a product on promotion but also motivated and influenced by their impulsiveness, innovativeness, and shopping enjoyment (Martínez and Montaner, 2006). Consumers make trade-offs between maximizing immediate value by taking advantage of promotions and extending market knowledge via exploring the market in their purchase decision-making processes. In the next section, consumers' exploration and exploitation behaviours are presented.

2.3 Exploration and Exploitation

Exploration and exploitation are key concepts of the multi-armed bandit problem. The multi-armed bandit problem is faced by a decision maker when determining a strategy for sequential selections from no fewer than two options to maximize the total expected rewards over all selections (Macready and Wolpert, 1998). This problem has been applied in diverse fields, such as organizational learning, organizational design, statistics, control, knowledge management, adaptation, and economics (Audibert *et al.*, 2008; Brown and Eisenhardt, 1997; Brown and Duguid, 2001; Lavie *et al.*, 2010; March, 1991; Tushman and O'Reilly, 1996). Consumer purchasing in a reactive environment is a version of the multi-armed bandit problem (Ishikida and Varaiya, 1994). When a consumer is choosing from different brands which are of more or less identical features, it might appear equally "rational" either to stick with the same brand as before or to buy a different brand (Ehrenberg, 1988). In purchases, consumers determine a strategy for sequential selection from more than one brand in a product category by balancing exploration and exploitation to either optimize the total expected utility over all their selections or maximize the immediate utility in one purchase (Erdem and Keane, 1996; Hoyer, 1984; Macready and Wolpert, 1998; Mahajan and Teneketzis, 2008; March, 1991). As consumers' past choices and purchase experiences can significantly affect their current and future purchases, the decisions of consumers are made in a reactive environment (Farias and Megiddo, 2005). From the perspective of the multi-armed bandit problem, consumer purchases in a reactive environment involve a class of sequential resource allocation problems concerning decision-making strategy adoption and brand selection (Mahajan and Teneketzis, 2008).

2.3.1 The concepts of exploration and exploitation

In the multi-armed bandit literature, the definitions of exploration and exploitation are ambiguous (Gupta *et al.*, 2006). Some studies, including those of Baum *et al.* (2000), Benner and Tushman (2002), Gupta *et al.* (2006), He and Wong (2004), and March (1991), have argued that both exploration and exploitation are associated with learning and innovation and can be differentiated from each other in terms of the learning type. By contrast, others, including Rosenkopf and Nerkar (2001), Vassolo *et al.* (2004), and Vermeulen and Barkema (2001), have embraced the idea that only exploration activities are associated with learning and innovation because exploitation activities are associated with past knowledge adoption without learning.

In social science, all activities include at least some learning and innovation (Gupta *et al.*, 2006; March, 1991). For instance, in a reactive environment, consumers may learn from their experiences generated from consistently buying one or some small number of brands over time in a product category (Ehrenberg, 1988). Thus, both exploration and exploitation in brand selection are believed to be associated with learning and innovation. Specifically, exploration refers to the pursuit of new knowledge and information via searching and taking risks to try new products or brands (Gupta *et al.*, 2006; Lavie *et al.*, 2010; Levinthal and March, 1993; March, 1991). Exploitation refers to the learning and development of existing knowledge via local searches, experiential refinement, and the selection and implementation of existing routines (Baum *et al.*, 2000; Lavie *et al.*, 2010; Levinthal and March, 1993; March, 1991).

Bandit problems explore the balance between exploration and exploitation that is necessary for effective optimization (Macready and Wolpert, 1998). Due to the limited available resources, individuals make conscious decisions to allocate resources to support exploration or exploitation activities (Lavie *et al.*, 2010).

According to Gupta *et al.* (2006), for individuals, exploration and exploitation are mutually exclusive and treated as competing aspects of individual decisions. In each purchase, consumers either stick with their current best choice based on their past purchasing experiences to maximize immediate purchase value or choose to try alternatives to extend their market knowledge and discover a better choice that beats the current best choice (Audibert *et al.*, 2008; Lavie *et al.*, 2010). However, the findings on the association between exploration and exploitation are inconsistent. Some studies have found that exploration and exploitation coexist and complement each other in organizations (Katila and Ahuja, 2002; Knott, 2002; Rothaermel and Deeds, 2004). No matter what the association between exploration and exploitation is, inherent trade-offs between them exist and should not be negated (Lavie *et al.*, 2010). The tension between exploration and exploitation for utility optimization plays a critical role in multi-armed bandit problem solving (Macready and Wolpert, 1998). From the perspective of the multi-armed bandit problem, the expected utility from purchases is represented as a series of incremental rewards gained from the purchases (Ishikida and Varaiya, 1994). Consumers evaluate brands and make purchase decisions on the basis of their experiences and learning gained from exploration and exploitation activities in a product category (Heilman *et al.*, 2000). Their decision-making and evaluation process is explained by and reflected from their exploration and exploitation activities in purchases (Gupta *et al.*, 2006; Hoyer, 1984).

2.3.2 Dynamic choice process – exploration and exploitation behaviours in brand selection

From the perspective of the multi-armed bandit problem, all purchase decisions are associated with benefits and costs. Consumers regard the opportunities for discovering a better choice and obtaining product category knowledge and experiences as the benefits from purchases (Heilman *et al.*, 2000). The costs of purchases are always associated with obtaining information in various ways (Heilman *et al.*, 2000). Summarizing the literature, consumers normally collect information about a product category from advertising, critic reviews, word of mouth, and their own experiences from trying out unfamiliar brands (Erdem and Keane, 1996; Foxall, 1993; Heilman *et al.*, 2000; Neelamegham and Jain, 1999). Getting information through advertising has a low cost. Therefore, the heavily advertised big brands will be chosen before lesser-known brands by consumers who are new to a market (Erdem and Keane, 1996; Heilman *et al.*, 2000). Obtaining information through trying out unfamiliar brands has potentially high costs because of the risks of buying a brand that does not meet expectations. Thus, consumers' choice behaviour is thought to be driven by two contradictory needs: the need to gain market knowledge and the need to avoid risks (Erdem and Keane, 1996; Heilman *et al.*, 2000). On the one hand, they are eager to gain more information about alternatives to reduce uncertainties and risks in making choices; on the other hand, they are averse to risks from obtaining new information and are inclined to choose familiar brands, rather than try risky alternatives (Erdem and Keane, 1996; Heilman *et al.*, 2000). In other words, consumers adapt their strategies for sequential selections from a set of brands to optimize the expected utility by making trade-offs between exploration and exploitation (Macready and Wolpert, 1998; Payne *et al.*, 1993). For instance, when consumers perceive that the purchase of the same brand is reasonably rewarding, they will buy the brand consistently (Evans *et al.*, 2009). In terms of the psychological process (i.e. decision making and evaluation) of consumers, exploitation behaviours can be differentiated into two extreme subsets of behaviours – brand loyalty and habitual purchases (Odin *et al.*, 2001; Hoyer, 1984). When consumers have sufficient category experiences and knowledge, they will intend to be brand loyal and will exploit their preferred brands without further exploration.

Under uncertainties, consumers' past experiences in brand selections associated with or without promotional mix elements affect their current choices due to the change of their information set from market learning (Erdem and Keane, 1996; Foxall, 1993; Heilman *et al.*, 2000; Luo *et al.*, 2015; Neelamegham and Jain, 1999; Yang *et al.*, 2015). This decision-making problem is a typical dynamic choice problem in the marketing literature (Yang *et al.*, 2015). The study of exploration and exploitation behaviours in brand selection explains and enables marketers to understand the dynamic choice process of consumers. Both consumers' intrinsic knowledge about the product category gained from information searches and the external market changes (including promotions and price reductions) influence their choice process (Erdem and Keane, 1996; Heilman *et al.*, 2000). Heilman *et al.* (2000) divide the dynamic choice process into the following three learning stages based on consumers' willingness in information collection and risk taking.

Consumers start their learning journey in purchases when they first enter a market. To minimize risks at the beginning of the learning journey, consumers normally consistently buy the heavily advertised big brands with low perceived risks over some time to gain market knowledge (Erdem and Keane, 1996; Heilman *et al.*, 2000; Hoyer, 1984). Those consumers have low levels of involvement in the product category and initially have little incentive to engage in learning (Heilman *et al.*, 2000; Hoyer, 1984). They have low levels of brand sensitivity in the product category and experience difficulties in distinguishing among brands due to their lack of market knowledge, which discourages them from engaging in exploring unknown brands for the purpose of information seeking (Heilman *et al.*, 2000; Hoyer, 1984).

According to the definition and characteristics of repeat purchase behaviours (Hoyer, 1984; Odin *et al.*, 2001), they refer to habitual purchase behaviours. From the perspective of the multi-armed bandit problem, in order to avoid risks in purchases, consumers will stick to the big brands with maximum expected utility in the product category, rather than exploring and trying risky alternatives (Erdem and Keane, 1996; Hoyer, 1984). The exploitation activities in purchases are carried out based on consumers' existing knowledge and learning gained via local searches from critic reviews, word of mouth, and advertising about brands in the product category (Erdem and Keane, 1996; Gupta *et al.*, 2006; Hoyer, 1984).

The increase in market knowledge via consistently exploiting big brands gradually improves the ability of consumers to differentiate among brands in the market (Che *et al.*, 2015; Heilman *et al.,* 2000; Agrawal, 1995; Strang *et al.*, 1979). Consumers at stage two may start to sample lesser-known brands to pursue and acquire knowledge about alternatives and gain more experiences in the product category (Erdem and Keane, 1996; Heilman *et al.*, 2000). These sampling activities for obtaining experiences and learning reflect and represent consumers' exploration behaviours in purchases (Gupta *et al.*, 2006). During the brand sampling process for learning, consumers may buy a subset of brands consistently when they think that the expected exploration costs exceed the expected rewards (Erdem and Keane, 1996). The exploitation activities in the second stage, which are different from the exploitation activities in habitual behaviours, are carried out on the basis of the existing experiences and learning gained from the previous exploration and exploitation activities (Gupta *et al.*, 2006; Heilman *et al.*, 2000).

As the increased market knowledge and learning gained from exploration and exploitation activities make consumers aware of more attributes and able to distinguish among brands, consumers are highly motivated to conduct exploration activities at this stage (Heilman *et al.*, 2000). The increase in market knowledge reduces consumers' perceived risks from purchasing the lesser-known brands and increases their perceived benefits of making better-informed decisions (Che *et al.,* 2015; Erdem and Keane, 1996; Heilman *et al.,* 2000; Yang *et al.,* 2015). Consumers make their purchase decisions on the basis of utility optimization via making trade-offs between exploration and exploitation (Heilman *et al.*, 2000; Macready and Wolpert, 1998). After carrying out exploitation activities over a certain period of time, in reactive environments, the exploration activities for learning may be resumed with the incentives of market changes, such as price changes, coupon promotions, and advertisements, in favour of competitive brands (Erdem and Keane, 1996; Heilman *et al.*, 2000; Amine,

1998).

To summarize, consumers in stage two can be regarded as learners who have the increased experiences and learning gained from their exploration and exploitation activities (Gupta *et al.*, 2006; Heilman *et al.*, 2000). They have an increased level of involvement and brand sensitivity in the product category and gradually develop their brand preferences based on their pre- and post- purchase evaluations in terms of the expected utility associated with the exploration and exploitation activities (Amine, 1998; Hoyer, 1984). With the development of consumers' brand preferences, extra information about the product market will not be perceived as valuable as before (Heilman *et al.*, 2000).

Heilman *et al.* (2000) found that after a certain period of exploration, information searching gradually decreases and consumers become loyal to a subset of preferred brands. Che *et al.* (2015) explain this finding by suggesting that the motivation for information searching decreases with the reduction of perceived uncertainty about the market. According to the definition and characteristics of brand loyalty, loyal consumers have high levels of involvement and brand sensitivity and can differentiate among brands in the product category in terms of expected utility (Amine, 1998; Lodorfos *et al.*, 2006). In stage three, extra information searching and learning have no value because the uncertainties associated with brands in the product category are considered as limited by these experienced consumers (Heilman *et al.*, 2000). In a stable market, consumers with full market knowledge are certain about the market. It might be impossible for these consumers to extend their market knowledge via trying alternatives. Instead of exploring the market, these consumers will consistently buy their preferred brands, which were evaluated and perceived to have the maximum utility on the basis of their existing experiences and learning gained from exploration and exploitation activities (Hoyer, 1984; Erdem and Keane, 1996; Heilman *et al.*, 2000; Gupta *et al.*, 2006). As they clearly understand the value of each brand in the product category, small changes of prices in the product category may not be able to influence their purchase decisions (Foxall, 1993; Heilman *et al.*, 2000). However, in a turbulent market, in which the characteristics of existing brands change and new brands are introduced, the motivation for learning may remain (Che *et al.*, 2015). Thus, consumers are not expected to become entirely brand loyal in a turbulent market.

Overall, exploration and exploitation activities not only explain and reflect the dynamic choice and evaluation process of consumers (Hoyer, 1984) but also can be used to differentiate and explain repeat purchase behaviours (Gupta *et al.*, 2006; Heilman *et al.*, 2000; Hoyer, 1984). As presented above, exploration and exploitation activities are determined and carried out on the basis of the existing experiences and knowledge about a product category gained from prior purchases (Gupta *et al.*, 2006; Heilman *et al.*, 2000). Those experiences and knowledge influence the decision-making and evaluation process of consumers (Hoyer, 1984). Thus, the experiences and knowledge gained from exploration and exploitation activities are essential in predicting consumers' brand selection behaviours (Heilman *et al.*, 2000).

2.3.3 Relationships among promotion proneness, market knowledge, and exploration and exploitation behaviours

Brand choice is influenced by market changes (i.e. the promotional mix), such as price reductions, coupon offers, and advertisements, or an interaction between market changes and consumers' experiences and knowledge (Deighton *et al.*, 1994). Researchers have reached an agreed conclusion that purchase and brand usage history influences the reactions of consumers to price reductions, coupon promotions, and advertisements. However, different researchers have different views about the effects of purchase and brand usage history on consumers' reactions to the promotional mix (Bridges *et al.*, 2006; Heilman *et al.*, 2000; Hsieh and Chang, 2004). Some studies have suggested that expert consumers primarily rely on their direct experiences gained from exploration and exploitation activities and use these as the dominant information source for forming commitment attitudes and making purchase decisions (Bridges *et al.*, 2006; Deighton *et al.*, 1994; Fazio and Zanna, 1978; Fazio *et al.*, 1982, 1989; Heilman *et al.*, 2000; Krishnamurthi and Raj, 1991; Smith and Swinyard, 1983). Their experiences in a product category make them better able to understand and be more aware of their own likes and dislikes, as well as the utility of various brands in the product category; their choice processes are thus less likely to be influenced and driven by the presence of the promotional mix (Heilman *et al.*, 2000; Kopalle and Lehmann, 2006). On the contrary, advertising, reduced prices, and coupon promotions in favour of small-share brands work well in influencing new consumers' habitual behaviours and motivate them to switch from big brands to the small-share brands in the product category to extend their market knowledge with reduced costs (Deighton *et al.*, 1994; Chakrabortty *et al.*, 2013; Krishnamurthi and Raj, 1991; Heilman *et al.*, 2000).

Other studies have argued that experienced consumers are motivated to buy brands on promotion because their rich market knowledge and experiences enable them to distinguish and identify the brand offering a better deal in the product category (Bettman and Park, 1980; Johnson and Russo, 1984; Moorthy *et al.*, 1997). They are more responsive to the price-related and promotional activities of all brands in a product category after they have made a promotional purchase of any brand (Bridges *et al.*, 2006). According to Che *et al.* (2015), the motivation for exploration shifts from market learning to money saving over time in the purchase lifecycle. Market changes in the product category thus work well in influencing the purchase decisions of experienced consumers (Bridges *et al.*, 2006). Besides the stated two conflicting points of view regarding the reactions of consumers with different levels of market knowledge to the promotional mix, Bridges *et al.* (2006) argue that these two conflicting points of view coexist in practice. In other words, a consumer with rich market knowledge and experiences may be either vulnerable to the presence of the promotional mix or reluctant to adapt their purchase decisions in response to the promotional mix.

Even though there are no conclusive findings about the relationship between market experiences and promotion proneness, the findings about the relationship between market experience and information searching (i.e. exploration and exploitation behaviours) are consistent in prior research. As presented in Section 2.3.2, the relationship between information searching and market experience presents as an inverted U-shape (Bettman and Park, 1980; Heilman *et al.*, 2000; Johnson and Russo, 1984; Moorthy *et al.*, 1997), which is demonstrated in Figure 2.2.

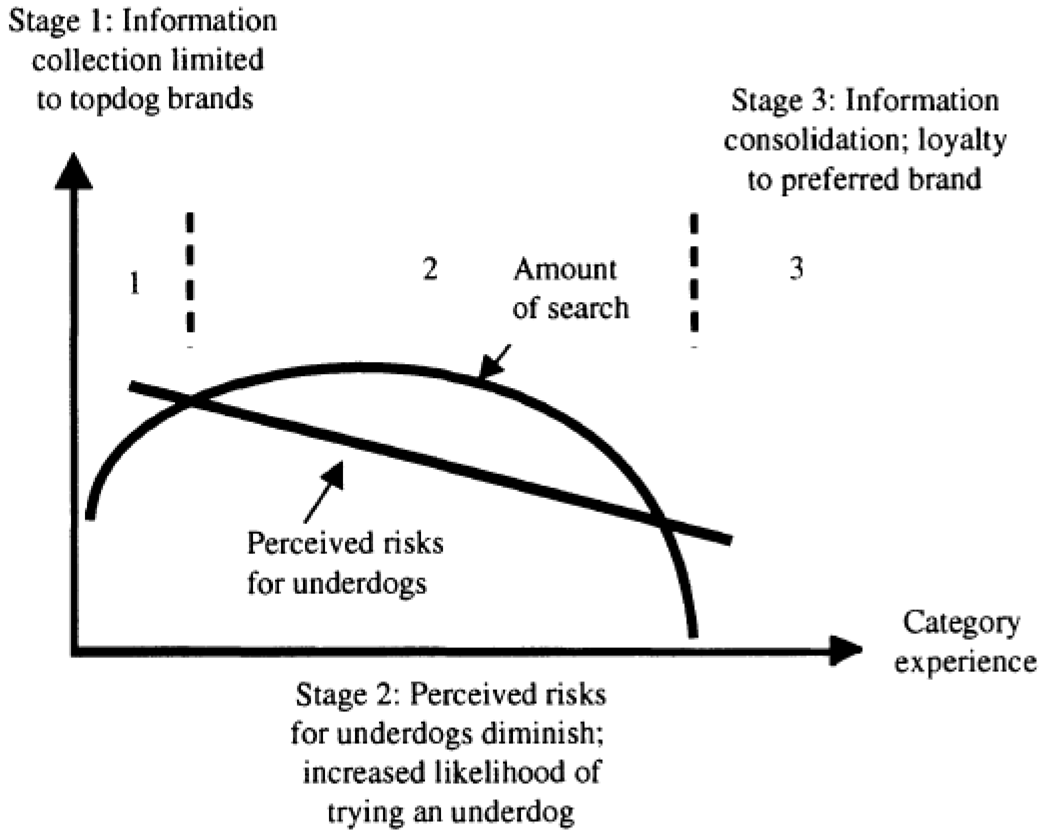

Figure 2.2: Dynamic choice process (Heilman *et al.*, 2000, p.141)

With the increase in market knowledge and experiences, the amount of information searching gradually increases to a maximum before decreasing toward a minimum (Heilman *et al.*, 2000). When consumers are new to a product market, they perceive lesser-known brands as having higher risks (Agrawal, 1995; Strang *et al.*, 1979). The perceived high costs for information searching and the inability to differentiate among brands due to the lack of market knowledge make consumers reluctant to search for information via exploring lesser-known brands (Heilman *et al.*, 2000). The increase in market knowledge and experiences improves consumers' ability to differentiate among brands in a product category and makes them more certain about the product category, which results in a decrease in perceived risks for lesser-known brands (Agrawal, 1995; Heilman *et al.*, 2000; Strang *et al.*, 1979). Consumers with expertise and experiences in a product category are more willing to take risks and try alternatives than other consumers are (Foxall, 1993; Heilman *et al.*, 2000; McDonald *et al.*, 2003). These consumers thus engage in additional exploration activities and are more willing to search for information about lesser-known brands (Heilman *et al.*, 2000). Even though the perceived risks for lesser-known brands gradually decrease with the increase in market knowledge and experiences, the rewards from further exploring a product market might not always increase, as sufficient market knowledge may enable consumers to make a good purchase decision with little uncertainty (Heilman *et al.*, 2000; Moorthy *et al.*, 1997). Consumers are thus reluctant to participate in exploration activities with limited incremental value and become loyal to a subset of preferred brands that provide the greatest utility.

In the purchase lifecycle, consumers make choices according to their experiences obtained from exploration and exploitation activities and their proneness to the promotional mix in the market (Che *et al.*, 2015; Luo *et al.*, 2015; Ratchford, 1980; Teunter, 2002). In purchase decision making, consumers make trade-offs between the product attributes and the price paid for the product (Gázquez-Abad and Sánchez-Pérez, 2009). Brand-loyal consumers, who are inclined to exploit their preferred brands, attach more importance to the product attributes than to the price of the product (Massy and Frank, 1965; Wakefield and Barnes, 1996). On the contrary, non-loyal consumers, who are inclined to explore different brands in a product market, attach more importance to the price than to the product itself (Bawa and Shoemaker, 1987; Webster, 1965). The majority of prior research has indicated that brand-loyal consumers are less responsive to promotions and that non-loyal consumers are more prone to promotions (Gázquez-Abad and Sánchez-Pérez, 2009; Krishnamurthi and Raj, 1991; Neslin *et al.*, 1985; Schneider and Currim, 1991; Wernerfelt, 1986, 1991; Yoon and Tran, 2011). In addition, promotion-prone consumers are more likely to engage in exploration activities and take advantage of promotions to buy a wider variety of brands to extend their market knowledge (Montgomery, 1971; Schneider and Currim, 1991; Webster, 1965; Wirtz and Chew, 2002). In general, promotion proneness is positively related to exploration behaviours and negatively related to exploitation behaviours (Blattberg and Neslin, 1990; Dodson *et al.*, 1978; Laroche *et al.*, 2003; Lichtenstein *et al.*, 1997; Lim *et al.*, 2005; Kumar and Advani, 2005). However, Ailawadi *et al.* (2001) and Martínez and Montaner (2006) did not find a clear and significant relationship between promotion proneness and exploration and exploitation behaviours. Thus, the argument about the strictly negative relationship between promotion proneness and brand loyalty has been weakened by those studies.

2.3.4 The brand choice model in a reactive environment

The Dirichlet model amalgamates several earlier brand performance measures and models and is regarded as an advanced and comprehensive empirical model for measuring repeat purchase behaviours within a product category in marketing (Bassi, 2011; Evans *et al.*, 2009; Uncles *et al.*, 1995). It was developed to measure consumer behaviours in a stationary market without considering consumers' purchase experiences and the influence of market change (Bassi, 2011; Goodhardt *et al.*, 1984; Uncles *et al.*, 1995). This model assumes that consumers' purchase decisions are independent from each other and are not influenced by their previous purchase experiences and marketing strategies (Bassi, 2011; Goodhardt *et al.*, 1984). The assumptions of this model violate the conception of the dynamic choice process, which thus limits the ability of the model to measure consumer brand selection behaviours reflecting the dynamic choice process.

The Dirichlet model describes purchase frequency and brand choice in a stationary and unsegmented market through counting the number of purchases of each brand that a consumer makes in a time period (Bassi, 2011; Goodhardt *et al.*, 1984). This model measures consumer behaviours in terms of brand market share and market penetration rate in the whole product market, rather than in terms of each consumer's decision-making behaviour (Uncles *et al.*, 1995; Goodhardt *et al.*, 1984). It is thus not suitable for measuring and predicting the brand selection behaviour of an individual consumer in a reactive environment.

In a reactive environment, the consumers' experiences and knowledge about a product category and the market change in the product category influence consumers' decision-making and evaluation process (Heilman *et al.*, 2000; Hoyer, 1984; Odin, *et al.*, 2001). In the decision-making process, consumers optimize their rewards by balancing learning from their existing knowledge and trying alternatives to increase their category knowledge, which is known as the exploration and exploitation trade-off in reinforcement learning (Vermorel and Mohri, 2005). Exploration and exploitation can be quantified to measure consumers' brand selection behaviours and reflect the associated dynamic choice process (Hoyer, 1984; Heilman, *et al.*, 2000). Many algorithms for measuring bandit problems in studying the trade-offs between exploration and exploitation have been proposed in the last two decades (Kuleshov and Precup, 2010; Vermorel and Mohri, 2005; Farias and Megiddo, 2005). However, to the researcher's knowledge, there has been no bandit algorithm specifically proposed for measuring consumers' exploration and exploitation activities in a reactive environment. The bandit algorithms in the literature measure exploration and exploitation by using the rewards observed and expected by decision makers. However, consumers' observed and expected rewards do not directly show in store scanner data (Bronnenberg *et al.*, 2008). Thus, prior proposed algorithms and models for quantifying exploration and exploitation activities cannot be used to measure brand selection behaviours in reactive environment by analysing store scanner data (Bronnenberg *et al.*, 2008; Bassi, 2011; Goodhardt *et al.*, 1984; Uncles *et al.*, 1995).

In prior research, dynamic choice problems have been modelled by using dynamic discrete choice models (Ching *et al.*, 2012; Chintagunta *et al.*, 2012; Dube *et al.*, 2014; Hartmann and Nair, 2010; Huang *et al.*, 2015; Misra and Nair, 2011; Rust, 1987, 1994; Toubia and Stephen, 2013; Yao and Mela, 2011). However, this approach requires numerical integration, repeated optimization, large state space, more assumptions about the problem, and intensive and complicated computations (Rust, 1994). It is thus not suitable for dealing with a large amount of data to measure consumers' brand selection behaviours in a frequently purchased consumer goods market. For example, in the salty snack market, around 100 brands are available for purchase in a typical US market. Suppose consumers make decisions by considering whether a brand can provide new market information and whether the price of the brand is acceptable. In this typical scenario, simply keeping track of which brands a consumer purchases requires 2^{100} possible states. The required large state space may make the estimation of a traditional dynamic discrete choice model difficult using the tools and computers available today (Yang *et al.*, 2015).

The idea that sales promotions are associated with exploration and exploitation behaviours is supported by substantive evidence in prior research (Bawa and Shoemaker, 1987; Blattberg and Neslin, 1990; Niraj *et al.* 2008; Pieters *et al.*, 2007; Song and Chintagunta, 2007; van Heerde and Bijmolt, 2005). Bucklin *et al.* (1998) modelled brand choice by using a multinomial logit for each particular household in purchasing each brand. In the brand choice model, exploitation behaviours were measured as the within-household market share of each brand through dealing with the store scanner data. Seven particular brands were targeted and selected for use in this model to find out consumers' loyalty to those brands in response to promotions. The utility derived by a household for purchasing a particular brand at a particular time was measured in terms of exploitation behaviours, price, and promotion of the brand. This model is not feasible for measuring consumers' exploration and exploitation behaviours when a large number of brands are available in a product market, as the model involves a large number of complicated calculations. In addition, the measurement of exploitation behaviours in terms of the within-household market share of each brand only considers consumers' purchased brands and ignores all other brands available for purchase in the product market. Thus, consumers' willingness and expected value of exploring the product market are not considered in the model. Brand choice behaviour consists of exploiting purchased brands and exploring new brands in a product market. The brand choice model developed by Bucklin *et al.* (1998) thus has potential limitations in measuring consumers' brand choice behaviours.

2.4 Behavioural Segmentation

Market segmentation is a proactive part of marketing strategy development that aims to divide consumers into several well-defined and manageable homogenous groups for making and implementing different marketing tactics for different components of the overall market to satisfy the needs and wants of consumers in different groups (Blattberg and Sen, 1974; Bose, 2009; Brassington and Pettitt, 2006; Kotler and Keller, 2012; Lin, 2002). Consumers within a segment are similar in their needs, wants, characteristics, and behaviours (Kotler and Keller, 2012; Lin, 2002) and are different in these characteristics from consumers in other segments. The segmentation can be based on the "*demographics, psychographics, purchase and consumption behaviours, geographical characteristics, and/or situational factors*" (Blackwell *et al.*, 2006, p.44).

In this research, behavioural segmentation, which refers to the division of consumers into groups based on their knowledge of, attitude toward, use of, or response to a product (Kotler and Keller, 2012), is discussed and focused on as one of the main research disciplines. To improve the response rates of consumers toward the promotional mix, marketers usually segment consumers and target segments of potential consumers by providing specially designed offers (Blattberg and Sen, 1974; Blackwell *et al.*, 2006). Correctly identifying shopping pattern variables and understanding potential consumers enable marketers to identify and target the right segments, which is essential for producing effective and attractive sales promotions (Feinberg *et al.*, 2002; Huchzermeier *et al.*, 2002; Kim *et al.*, 1999). The segments of potential consumers are regarded as opportunities, and segmentation is thus perceived as an approach to identify opportunities (Beane and Ennis, 2007). Companies with limited resources need to focus on and allocate their resources to the best opportunities to increase resource utilization rates and competitive advantages (Beane and Ennis, 2007).

For example, as Britain's largest supermarket, Tesco devotes itself to understanding consumers through analysing the mass consumer data collected from Clubcard holders (Davis, 2007). The sales data analysis enables Tesco to construct advanced marketing strategies and promotional campaigns to gain competitive advantages (Davis, 2007). In recent years, through analysing the data collected from 10 million Tesco Clubcard holders to study consumers' shopping behaviours, Tesco has segmented its customers into six segments: healthy (17%), traditional (15%), mainstream (24%), price sensitive (16%), finer foods(19%), and convenience (9%), based on consumers' lifestyles (Coriolis Research, 2004). Recently, Tesco revealed plans to invest £1 billion in segmenting its 18 million Clubcard holders into sub-groups when they log on to the company website (Annesley, 2012). For each segment of consumers, Tesco will offer specific promotions to meet their specific needs. In order to retain consumers and stimulate their consumption, Tesco designs and provides different vouchers to different consumers based on their purchase behaviours and those of their associated segments (McElhatton, 2002). Reviewing the strategies of Tesco in recent years, behaviour segmentation has played an important role in achieving competitive advantages and increasing market share.

Segmentation is not only widely discussed and used by managers in enterprises like Tesco, Sainsbury's, and Waitrose to gain competitive advantages but has also received considerable attention and is widely explored in the academic literature on marketing (e.g. Ailawadi *et al.*, 2001; Beane and Ennis, 2007; Blattberg and Sen, 1974; Chan *et al.*, 2008; Dibb and Stern, 1995; Gázquez-Abad and Sánchez-Pérez, 2009; Heilman *et al.*, 2000; Knox, 1998; Lichtenstein *et al.*, 1997; Lin, 2002; Rowley, 2005; Seetharaman and Chintagunta, 1998; Yoon and Tran, 2011). This research focuses on behavioural segmentation based on promotion proneness and brand selection (i.e. exploration and exploitation) behaviours via dealing with store scanner data (i.e. transactional data). In prior research, many studies have segmented consumers based on promotion proneness and/or brand selection behaviours (e.g. Ailawadi *et al.*, 2001; Blattberg and Sen, 1974; Gázquez-Abad and Sánchez-Pérez, 2009; Heilman *et al.*, 2000; Lichtenstein *et al.*, 1997; Lin, 2002; Seetharaman and Chintagunta, 1998; Yoon and Tran, 2011). The data used for behavioural segmentation in prior research has been either actual purchase data (i.e. panel/transactional data) (e.g. Blattberg and Sen, 1974; Gázquez-Abad and Sánchez-Pérez, 2009; Heilman *et al.*, 2000; Seetharaman and Chintagunta, 1998; Yoon and Tran, 2011) or self-report data collected from interviews and/or questionnaires (e.g. Ailawadi *et al.*, 2001; Lichtenstein *et al.*, 1997; Lin, 2002). As consumers may not necessarily do what they say, self-report data may not be reliable in representing real consumer behaviours (Hensher *et al.*, 1988; Kroes and Sheldon, 1988; Teunter, 2002; Wardman, 1988). Segmenting consumers based on their real purchase records may thus be more reliable.

Blattberg and Sen (1974) segmented consumers based on their brand loyalty, promotion proneness, and preferred type of brand. The transactional records of 50 consumers in the purchases of aluminium foil from seven brands were dealt with via careful visual analysis for segmenting consumers into eight segments. Complementing the judgemental classification via observing the raw transactional records (i.e. subjective visual analysis), the Bayesian model discrimination procedure was used to model the segments for classifying each consumer into the segment that best represented their purchase behaviour. However, the classification model generated in the study may not be valid for the following two reasons. First, the behavioural segments were generated via subjective visual analysis without providing confident evidence. This brings doubts about the membership status of consumers (i.e. the dependent variable in the classification model) and thus weakens the validity of the developed classification model. In addition, only 50 consumers were used in the panel for the behavioural segmentation and the development of the classification model. The number of consumers in each of the eight segments was no more than ten. Particularly, in one behavioural segment, only one consumer was a member. The lack of panel data makes it difficult to validate the classification model developed in the study. The other limitation of the study is that the segmentation approach was not generalized and cannot be used in dealing with a large amount of data, as it is impossible for human beings to classify consumers manually based on a huge amount of raw transactional data.

Heilman *et al.* (2000) is another study that segments consumers based on their purchase behaviours by dealing with actual purchase records. Different from Blattberg and Sen (1974), Heilman *et al.* (2000) segmented consumers based on the processed transactional data from 236 consumers who bought 14,732 nappies from 1992 to 1995, rather than raw data. In their study, consumers were classified into three segments based on their purchase experiences since they had first entered the nappies market. Consumers' characteristics in price sensitivity were then used to profile the associated behavioural segments. According to the segmentation and profiling results, the study found out how consumers' brand preferences change in their purchase lifecycles and how consumers will respond to prices in reaction to an increase in category experiences. However, the study did not consider the interactions between price sensitivity and brand selection behaviours.

Similar to Heilman *et al.* (2000), Gázquez-Abad and Sánchez-Pérez (2009) employed a multinomial logistic latent class model to deal with store scanner data to assess the promotion proneness of consumers with respect to price reductions and store flyers to identify three behavioural segments. Consumers were then classified into one of the three behavioural segments based on their price sensitivity and brand loyalty. The three identified behavioural segments were loyal consumers, deal seekers, and preferred-brand seekers. The definitions of the three behavioural segments imply that consumers make their purchase decisions based on the weights they assign to the availability of price-reduction promotions and the characteristics of the brand itself. In other words, consumers in each segment may be driven by different motivations (Yoon and Tran, 2011), such as price reduction, brand loyalty, and the combination of price reduction and brand loyalty. However, the classification model used in the study is a predictive model and has limitations in discovering and modelling the implied trade-offs between price sensitivity and brand loyalty in purchase decision making. Therefore, clustering analysis, which is used to search for patterns in complex data, may have been more suitable to segment consumers in the study of Gázquez-Abad and Sánchez-Pérez (2009).

Like Gázquez-Abad and Sánchez-Pérez (2009), Yoon and Tran (2011) also explored the relationships between price sensitivity and brand loyalty. Extending the work of Gázquez-Abad and Sánchez-Pérez (2009), Yoon and Tran (2011) found heterogeneous motivations in purchase decision making, which may mean that consumers with the same degree of brand loyalty may respond to price changes differently, via investigating the moderating role of promotion proneness on the relationship between brand loyalty and price sensitivity. This finding suggests that it is necessary and important to consider and discover the trade-offs among different purchase motivations in predicting consumers' purchase behaviours. Yoon and Tran (2011) classified consumers based on a predetermined cut-off level of brand loyalty (this was category specific) into loyal and non-loyal groups via dealing with store scanner data. Then, they applied the latent class brand choice model to profile and further classify each of the behavioural segments into two segments, based on consumers' levels of deal proneness. The study, however, had two limitations. Firstly, the segmentation approach did not consider the interactions between promotion proneness and brand loyalty in consumer decision making when determining the membership of each behavioural segment. Secondly, determining the cut-off level of brand loyalty based on the proposed model is a complicated process when dealing with a large amount of data from a large market.

In general, behavioural segmentation based on promotion proneness and/or brand selection behaviours has been widely discussed in prior research. However, no study has taken the trade-offs between promotion proneness and brand selection behaviours into account in determining the behavioural segments. Discovering the implied trade-offs between maximizing immediate value via taking advantage of promotions and extending marketing knowledge via exploring among brands enables marketers to predict consumers' purchase behaviours in the purchase lifecycle.

2.5 Household Characteristics Related to Consumer Purchase Behaviours

Segmenting consumers by dealing with their purchase histories is limited by the availability of the purchase records. Without the required transactional data, the behavioural segmentation cannot be implemented by using the models developed for dealing with purchase histories. Therefore, characterizing behavioural segments on the basis of other characteristics relevant to purchase behaviours would be interesting. In prior research, consumer behaviours have been found to be closely tied to their associated demographics (Ailawadi *et al.*, 2001; Bashar *et al.*, 2013; Bawa and Shoemaker, 1987; Beane and Ennis, 1987; Che *et al.*, 2015; Lin, 2002). Unlike transactional data, demographic data is readily available from census data (Blattberg and Sen, 1974). According to Blattberg and Sen (1974), exploring whether behavioural segments can be identified on the basis of the demographic characteristics of the associated members is necessary. Marketers usually combine several demographic variables to define a demographic profile of a behavioural segment to create a mental picture about the typical members of the segment (Saad *et al.*, 2013). Identifying the demographic profiles of behavioural segments allows marketers to take advantage of the demographic indicators to predict the behaviours of consumers for segmentation purposes and to target the 'smart' consumers without processing their associated transactional data to make and deliver tailored promotions (Ailawadi *et al.*, 2001; Schneider and Currim, 1991).

In addition, identifying behavioural segments in terms of demographics is a powerful approach in assessing the quality of behavioural segmentation (Beane and Ennis, 1987; Bucklin and Gupta, 1992; Nairn and Bottomley, 2003). In prior research, behavioural segments have been commonly described and identified by using demographic variables (Beane and Ennis, 1987). If the behavioural segments do not clearly exist, demographics will not be able to describe the segments. In general, associating demographics with behavioural segments is essential in validating the behavioural segmentation and quickly targeting the 'smart' consumers to tailor and provide attractive promotions.

2.5.1 Household characteristics related to promotion proneness

Prior research has suggested that it is possible to use demographic variables to identify a deal-prone household (Bawa and Ghosh, 1999; Bell *et al.*, 1999; Blattberg *et al.*, 1978; Kwon and Kwon, 2007; Lichtenstein *et al.*, 1997; Teunter, 2002; Urbany *et al.*, 1996). For example, a large household that lives in a large house and that includes older children has typically been found to be promotion responsive (Teunter, 2002). Blattberg *et al.* (1978) suggest that household income, family size, and available time for shopping determine proneness to promotions. Besides, Webster (1965) argues that the age of the primary shopper is an indicator of promotion proneness. In the rest of this section, the household characteristics related to promotion proneness are discussed in terms of household income, education, age, employment situation and occupation, children status, family size, and marital status.

2.5.1.1 Income

Household income is strongly associated with promotion proneness (Blattberg *et al.*, 1978). However, the relationship between household income and promotion proneness is not clear, and the findings about the relationship are inconsistent (Ainslie and Rossi, 1998; Bawa and Ghosh, 1999; Blattberg *et al.*, 1978; Caplovitz, 1963; Inman *et al.*, 2004; Narasimhan, 1984; Teunter, 2002; Urbany *et al.*, 1996). Table 2.3 shows the findings of studies on the relationship between household income and promotion proneness.

Table 2.3: Relationships between household income and promotion proneness

Relationship	**Study**	**Data Used in the Study**	**Type of Promotional Mix**
Positive	Gupta and Denbleyker (2015)	Interviews in India	Various types
	Kwon and Kwon (2007)	Lifestyle survey database in the US	Coupons and rebates

	Inman *et al.* (2004)	Interviews and survey in US	In-store stimuli
	Laroche *et al.* (2003)	Survey in the greater metropolitan area of a US city	Two-for-one promotion
	Bawa and Ghosh (1999)	Shopping trip records in IRI panel data	Various types
	Beatty and Ferrell (1998)	Exploratory interviews and surveys in the US	Various types
	Levedahl (1988)	Panel data on the purchase of paper towels	Coupon
	Bawa and Shoemaker (1987)	Panel data in seven product categories in the US	Coupon
Negative	Carpenter and Moore (2008)	Panel data in various product categories in the US	Non-price retail promotions
	Martínez and Montaner (2006)	Self-administered survey in Spain	Various types
	Ainslie and Rossi (1998)	Nielsen panel data in five product categories	Various types
	Mittal (1994)	Self-administered survey in the US	Coupon
Inverse U-shaped	Narasimhan (1984)	Diary panel data in 20 product categories	Coupon
No significant relationship	Vaishnani (2011)	Survey in India	Various types
	Teunter (2002)	Household and retail data from GfK in six product categories	Various types
	Lichtenstein *et al.* (1997)	Interviews and self-administered survey	Various (eight) types
	Blattberg *et al.* (1978)	Chicago Tribune panel purchase data in five product categories	Various types
	Webster (1965)	Market Research Corporation US panel data for purchasing food items	Various types

High-income consumers are found to be more promotion responsive due to their better information-processing capabilities for judging sales promotions and their fewer budget restrictions in impulse purchases (Inman *et al.*, 2004; Bawa and Ghosh, 1999; Caplovitz, 1963). Unlike high-income households, households with low incomes do not spend a large amount of money on purchasing large quantities and instead shop frequently (Levedahl, 1988; Viswanathan *et al.*, 2010). They usually conserve their limited incomes for an unforeseen emergency in the future and are less likely to spend time on locating, sorting, and redeeming coupons (Levedahl, 1988; Viswanathan *et al.*, 2010).

On the contrary, some studies have found a negative relationship between household income and promotion proneness (e.g. Ainslie and Rossi, 1998; Carpenter and Moore, 2008; Martínez and Montaner, 2006; and Mittal, 1994). The limited shopping budgets for low-income consumers make them more price conscious and more sensitive to price changes (Ailawadi *et al.*, 2001; Ainslie and Rossi, 1998; Kim *et al.*, 1999). Low-income consumers are thus more willing to make an additional effort to search for price information and to take advantage of promotions (Chen *et al.*, 1998; Kim *et al.*, 1999). Martínez and Montaner (2006) conclude that price-conscious consumers with low-income levels actively respond to promotional actions.

In addition to these contradictory findings about the relationship between household income and promotion proneness, Narasimhan (1984) found that the most promotion-responsive consumers are those with moderate incomes. Different from all the stated findings about the relationship, some studies (e.g. Blattberg *et al.*, 1978; Lichtenstein *et al.,* 1997; Teunter, 2002; Vaishnani, 2011; Webster, 1965) have not found a significant relationship between household income and promotion proneness. The information shown in Table 2.3 suggests that the inconsistent findings on the relationship might result from the use of different measures, different data collection and processing methods, and studies of different types of promotions in different product categories and retail markets.

2.5.1.2 Education

Household income and education level are positively related (Teunter, 2002). Well-educated people normally have higher incomes than those without sufficient education. Like household income, no conclusive and consistent relationship between household education and promotion proneness has been identified in prior research. Table 2.4 summarizes the relationships identified in prior studies. As can be seen from Table 2.4, the inconsistent findings on the relationship between household education and promotion proneness might result from the different measures and data collection and processing methods used in studying different types of promotions in different product categories and retail markets.

Table 2.4: Relationships between education and promotion proneness

Relationship	**Study**	**Methodology Used in the Study**	**Type of Promotional Mix**
Positive	Gupta and Denbleyker (2015)	Interviews in India	Various types
	Kwon and Kwon (2007)	Lifestyle survey database in the US	Coupons and rebates
	Levedahl (1988)	Panel data on the purchase of paper towels	Coupon
	Bawa and Shoemaker (1987)	Panel data in seven product categories in US	Coupon
	Narasimhan (1984)	Diary panel data in 20 product categories	Coupon
Negative	Lichtenstein *et al.* (1997)	Interviews and self-administered survey	Various (eight) types
No significant relationship	Vaishnani (2011)	Survey in India	Various types
	Carpenter and Moore (2008)	Panel data in various product categories in the US	Non-price retail promotions

Many of the studies found that household education and promotion proneness were positively related (e.g. Bawa and Shoemaker, 1987; Gupta and Denbleyker, 2015; Kwon and Kwon, 2007; Levedahl, 1988; Narasimhan, 1984). Kwon and Kwon (2007) suggest that high education represents the cognitive resources needed to store knowledge for judging information. Well-educated consumers thus have a higher level of marketplace literacy and are expected to have a greater capability to engage in research and process information for judging the promotions offered to them (Gupta and Denbleyker, 2015; Robertson *et al.*, 1984; Urbany *et al.*, 1996). They are expected to be more sensitive to promotions than those with lower education levels (Narasimhan, 1984; Urbany *et al.*, 1996). Gupta and Denbleyker (2015) found that most consumers with low education levels do not actively seek information about promotional offers.

However, Lichtenstein *et al.* (1997) found that consumers who have lower levels of education are more likely to react to and accept promotions. It might be because consumers with low education levels are more likely to be poor consumers. Consumers with limited purchase budgets respond well to promotional actions to obtain additional benefits from promotions (Martínez and Montaner, 2006).

In prior research, a relationship between household education and promotion proneness has not always been identified. Carpenter and Moore (2008) and Vaishnani (2011) did not find a significant relationship between household education and promotion proneness.

2.5.1.3 Age

Like household income and education, the relationship between the consumer's age and promotion proneness is not conclusive in prior research due to the same suggested reasons. Table 2.5 presents the relationships identified in prior research.

Table 2.5: Relationships between age and promotion proneness

Relationship	**Study**	**Data Used in the Study**	**Type of Promotional Mix**
Positive	Urbany *et al.* (1996)	Interviews and survey in the US	Price
	Webster (1965)	Market Research Corporation US panel data for purchasing food items	Various types
Negative	Carpenter and Moore (2008)	Panel data in various product categories in the US	Non-price retail promotions
	Inman *et al.* (2004)	Interviews and survey in the US	In-store stimuli
	Ainslie and Rossi (1998)	Nielsen panel data in five product categories	Various types
	Lichtenstein *et al.* (1997)	Interviews and self-administered survey	Various (eight) types
	Bawa and Shoemaker (1987)	Panel data in seven product categories in the US	Coupon
	Teel *et al.* (1980)	Interviews and survey in the US	Coupon
U-shaped	Bellenger *et al.* (1978)	Interviews in various categories in the US	Various types
Inverse U-	Teunter (2002)	Household and retail data from	Various types

shaped		GfK in six product categories	
Not significant	Burton *et al.* (1998)	Interviews and survey in the US	Advertisement and coupon

Compared to young consumers, older consumers are more-experienced shoppers and have more knowledge about how to search for promotions in the marketplace (Webster, 1965). In addition, older consumers may have more-flexible budgets for shopping, which allows them to take advantage of promotions to stock up via purchasing larger quantities when a product is on sale (Webster, 1965). The findings and arguments of Webster (1965) are also supported by Urbany *et al.* (1996). According to Urbany *et al.* (1996), older consumers have greater price knowledge about products, fewer time and grocery budget constraints for shopping, stronger maven tendencies, and greater shopping enjoyment and psychosocial returns to search than younger consumers do. Older consumers in the US therefore conduct more-extensive searches for promotions.

On the contrary, younger consumers have been found to be more motivated to process in-store information and to be more sensitive to in-store stimuli than older consumers are (Inman *et al.*, 2004; Lichtenstein *et al.*, 1997). Unlike older consumers, younger consumers make more decisions at the point of purchase (Inman *et al.*, 2004) and are more likely to participate in non-price retail promotions (Carpenter and Moore, 2008).

In addition, Teunter (2002) used household and retail data in the Netherlands and found that consumers who are around 35 years old are more responsive to promotions than any others are. However, Bellenger *et al.* (1978) used interviews and found that consumers in the US who are aged under 35 and over 65 are more likely to make impulse purchases. These consumers are more likely to be attracted by in-store promotions like in-store advertising and merchandise displays.

Besides the inconsistent relationship discussed above, via conducting interviews and a survey in the US, Burton *et al.* (1998) did not find a significant relationship between age and proneness to react to advertising and coupons.

2.5.1.4 Employment situation and occupation

A consumer's employment situation and occupation are more or less related to their associated income, age, and education. The relationship between consumers' employment situations/occupations and their promotion proneness is not clearly and consistently discussed in prior research. Blattberg *et al.* (1978) analysed Chicago Tribune panel purchase data in five product categories and found that consumers living on welfare or being retired are more sensitive to promotions. These unemployed consumers have limited shopping budgets and fewer time constraints, which allow them to spend more time on shopping by searching and taking advantage of promotions to maximize purchase value and savings (Blattberg *et al.,* 1978; Inman *et al.,* 2004). This argument is also supported by Bawa and Shoemaker (1987), who dealt with panel data from the US in seven product categories and found that unemployed consumers are more inclined to accept and take advantage of coupons. However, Caplovitz (1963) argues that consumers with lower income rely more on brand names, rather than their own judgement. Unemployed consumers, including those living on welfare, are therefore more likely to not react to promotions (Teunter, 2002).

A relationship between employment situation and promotion proneness has been identified in the US and Dutch markets by researchers, as discussed above. However, in the Indian market, Vaishnani (2011) did not find a significant relationship between employment situation and promotion proneness via a survey. The different findings on the relationship in different markets suggest that the influential factors of promotion proneness differ across different retail markets/countries.

In Canada, the occupation of the wife in a family has been found to influence purchases of promoted products (Schaninger and Allen, 1981). Schaninger and Allen (1981, p.193) analysed the data collected from a survey in Canada and found that "*high-occupational-status working wives (i.e. managerial, professional, administrative and semiprofessional, e.g., doctors, accountants, engineers, teachers, nurses, professional sales) tend to pay less attention to grocery specials in the newspaper, to read grocery sale ads less carefully, and to utilize mail and newspaper coupons to a lesser degree than nonworking wives (i.e. those* *not working) or low-occupational-status working wives (i.e. secretarial, clerical, retail sales, technicians, and blue-collar and service workers)*". By contrast, in India, Vyas (2005) and Rao (2009) did not find a significant relationship between the occupation of the wife and promotion proneness by using interviews and a survey. These findings also support the argument stated above that the influential factors of promotion proneness differ across different retail markets/countries.

2.5.1.5 Children status

Unlike the demographic variables discussed above, children status and promotion proneness have been found to be negatively related in prior research (Bawa and Shoemaker, 1987; Blattberg *et al.*, 1978; Narasimhan, 1984). Table 2.6 presents the literature about the relationship reviewed in this research. Narasimhan (1984) found that coupon-prone consumers are less likely to have children (especially non-school-age children) at home. Children, especially non-school-age children, require households to allocate a great deal of time to take good care of them (Urbany *et al.*, 1996). Without the presence of children, the household can spend more time on shopping and searching for promotions (especially out-of-store promotions) (Blattberg *et al.*, 1978; Teunter, 2002).

Table 2.6: The relationship between the presence of young children and promotion proneness

Relationship	**Study**	**Data Used in the study**	**Type of Promotional Mix**
Negative	Bawa and Shoemaker (1987)	Panel data in seven product categories in the US	Coupon
	Narasimhan (1984)	Diary panel data in 20 product categories	Coupon
	Blattberg *et al.* (1978)	Chicago Tribune panel purchase data in five product categories	Various types

2.5.1.6 Family size

In the US market, family size has been found to be positively related to promotion proneness in prior research (Ainslie and Rossi, 1998; Bawa and Shoemaker, 1987; Carpenter and Moore, 2008; Inman *et al.*, 2004). Table 2.7 presents a summary of the relationship between family size and promotion proneness in prior research. A larger family size results in a greater economic burden on the shopping budget and greater grocery expenditures, as more household members need to be fed in a larger family (Bawa and Ghosh, 1999; Teunter, 2002). Ainslie and Rossi (1998) found that larger families are more price sensitive. In addition, in-store decision making increases with family size (Inman *et al.*, 2004). Therefore, targeting households with large family sizes enables retailers to successfully employ both price and non-price retail promotions (Ainslie and Rossi, 1998; Carpenter and Moore, 2008; Inman *et al.*, 2004).

Table 2.7: Relationships between family size and promotion proneness

Relationship	**Study**	**Data Used in the Study**	**Type of Promotional Mix**
Positive	Carpenter and Moore (2008)	Panel data in various product categories in the US	Non-price retail promotions
	Inman *et al.* (2004)	Interviews and survey in the US	In-store stimuli
	Ainslie and Rossi (1998)	Nielsen panel data in five product categories in the US	Various types
	Bawa and Shoemaker (1987)	Panel data in seven product categories in the US	Coupon
No significant relationship	Vaishnani (2011)	Survey in India	Various types

2.5.1.7 Marital status

Unlike the demographic variables discussed above, marital status and its associated relationship with promotion proneness have rarely been discussed in prior research. Vaishnani (2011) conducted a survey in Gujarat state, India, and found that married consumers are more prone to promotions than unmarried consumers are. He suggests that married consumers may not have and enjoy the freedom of shopping without the additional responsibilities of family. The responsibilities of family and the availability of alternative products in the market make married consumers more prone to take advantage of promotions to maximize the benefits from purchases (Vaishnani, 2011). However, in the US, Yavas (1983) did not find a significant relationship between marital status and promotion proneness by using a survey.

2.5.2 Household characteristics related to dynamic choice processes

Like promotion proneness, a consumer's dynamic choice behaviours (i.e. exploration and exploitation behaviours in brand selection) have also been found to be related to their associated income, education, age, employment situation, occupation, children status, family size, and marital status (Bawa, 1990; East *et al.*, 1995; Flavian *et al.*, 2001; Leszczyc and Timmermans, 1997; Mann and Rashmi, 2010; McDonald *et al.*, 2003; McGoldrick and Andre, 1997; Patterson, 2007; Rogers, 1995; Saad *et al.*, 2013; Skogland and Siguaw, 2004; Straughan and Albers-Miller, 2001; Wood, 2004; Wright and Sparks, 1999). For example, in a survey of Indian consumers, Mann and Rashmi (2010) found that those who were older, had lower incomes, had higher levels of education, or were retired showed more brand loyalty and engaged in fewer exploration activities in their purchases. The use of demographic characteristics is thus expected to be able to differentiate consumers in terms of their dynamic choice behaviours. It is thus suggested that marketers can design effective marketing strategies by associating demographic characteristics with choice behaviours (Mann and Rashmi, 2010). In the rest of this section, the household characteristics related to exploration behaviours in brand selection are discussed in terms of household income, education, age, employment situation and occupation, children status, family size, and marital status.

2.5.2.1 Income

Household income is suggested to have a strong influence on consumer choice decisions (Zeithaml, 1985). However, the findings on the influence of household income on exploration behaviours in brand selection are inconclusive and inconsistent in prior research.

Table 2.8 summarizes the literature on the relationship between household income and exploration behaviour. The inconsistency of the identified relationship, as suggested by the information in Table 2.8, might result from the use of different measures and different data collection and processing methods in different retail markets.

Table 2.8: Relationships between income and exploration behaviours

Relationship	**Study**	**Data Used in the Study**
Positive	Mann and Rashmi (2010)	Survey in India
	Leszczyc and Timmermans (1997)	Nielsen panel data
	Rogers (1995)	Interviews and survey in the US
	Farley (1964)	Purchase data in the US
	Tate (1961)	Prior results discussion
Negative	Saad *et al.* (2013)	Survey in Malaysia
	McGoldrick and Andre (1997)	Interviews and survey in the UK
	East *et al.* (1995)	Survey in the UK
No significant relationship	McDonald *et al.* (2003)	Interviews and survey in Australia
	Raju (1980)	Survey in the US

Many studies have found that household income and exploration behaviours are positively related (Farley, 1964; Leszczyc and Timmermans, 1997; Mann and Rashmi, 2010; Rogers, 1995; Tate, 1961). According to Mann and Rashmi (2010), an increase in income induces consumers to explore via trying new brands, products, ideas, and services. Via analysing Nielsen panel data, Leszczyc and Timmermans (1997) found that high-income Americans have low repeat purchase probability. Consumers with high incomes are thus more likely to be brand disloyal than those with low incomes (Farley, 1964; Mann and Rashmi, 2010). Tate (1961) found that low-income families are inclined to be loyal to their previous brands, whereas households with middle or upper-middle incomes are more inclined to explore alternative brands.

However, some studies found that with an increase in household income, consumers become more brand loyal (East *et al.*, 1995; McGoldrick and Andre, 1997; Saad *et al.*, 2013). Low-income consumers have limited budgets for shopping, which makes them more conscious of pricing (Ailawadi *et al.*, 2001; Ainslie and Rossi, 1998; Kim *et al.*, 1999). East *et al.* (1995) found that price-conscious consumers are less loyal to brands, so low-income consumers are more likely to explore than high-income consumers are. This might be because low-income consumers are more willing to make an additional effort to search for price information and to take advantage of promotions regardless of the brand (Chen *et al.*, 1998; Kim *et al.*, 1999).

Besides the positive and negative relationships identified in prior research, McDonald *et al.* (2003) and Raju (1980) did not find a significant relationship between household income and exploration behaviours via conducting interviews in Australia and the US, respectively.

2.5.2.2 Education

Household education level also plays an important and significant role in determining purchase behaviours in brand selection (Mann and Rashmi, 2010). However, like household income, the relationship between household education and exploration behaviours is not conclusive in prior research due to the same reason stated above. Some studies have found a positive relationship between education and exploration behaviours (Frank *et al.*, 1968; Gupta and Denbleyker, 2015; McDonald *et al.*, 2003; Raju, 1980; Rogers, 1995), while others have found a negative relationship (Flavian *et al.*, 2001; Leszczyc and Timmermans, 1997; Mann and Rashmi, 2010). Table 2.9 shows the findings on the relationship in prior studies.

Table 2.9: Relationships between education and exploration behaviours

Relationship	**Study**	**Data Used in the Study**
Positive	Gupta and Denbleyker (2015)	Interviews in India
	McDonald *et al.* (2003)	Interviews and survey in Australia
	Rogers (1995)	Interviews and survey in the US
	Raju (1980)	Survey in the US
	Frank *et al.* (1968)	Chicago Tribune consumer panel data
Negative	Mann and Rashmi (2010)	Survey in India
	Flavian *et al.* (2001)	Interviews and survey in Spain

	Leszczyc and Timmermans (1997)	Nielsen panel data

Gupta and Denbleyker (2015) interviewed Indian consumers and found that consumers with low education levels did not actively seek information about product attributes. This might be because a low level of education results in a low level of marketplace literacy and a low level of capability to engage in research and to process information (Gupta and Denbleyker 2015; Robertson *et al.*, 1984; Urbany *et al.*, 1996). By the same token, consumers with lower education levels are found to be more likely to stick with their previous brands, rather than try alternative brands (Frank *et al.*, 1968).

On the contrary, Leszczyc and Timmermans (1997) found that consumers with higher education levels have a higher probability of repeat purchases and a lower probability of exploration activities. In other words, well-educated consumers are more likely to stick with their previous brands on the next purchase occasion (Flavian *et al.*, 2001). As stated above, household education is positively related to household income (Teunter, 2002). Well-educated consumers are thus more likely to have high incomes, which allow them to buy their preferred brands regardless of the price.

2.5.2.3 Age

In prior research, household age has also been identified as an important factor influencing brand purchasing behaviours (Wood, 2004). As can be seen from Table 2.10, the findings about the relationship between household age and exploration behaviours in prior research are inconsistent. Using panel data, Uncles and Ehrenderg (1990) concluded that there was no difference in purchasing habits between younger and older consumers. This finding is supported by Inman *et al.* (2004), who did not find a significant relationship between age and brand switching using interviews and a survey in the US.

Table 2.10: Relationships between age and exploration behaviours

Relationship	**Study**	**Data Used in the Study**
Negative	Mann and Rashmi (2010)	Survey in India

	Patterson (2007)	Interviews and survey in Australia
	Lambert-Pandraud *et al.* (2005)	Survey in the EU
	Straughan and Albers-Miller (2001)	Survey across four countries
	Moutinho *et al.* (1996)	Survey in the US
	Bawa (1990)	Nielsen panel data in the cereal category
	Raju (1980)	Survey in the US
U-shaped relationship	Wright and Sparks (1999)	Interviews and survey in the UK
	McGoldrick and Andre (1997)	Interviews and survey in the UK
	East *et al.* (1995)	Survey in the UK
No significant relationship	Inman *et al.* (2004)	Interviews and survey in the US
	Uncles and Ehrenderg (1990)	MRCA panel data

The studies conducted in the UK via surveys and/or interviews, however, identified a U-shaped relationship between household age and exploration behaviours (East *et al.*, 1995; McGoldrick and Andre, 1997; Wright and Sparks, 1999). East *et al.* (1995) found that consumers aged between 25 and 44 have higher loyalty. Similarly, Wright and Sparks (1999) indicate that consumers aged between 35 and 44 are more likely to be loyal. These findings were also confirmed by McGoldrick and Andre (1997), who found that loyal consumers are more likely to be in an unspecific 'middle age'. In other words, consumers who are either old or young have a higher probability to explore and try alternatives. According to East *et al.* (1995), the U-shaped relationship is mainly attributed to the low incomes of the young and the old. They argue that the limited shopping budgets of low-income consumers oblige them to seek bargains and buy brands on promotion. Even though older consumers are inclined to be loyal to familiar brands, their low income levels may not allow them to buy their preferred brands without promotions (East *et al.*, 1995).

By contrast, studies conducted in other countries, like India, the US, and Australia, have identified a negative relationship between age and exploration behaviours (Bawa, 1990; Lambert-Pandraud *et al.*, 2005; Mann and Rashmi, 2010; Moutinho *et al.*, 1996; Patterson, 2007; Raju, 1980; Straughan and Albers-Miller, 2001). These studies found that older consumers are more likely to exhibit loyal behaviour and have a higher probability of repeat purchases than younger consumers do. East *et al.* (1995) suggest that the low involvement in purchasing behaviours is the reason why older consumers are more loyal. Moutinho *et al.* (1996) found that older consumers are less price conscious, which makes them more loyal. Compared to younger consumers, older consumers are normally more conservative and have more-routine behaviours (Straughan and Albers-Miller, 2001). The cognitive abilities of older consumers are reduced with age, and thus they are less willing to accept new ideas and alternatives in order to avoid risks and uncertainties (Straughan and Albers-Miller, 2001). Lambert-Pandraud *et al.* (2005) found that older consumers simplify their decision-making process and prefer to purchase repeatedly. Besides, the brand-loyal tendency of older consumers results from their reduced mobility in later life, which restricts their brand choice (Patterson, 2007).

2.5.2.4 Employment situation and occupation

The employment situations of consumers influence the amount of time that they can use for shopping (Gross, 1987). It can thus affect consumers' ability to search for and compare alternatives due to time constraints. In this vein, dual-career families are less able to engage in extensive search processes, as the adult partners in the family hold jobs that require a high degree of commitment (Heilman *et al.*, 2000; Schaninger and Allen, 1981). The time constraints for shopping make those families less likely to explore via trying alternatives, especially private-label brands (Heilman *et al.*, 2000).

Consumers' exploration behaviours have been found to be positively related to their associated social status, which can be best predicted by using their associated occupation (Kahl and Davis, 1955; Rogers, 1995). Kohn *et al.* (1990, p.13080) define high-status occupations in terms of "*ownership, control of the means of production, and control over the labor power of others*". On the basis of the definition of occupation status, consumers with high-status occupations are suggested to have high incomes, which thus allow and induce consumers to explore via trying new brands, products, ideas, and services (Mann and Rashmi, 2010).

Retired consumers have a low occupation status and thus show more brand loyalty (Mann and Rashmi, 2010). The higher brand loyalty of retired consumers is also attributed to their age. The average retirement age in the world is around 60 years old (OECD, 2014). As explained in the above section, old consumers have a higher probability of repeat purchases and are more likely to follow the same trend of purchasing the same brands on the next purchase occasion (Mann and Rashmi, 2010).

2.5.2.5 Children status

Children are regarded as key influences of their parents' purchases, even though they have very limited purchase power and cannot directly determine the brand for purchase (Danovitch and Mills, 2009; Schor, 2004). They are most vulnerable to advertising messages and are inclined to accept the new things delivered in messages (Danovitch and Mills, 2009; Radunovic, 2014; Schor, 2004). In the US, children are inundated with various advertising messages (Linn, 2004). According to Thomas (2007), cereal, which targets children by providing promotions, is heavily advertised, affecting children's purchases in the US. Therefore, households with children may engage in greater brand exploration activities in order to meet the requests of the children. This argument is supported by Bawa (1990), who found that households with young children are more likely to explore the cereal market.

However, the stated finding cannot be generalized to all product and retail markets. Frank *et al.* (1968) and Dunn and Wrigley (1984) found a negative relationship between children status (i.e. the time needed for taking care of children) and exploration behaviours by using the data of different product categories from different retail markets. Table 2.11 summarizes the identified relationships in prior research. Frank *et al.* (1968) found that exploration activities increase as the age of the youngest child increases because housewives can allocate and spend more time on searching for alternatives when the child grows older. By the same token, households with children of school age or below have less time for shopping and searching for alternatives, as those households need to allocate a great deal of time to take care of their children (Blattberg *et al.*, 1978; Teunter, 2002; Urbany *et al.*, 1996). Thus, households with children are more likely to be loyal to stores and brands (Dunn and Wrigley,

1984).

Table 2.11: Relationships between children status and exploration behaviours

Relationship	**Study**	**Data Used in the Study**
Positive	Bawa (1990)	Nielsen panel data in the cereal category
Negative	Dunn and Wrigley (1984)	Consumer panel survey in the UK
	Frank *et al.* (1968)	Chicago Tribune consumer panel data across many product categories
No significant relationship	East *et al.* (1995)	Survey in the UK

Researchers have identified either a positive or negative relationship between children status and exploration behaviours by dealing with panel data. However, East *et al.* (1995) did not find a significant relationship between children status and exploration behaviours by using data collected from a survey in the UK.

2.5.2.6 Family size

Family size indirectly influences a consumer's exploration behaviours via their income (Frank *et al,*. 1968). Frank *et al.* (1968) and Bawa (1990) analysed the panel datasets and found that American households with large family sizes are more likely to explore a product market via trying alternatives than those with small family sizes. With the same household income, the shopping budget for each member in a large family is less than that in a small family, Consumers in a large family need to use their incomes more efficiently to maintain the same standard of living as those in a small family (Frank *et al,*. 1968). The relatively limited shopping budgets for large families thus induce them to make an additional effort to look for alternatives with promotions (Chen *et al.*, 1998; Kim *et al.*, 1999). Table 2.12 shows a summary of the relationships between family size and exploration behaviours in prior research.

Table 2.12: Relationships between family size and exploration behaviours

Relationship	**Study**	**Data Used in the Study**

Positive	Bawa (1990)	Nielsen panel data in the cereal category
	Frank *et al.* (1968)	Chicago Tribune consumer panel data
Negative	McGoldrick and Andre (1997)	Interviews and survey in the UK
	East *et al.* (1995)	Survey in the UK

Unlike the studies in the US, the studies in the UK have identified a negative relationship between family size and exploration behaviours via dealing with survey and/or interview data (East *et al.*, 1995; McGoldrick and Andre, 1997). East *et al.* (1995) found that a British household with a single person is more likely to show high exploration among brands. This might be because a single person does not have responsibility for family members (i.e. the only member in the family is him/her) and can enjoy the freedom of shopping and seek alternatives in line with their interest (Vaishnani, 2011).

2.5.2.7 Marital status

Like promotion proneness, exploration behaviours have rarely been discussed with consumers' marital statuses in prior research. McGoldrick and Andre (1997) used interviews and a survey and found that unmarried British people are more likely to have exploration behaviours. However, no explanation of this finding has been provided in prior studies. As marriage is associated with responsibility to the family, unmarried consumers can enjoy freedom in shopping and seek whatever they like without considering additional family responsibility and the preferences of other family members (Vaishnani, 2011).

2.6 Conclusion

In general, Chapter 2 reviewed the literature about the four main research areas demonstrated in Figure 2.1. It provides a theoretical basis for this research via describing, summarizing, evaluating, and clarifying the relevant literature. Chapter 2 consisted of six sub-sections. Section 2.1 briefly introduced the structure and the contents presented in each sub-section. Section 2.6 concludes the findings and reviews in Chapter 2. The other four sub-sections reviewed the relevant literature and were the main body of Chapter 2.

The promotional mix is a set of communication tools that a company uses to carry out the promotion process and to effectively transfer messages about the benefits of its products or services to consumers (The Chartered Institute of Marketing, 2009; Karunanithy and Sivesan, 2013). Advertising and sales promotions are two commonly used communication tools of the promotional mix in the frequently purchased consumer goods market. Advertising is defined as any sponsored, paid message that is communicated in a non-personal way to create and reinforce brand awareness and to persuade consumers to make purchases from a company (Keegan and Green, 2008; The Chartered Institute of Marketing, 2009). Sales promotions, which are the offer of an incentive, play an essential role in most retailers' communication mixes to induce desired sales results (McGoldrick, 2002; Gilbert and Jackaria, 2002). Sales promotions consist of a diverse collection of incentive tools, which are used to shift the time of purchase, stimulate brand exploration, or encourage brand loyalty (Blythe, 2014; Kotler *et al.*, 2008).

The use of advertising and sales promotions is very expensive for retailers; the effectiveness of promotions is thus essential for retailers to achieve expected marketing goals (Anic and Radas, 2006; Walters and MacKenzie, 1988). Promotion proneness reflects the general psychological propensity of a consumer to react to the promotional mix and is used as a criterion to examine the effectiveness of the promotional tools (Anic and Radas, 2006; Danziger *et al.,* 2014; Teunter, 2002). There is no consistent definition of promotion proneness in prior research. Drawing from the definitions provided in prior research, promotion proneness is defined as an individual consumer's psychological propensity to use, search for, and take advantage of promoted products to maximize the perceived immediate purchase value and the psychological benefits from buying a deal.

Promotion proneness can be classified on the basis of two approaches. It is classified into overt or intrinsic promotion proneness based on the indicators of promotion proneness. The second approach classifies promotion proneness into active or passive promotion proneness based on the promotional tools and the efforts in information searches. The findings on the promotion proneness of a consumer across types of promotions are inconclusive. Some studies have found that the promotion proneness of a consumer is the same across different types of promotions, while others have found that promotion proneness varies across either promotion classifications or each type of promotion. In different product categories, the promotion proneness of a consumer has not been found to be the same by all studies.

In prior research, promotion proneness has been measured by using different models in dealing with different types of data, such as self-report data (Lichtenstein *et al.*, 1995) and redemption intention data (Bawa *et al.*, 1997) obtained from experiments, and actual transactional data (Hackleman and Duker, 1980; Henderson, 1994; Webster, 1965). Using transactional data to measure promotion proneness, which enables marketers to understand consumers' actual behaviours toward promotions, has advantages over the use of self-report data and redemption intention data. Even though there is little consensus in prior research on how promotion proneness must be measured, promotion proneness reflects and can be quantified as the percentage of purchases made on a promotion basis, according to the conceptual findings (Hackleman and Duker, 1980; Henderson, 1994; Montgomery, 1971; Rao, 2009; Wierenga, 1974). In general, consumers are encouraged by and take advantage of promotions to switch brands, stockpile, accelerate purchases, seek and try new products, and spend larger amounts (Gázquez-Abad and Sánchez-Pérez, 2009; Gupta and Denbleyker, 2015; Pechtl, 2004; Teunter, 2002).

Consumer purchases in a reactive environment are a version of the multi-armed bandit problem (Ishikida and Varaiya, 1994). Exploration and exploitation are key concepts of the multi-armed bandit problem. Exploration refers to the pursuit of new knowledge and information via searching and taking risks to try new products or brands (Gupta *et al.*, 2006; Lavie *et al.*, 2010; Levinthal and March, 1993; March, 1991). Exploitation refers to the learning and development of existing knowledge via local searches, experiential refinement, and the selection and implementation of existing routines (Baum *et al.*, 2000; Lavie *et al.*, 2010; Levinthal and March, 1993; March, 1991). Consumers' choice behaviour is thought to be driven by the need to gain market knowledge and the need to avoid risk (Erdem and Keane, 1996; Heilman *et al.*, 2000). They adapt their strategies for sequential selections from a set of brands to optimize expected utility by making trade-offs between exploration and exploitation (Macready and Wolpert, 1998; Payne *et al.*, 1993). The choice processes of consumers are dynamic, as their past experiences in brand selections affect their current choices under uncertainty due to the change of their information set from market learning (Erdem and Keane, 1996; Foxall, 1993; Heilman *et al.*, 2000; Luo *et al.*, 2015; Neelamegham and Jain, 1999; Yang *et al.*, 2015). Exploration and exploitation activities explain and reflect the dynamic choice and evaluation process of consumers (Hoyer, 1984).

With the increase in market knowledge from exploiting and exploring brands, the amount of information searching via exploring different brands presents as an inverted U-shape due to the reduced perceived risks and the increased ability in differentiating brands in the market. By contrast, with an increase in market knowledge, the findings about the change of the promotion proneness of a consumer are inconsistent in prior research. In terms of the relationship between promotion proneness and exploration and exploitation behaviours, the majority of prior research has found a positive relationship between promotion proneness and exploration behaviours. However, this identified relationship is not strictly supported, as Ailawadi *et al.* (2001) and Martínez and Montaner (2006) did not find a clear and significant relationship between promotion proneness and exploration and exploitation behaviours.

Consumers' brand choice behaviours have been measured by using various choice models in prior research. Four typical behavioural measurement models were reviewed in this chapter. The Dirichlet model is a comprehensive empirical model for measuring consumer behaviours in a stationary market without considering consumers' purchase experiences and the influence of market change (Bassi, 2011; Evans *et al.*, 2009; Goodhardt *et al.*, 1984; Uncles *et al.*, 1995). It is thus not suitable for measuring consumer brand selection behaviours in a reactive environment. Even though many algorithms have been proposed to measure bandit problems in studying the trade-offs between exploration and exploitation, none of these algorithms has been specifically developed to measure the exploration and exploitation behaviours in a reactive environment by dealing with store scanner data (Kuleshov and Precup, 2010; Vermorel and Mohri, 2005; Farias and Megiddo, 2005). The dynamic discrete choice model, which is used to model dynamic choice problems, involves intensive and complicated computations (Rust, 1994). It is thus not suitable for dealing with a large amount of data in quantifying brand selection behaviours in a frequently purchased consumer goods market. To measure the brand selection behaviour of an individual household, Bucklin *et al.* (1998) modelled brand choice by using a multinomial logit. However, the multinomial logit has limitations in measuring consumer behaviours in a product market with a large number of brands.

In Section 2.4, customer segmentation was reviewed to illustrate how consumers have been segmented in prior studies. Especially, behavioural segmentation, which refers to the division of consumers into groups based on their knowledge of, attitude toward, use of, or response to a product (Kotler and Keller, 2012), was focused on and discussed in this chapter. It is widely used by marketers to achieve competitive advantage and to increase market share via developing effective and attractive sales promotions on the basis of the characteristics of a behavioural segment. In prior research, many studies have segmented consumers based on promotion proneness and/or brand selection behaviours by dealing with either actual purchase data or self-report data (e.g. Ailawadi *et al.*, 2001; Blattberg and Sen, 1974; Gázquez-Abad and Sánchez-Pérez, 2009; Heilman *et al.*, 2000; Lichtenstein *et al.*, 1997; Lin, 2002; Seetharaman and Chintagunta, 1998; Yoon and Tran, 2011). However, the segmentation models used in these studies were classification models. None of these studies took the implied interactions between promotion proneness and brand selection behaviours into account in determining the behavioural segments.

Helping marketers to better identify their targeted behavioural segments and understand the associated purchase behaviours, promotion proneness and exploration and exploitation behaviours are associated with household demographic characteristics. Identifying behavioural segments in terms of demographics is a powerful approach in assessing the quality of behavioural segmentation (Beane and Ennis, 1987; Bucklin and Gupta, 1992; Nairn and Bottomley, 2003). In prior research, there are inconsistent findings about the relationships between promotion proneness and household income, household education, household age, employment situation and occupation, family size, and marital status. The inconsistent findings on demographics and promotion proneness across studies result from the different measures, data collection and processing methods, and different types of promotions in different product categories and retail markets. This argument is supported by Blattberg and Neslin (1990). Unlike the former demographic variables, children status and promotion proneness have been found to be negatively related in prior research (Bawa and Shoemaker, 1987; Blattberg *et al.*, 1978; Narasimhan, 1984). Without the presence of children, a household can spend more time on shopping and searching for promotions (especially out-of-store promotions) (Blattberg *et al.*, 1978; Teunter, 2002).

With the same reason as for the inconsistent findings of promotion proneness and demographic characteristics, the findings on exploration and exploitation behaviours and many household demographics (i.e. household income, household education, household age, children status, and family size) across studies are inconsistent as well. Studies on the relationship between brand exploration behaviours and employment situation/occupation or marital status are relatively rare. In prior research, dual-career families, households with low occupation status, households in retirement, and households with married adults have been found to be more likely to follow the same trend of purchasing the same brands on the next purchase occasion (Heilman *et al.*, 2000; Mann and Rashmi, 2010; Schaninger and Allen, 1981).

CHAPTER 3: METHODOLOGICAL AND ANALYTICAL RESEARCH DESIGN

3.1 Introduction

The research background and a review of the relevant literature were provided in Chapter 2; Chapter 3 presents the methodological and analytical research design. This chapter consists of seven sections. In Section 3.1, a brief introduction to the contents in Chapter 3 is presented. In the last section, the behavioural measurements and the research design are concluded.

To answer the first research question, by using transactional data, the research aims to measure how consumers respond to promotions and how they behave in selecting a brand in their purchase lifecycles. Section 3.2 discusses how the reactions of consumers to promotions could be potentially measured by using transactional data. The reason why the proposed behavioural measurement could potentially quantify consumers' reactions to promotions is clarified in the section. In order to find out the reactions of a consumer to a particular type of promotion and whether the behavioural segments identified differ in terms of their sensitivity to different types of promotions, Section 3.3 provides the measurements that are used for quantifying a consumer's responses to advertising, point of display, and price reduction, with the provision of the measurements' rationality.

In a frequently purchased consumer goods market, many brands are available for selection. Sections 3.4 and 3.5 discuss how the brand selection behaviours of consumers could be measured. Section 3.4 discusses and clarifies how and why the dynamic choice behaviour of a consumer could be measured using transactional data. In brand selection, consumers may not only have dynamic choice behaviours but also have brand-switching behaviours. Section 3.5 discusses how the brand-switching behaviours of consumers could be measured by using transactional data, with the provision of the measurement's rationality.

After presenting the data-mining algorithms developed to quantify a consumer's brand selection behaviours in relation to promotions, the six analytical steps are presented in Section 3.6.

3.2 Measuring the Consumer's Responses to Promotions in Retail Purchase Data

3.2.1 The rationale of the measurement

Experiences with the marketing mix modify consumers' perceived value of the marketing mix (Yeshin, 2006; McGoldrick, 2002). Positive experiences with the marketing mix encourage consumers to respond to it and reinforce positive attitudes toward the use of the marketing mix. Consumers with positive experiences in responding to promotions become more promotion prone and more inclined to select brands on promotion to maximize purchase utility. As stated in Chapter 2, promotion proneness reflects the general psychological propensity of a consumer to use, search for, and take advantage of promoted products to maximize their perceived immediate purchase value and the psychological benefits from buying on deal (Alba *et al.*, 1999; Anic and Radas, 2006; Danziger *et al.*, 2014; DelVecchio, 2005; Gupta and Denbleyker, 2015; Krishna, 1991; Krishna *et al.*, 2002; Wakefield and Barnes, 1996). Consumers who engage in purchasing products on promotion are found to be more prone to promotions, and promotion-prone consumers are more sensitive to promotions and buy a larger number of promoted products than those who have low promotion proneness (Anic and Radas, 2006; Umesh *et al.*, 1989). Therefore, promotion proneness reflects and can be quantified as the prevalence of promotion in consumer purchases.

3.2.2 Prevalence of promotion

In this research, Prevalence of promotion is defined as the number of purchases on promotion relative to the total number of purchases in a certain period. Formula 3.1 shows the calculation of the Prevalence of Promotion for quantifying the promotion proneness of a consumer in a certain period.

$$\text{Prevalence of Promotion} = \frac{\text{The total number of purchases on promotion in a period}}{\text{The total number of purchases in the period}} \quad \textbf{(3.1)}$$

The denominator of Formula 3.1 indicates the purchases made by a consumer over a certain period, and the numerator reflects the promotional purchase experiences of the consumer. The Prevalence of Promotion thus quantifies the past purchase experiences of a consumer in response to the promotional mix. The more promotional purchases made by a consumer relative to their total purchases, the higher the Prevalence of Promotion is, and the more prone the consumer is to promotions (Anic and Radas, 2006; Umesh *et al.*, 1989). Consumers with a high Prevalence of Promotion thus have a stronger psychological propensity to use, search for, and take advantage of promoted products to maximize the perceived immediate purchase value (Alba *et al.*, 1999; Anic and Radas, 2006; Danziger *et al.*, 2014; DelVecchio, 2005; Gupta and Denbleyker, 2015; Krishna, 1991; Krishna *et al.*, 2002; Wakefield and Barnes, 1996). They are the targets of marketers, as their purchase decisions are voluntarily affected in accordance with marketers' expectations via reacting to the tailored promotions provided by the marketers. On the contrary, the more purchases a consumer makes without promotions relative to their total purchases, the more the Prevalence of Promotion approaches zero, and the less prone the consumer is to promotions in the market (Anic and Radas, 2006; Umesh *et al.*, 1989). Consumers with a low Prevalence of Promotion are less likely to use, search for, and take advantage of promotions in their purchases. Therefore, they are less likely to change their purchase decisions in accordance with the expectations of marketers.

As experiences of purchasing promoted products modify consumers' perceived value of the promotions (Yeshin, 2006; McGoldrick, 2002) and influence consumers' propensity to use promotions (Anic and Radas, 2006; Schneider and Currim, 1991; Umesh *et al.*, 1989), Prevalence of Promotion is used to predict the promotion responsiveness of a consumer in follow-up purchases in a certain period. Finding out consumers' proneness to promotions may allow retailers to differentiate consumers with high willingness to react to promotions from those with low willingness to respond to the promotions.

3.3 Measuring the Consumer’s Responses to Advertising, Point-of-Display, and Price-Reduction in Retail Purchase Data

Promotion proneness reflects consumers’ psychological propensity to take advantage of promotions regardless of the promotional type. In order to find out whether consumer purchase behaviours in relation to promotions dependent on the type of promotion and whether the behavioural segments identified differ in terms of their sensitivity to different types of promotions, this research created three behavioural variables to quantify a consumer’s willingness to accept a particular promotional type. These behavioural variables are the Prevalence of Advertising, the Prevalence of Point-of-Display, and the Prevalence of Price-Reduction. The Prevalence of Advertising is used to measure how prone to advertising a consumer is. Adapting the Prevalence of Promotion, the Prevalence of Advertising is quantified by using formula 3.2.

$$\text{Prevalence of Advertising} = \frac{The\ total\ number\ of\ purchases\ being\ advertised\ in\ a\ period}{The\ total\ number\ of\ purchases\ in\ the\ period} \quad \textbf{(3.2)}$$

Like the Prevalence of Promotion, the higher the value of the Prevalence of Advertising is, the more likely the consumer is to be attracted by the advertisement and to buy the advertised products. Consumers who have a low value in the Prevalence of Advertising are less likely to be motivated by advertisements to make purchases.

By the same token, the Prevalence of Point-of-Display and the Prevalence of Price-Reduction are developed to quantify a consumer’s psychological propensity to buy the products on a point of display and with a reduced price, respectively. Formula 3.3 shows the calculation of the Prevalence of Point-of-Display.

$$\text{Prevalence of Point-of-Display} = \frac{The\ total\ number\ of\ purchases\ on\ point-of-display\ in\ a\ period}{The\ total\ number\ of\ purchases\ in\ the\ period} \quad \textbf{(3.3)}$$

Formula 3.4 shows the calculation of the Prevalence of Price-Reduction.

$$\text{Prevalence of Price-Reduction} = \frac{\textit{The total number of purchases with reduced price in a period}}{\textit{The total number of purchases in the period}} \quad \textbf{(3.4)}$$

3.4 Measuring the Consumer's Dynamic Choice Behaviours

In a frequently purchased consumer goods market, a large number of brands are available for consumers to select. Consumers thus have opportunities and are allowed to freely switch brands in accordance with their preferences and requirements in a purchase. Generalized from the study of Bucklin *et al.* (1998), consumers' brand choice behaviours are not necessarily related to prices and sales promotions. Their willingness to extend market knowledge may also motivate them to explore the market via trying different brands, even without any promotional incentives (Teunter, 2002). In other words, consumers, on the one hand, are extrinsically motivated by promotions in the product market to explore brands; on the other hand, they are intrinsically motivated to try alternatives by their willingness to seek varieties to extend their market knowledge/information (Teunter, 2002).

Consumers are imperfectly informed and thus are uncertain about a product market (Erdem and Keane, 1996). They learn from their past experiences in brand selection and update their market information set from past purchases in order to make current brand choices (Erdem and Keane, 1996; Foxall, 1993; Heilman *et al.*, 2000; Luo *et al.*, 2015; Neelamegham and Jain, 1999; Yang *et al.*, 2015). Market information plays an essential role in determining a consumer's dynamic choice behaviour. In the dynamic choice process, market information, which is obtained from purchasing and consuming brands, reduces the perceived risks about the alternatives and the uncertainty about the product market (Erdem and Keane, 1996; Hagerty and Aaker, 1984). Luo *et al.* (2015) defines the reduction of uncertainty due to the increased market knowledge in improving consumers' decision making as the value of information from purchases. In this research, the value of information from purchases is quantified and used to predict a consumer's dynamic choice behaviour in purchases.

3.4.1 Value of information in the financial market

Entropy is theoretically defined as the level of disorder or chaos in a system (Lesser and Lusch, 1988). In an open system environment, a system can avoid movement toward maximum entropy. As humans are assumed to represent open systems that can avoid maximum entropy through the importation of information, entropy can theoretically reflect and be used to measure the value of information in avoiding disorder or chaos in a system.

In information theory, the value of information is a function of probability and must satisfy the following properties (Chen, 2004, p.3):

"*1. The information value of two events is higher than the value of each of them.*

2. If two events are independent, the information value of the two events will be the sum of the two.

3. The information value of any event is non-negative."

The only mathematical functions that satisfy all the above properties are of the form U=$-\log_2^{(I(X_n))}$, where U is the value of information and $I(X_n)$ is the probability associated with a given event.

To measure the value of information in understanding financial market behaviours, Chen (2004) provides a generalized entropy theory of information. He generalizes $I(X_n)$ to represent the percentage of people or money that is controlled by informed investors. In this vein, he states that the value of information that is already known to everyone is zero. He measures the value of information in the financial market as $-\log_2^{(I(X_n))}$. $I(X_n)$, which varies between zero and one. Zero represents that no one knows the information, while one represents that the information is announced publicly and is already known to everyone. The more $I(X_n)$ approaches one, the more investors know the information and thus the less valuable the information is. When $I(X_n)$ approaches zero, $-\log_2^{(I(X_n))}$ approaches infinity. This indicates that information that is known to few has a high value.

3.4.2 Adaption of the value of information in the retail market

In the retail market, when new information about a product market is received, consumers' uncertainty about the product market will be reduced. The reduction of uncertainty due to increased market knowledge is defined as the value of information in the retail market, which intrinsically motivates consumers to try alternatives (Luo *et al.*, 2015; Heilman *et al.*, 2000). This research adapts the generalized entropy notion proposed by Chen (2002, 2004, 2005) in information theory to quantify the value of information from purchases in the retail market by dealing with store scanner data.

3.4.2.1 Adopting the generalized entropy theory in the retail market

In the dynamic choice process, the information about a brand collected from trying that brand is unique and independent from the information collected from trying other brands. Thus, the information value of trying two brands is higher than the value of trying either of the brands and equals the sum of the information value of trying each of those two brands. The brand information collected from trying alternatives makes consumers understand the associated product market well and contributes to the reduction of risks in purchases. The information value of trying alternatives is always positive. In general, the value of information from trying alternatives satisfies all the required properties stated in information theory (Chen, 2004). It is thus suggested that the value of information from purchases can be quantified by adopting the generalized entropy notion.

In a frequently purchased consumer goods market, market knowledge plays a particularly important role in improving consumers' decision making and determining consumers' choices (Erdem and Keane, 1996). Consumers' information set, which is updated by their past experiences with brands and marketing mix elements, has significant influence on their current purchase decision making (Erdem and Keane, 1996; Meyer, 1982). Consumers are motivated to try different brands to extend their market knowledge (Erdem and Keane, 1996). They may choose the brands that give them the optimized information value, which is evaluated based on their knowledge about the market (Erdem and Keane, 1996; Meyer,

1982).

Adopting the generalized entropy measurement (Chen, 2004), the value of information from purchases is suggested to be calculated as U= $-\log_2^{\left(I\left(M_p\right)\right)}$, where U is the value of information from purchases and $I\left(M_p\right)$ represents the market knowledge the consumer has. In this case, for an expert consumer who has full market knowledge, the value of information from a purchase approaches zero. Expert consumers are therefore not motivated to further explore the product market through information searches, as they have tried all brands in the market and no new information can be obtained from the product market. When a consumer is new to a product market and does not have any knowledge about the product market, the value of information for the consumer approaches infinity. The new entrant is thus expected to be active in information-searching activities to extend their market knowledge. However, in prior research, the reflected behaviour of information searches has been found to be inconsistent with the amount of information searching conducted. Prior research has found that the amount of information searching presents an inverted U-shape with the increase in market knowledge (Bettman and Park, 1980; Heilman *et al.*, 2000; Johnson and Russo, 1984; Moorthy *et al.*, 1997). New entrants are found to be less engaged in information-searching activities in a product market due to the lack of market knowledge to differentiate brands in the market (Heilman *et al.*, 2000). The value of information from purchases that is quantified by adopting the generalized entropy measurement in the financial market thus cannot correctly reflect and indicate the information search behaviour of a consumer in the dynamic choice process. It is thus necessary to adapt the measurement of the value of information in the financial market based on the conditions in the retail market to quantify the value of information from purchases in the dynamic choice process.

3.4.2.2 Adaptation of generalized entropy to measure dynamic choice behaviour

In a frequently purchased consumer goods market, market knowledge is obtained by experiencing and using a brand in the product market. In this research, the knowledge of a consumer about a product market is quantified as the percentage of brands in the product market that have been consumed by the consumer. The algorithm for measuring the Market Knowledge $I(M_p)$ of a consumer about a product market is showed in formula 3.5 (Luo *et al.*, 2015).

Market Knowledge $I(M_p)$ =

$$\frac{The\ number\ of\ brands\ tried\ by\ a\ consumer\ in\ his\ (her)\ purchase\ lifecycle}{The\ total\ number\ of\ brands\ available\ in\ the\ product\ market\ in\ the\ consumer's\ purchase\ lifecycle} = \frac{n}{N} \quad \textbf{(3.5)}$$

$I(M_p)$ varies between zero and one. If a consumer never consumes a product, he/she does not have any knowledge about the product market. A consumer's market knowledge about a product market accumulates in his/her purchase lifecycle. After a consumer enters a product market, the market knowledge of the consumer increases by $\frac{1}{N}$ via consuming a new brand in the product market. If a consumer purchases and consumes all *N* brands available in the product market (i.e. *n*=*N*), the market knowledge of the consumer about the product market equals one, which means that the consumer has full knowledge and certainty about the product market.

Using market knowledge allows consumers to reduce risks and uncertainties about a product market. Adapted from the definition of value of information provided by Chen (2004, 2005), the Obtainable Value of Information from Purchases is defined as the reducible uncertainty about a product market due to an increase in market knowledge. The reducible uncertainty about a product market thus represents the obtainable value of information in the market that can be further obtained by a consumer from purchases. Adapting from the studies of Chen (2002, 2004, 2005), the generalized entropy measurement is used to quantify the Obtainable Value of Information from Purchases as a function of Market Knowledge. Formula 3.6 shows the calculation of the Obtainable Value of Information from Purchases.

$$\text{Obtainable Value of Information from Purchases} = -\log_2^{(I(M_p))} = -\log_2^{\left(\frac{n}{N}\right)} \quad \textbf{(3.6)}$$

The Obtainable Value of Information from Purchases decreased approaches zero with an increase in Market Knowledge. When $I(M_p)$ approaches zero, $-\log_2^{(I(M_p))}$ approaches infinity. It indicated that a new entrant has infinite Obtainable Value of Information from Purchases due to the lack of market knowledge. When $I(M_p)$=1, $-\log_2^{(I(M_p))}=0$. An expert has tried all brands available in a product market and has full knowledge about the market. His/her Obtainable Value of Information from Purchases is very limited, as the full market knowledge makes him/her certain about the product market.

This relationship between the Market Knowledge and the Obtainable Value of Information from Purchases has been found to be consistent with the identified relationship between market knowledge and reducible uncertainty about a product market in prior research. The reducible uncertainty about a product market is found to be the highest for new entrants due to the lack of market knowledge (Heilman *et al.,* 2000). With an increase in market knowledge, the perceived risks and the remaining uncertainties about a product market diminish (Che *et al.,* 2015; Heilman *et al.,* 2000; Agrawal, 1995; Strang *et al.,* 1979). When consumers have full knowledge about a product market, they are certain about the market, and the reducible uncertainty about the market approaches zero (Heilman *et al.,* 2000). In general, the quantified Obtainable Value of Information from Purchases seems to be able to reflect the reducible uncertainties and risks about a product market with an increase in market knowledge in consumer purchase lifecycle.

Even though the Obtainable Value of Information from Purchases reflects the decision-making process of a consumer in terms of the maximum reducible risks in a purchase, it cannot reflect the reduction of risks that can be achieved by purchasing a new brand. The risk and uncertainty reduction in a purchase is co-determined by a consumer's market knowledge and the remaining/reducible risks and uncertainties in a product market (Heilman *et al.,* 2000; Luo *et al.,* 2015). The Value of Information from Purchases, which refers to a reduction of uncertainties and risks due to an increase in market knowledge, is thus determined by both Market Knowledge and the Obtainable Value of Information from Purchases. In this research, formula 3.7 is created to quantify the Value of Information from

Purchases.

Value of Information from Purchases

$$= \text{Market Knowledge} \times \text{Obtainable Value of Information from Purchases}$$

$$= I(M_p) \times \left(-\log_2^{\left(I(M_p)\right)}\right) = \frac{n}{N} \times \left(-\log_2^{\left(\frac{n}{N}\right)}\right) \tag{3.7}$$

Consumers make choices via making trade-offs between the benefits and costs of purchases. The information obtained from purchases allows consumers to reduce risks in their future purchases. The Value of Information from Purchases thus reflects the motivations and propensity of a consumer in information searches via demonstrating the benefits (i.e. reduced risks) from purchasing a new brand. The Value of Information from Purchases indicated the possibility that a consumer is inclined to buy a new brand using their market knowledge to search for information through the purchase. Consumers who have a high Value of Information from Purchases have a higher possibility to sample brands to extend their market knowledge. Due to their high level of exploration tendency, these consumers are regarded as explorers. On the contrary, consumers who have a low Value of Information from Purchases are inclined to purchase a subset of familiar brands repeatedly to minimize risks. Due to the low motivation and propensity to explore a product market, these consumers are regarded as exploiters. Figure 3.1 shows the change in the Value of Information from Purchases with an increase in Market Knowledge in the consumer purchase lifecycle.

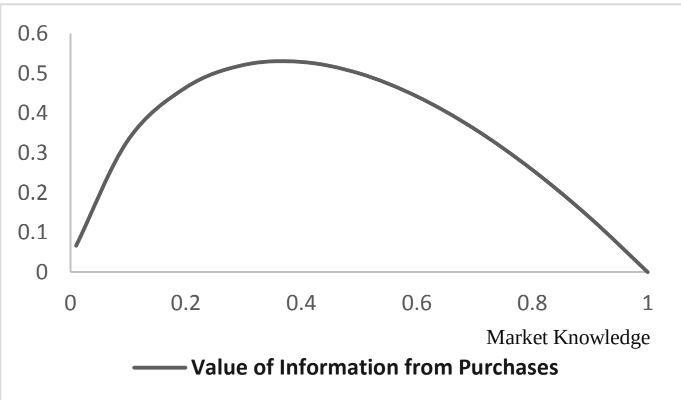

Figure 3.1: The Value of Information from Purchases in the consumer purchase lifecycle

When a consumer first enters a product market, both the Market Knowledge and the Value of Information from Purchases approach zero. This means that new entrants are more likely to be exploiters and rarely explore brands for the purpose of information searching. With an increase in market knowledge, the Value of Information from Purchases gradually increases to a maximum and then decreases, approaching zero when the consumer has full market knowledge. This means that the information search activities of a consumer increase before decreasing toward zero with an increase in market knowledge. Consumers with high market knowledge are also more likely to be exploiters and to continuously purchase a subset of preferred brands. In general, the Value of Information from Purchases that is quantified in this research presents an inverted U relationship with the market knowledge of a consumer. According to Heilman *et al.* (2000), with an increase in market knowledge, the amount of information searching presents as an inverted U-shape. The identified relationship between the Market Knowledge and the Value of Information from Purchases is thus consistent with, supported by, and explained by prior research.

When consumers first enter a product market, they are not able to differentiate among brands due to the lack of market knowledge (Heilman *et al.*, 2000). Even though the Obtainable Value of Information from Purchases is infinite at this time, consumers are not capable of achieving this value due to their lack of capability to differentiate among brands. The Value of Information from Purchases is thus very limited. Such consumers are risk averse and are inclined to purchase familiar brands with big names, without sampling lesser-known brands to seek information (Erdem and Keane, 1996; Heilman *et al.*, 2000).

After exploiting and exploring big brands for a period, consumers' market knowledge increases (Erdem and Keane, 1996; Heilman *et al.*, 2000). Even though the Obtainable Value of Information from Purchases decreases with an increase in market knowledge, an increase in capability in differentiating among brands improves consumers' capability in achieving the Obtainable Value of Information from Purchases. Consumers' Value of Information from Purchases thus increases and creates an incentive to try lesser-known brands (Erdem and

Keane, 1996; Heilman *et al.*, 2000; Luo *et al.*, 2015).

Brand sampling provides consumers with market knowledge to differentiate among brands and reduce risks from purchasing. After sufficient market knowledge has been obtained from purchases, consumers' perceived risks about the market become limited (Heilman *et al.*, 2000). Even though consumers may be able to distinguish among brands and fully achieve the Obtainable Value of Information from Purchases, the limited reducible uncertainty about the market results in a limited Value of Information from Purchases. Consumers in this stage are not motivated to sample brands for learning purposes and gradually settle on a subset of preferred brands (Erdem and Keane, 1996; Heilman *et al.*, 2000). In general, the adapted entropy measurement can be reasonably used to measure the dynamic choice behaviour of a consumer.

3.5 Measuring the Consumer's Brand-Switching Behaviour

To monitor and predict a consumer's brand choice in purchases, this research creates two sets of data-mining algorithms. In general, the Value of Information from Purchases reflects a consumer's intrinsic motivations for exploring a product market via trying alternatives. It indicates how likely the consumer is to select a new brand in a purchase. In this research, another set of algorithms is developed to quantify the brand-switching behaviour of a consumer in brand selection.

According to Ehrenberg (1988), most people tend to develop habits of consistently buying one or some small number of brands. Brand loyals are people who bought one or some small number of brands for the majority of their purchases (Ehrenberg, 1988; Romaniuk and Sharp, 2016; Sharp, 2010). Brand switchers are people who bought a new brand at least once in their purchases, although most of their buying is of other brands (Romaniuk and Sharp, 2016). In general, most consumers practise multi-brand purchasing and few are 100% loyal. They make purchases within a repertoire or consideration set of tried and tested – and thus trusted – brands that are essentially functional substitutes for one another, though they do not buy any brand exclusively. In new world view, brand loyals and brand switchers are regarded as loyal switchers in terms of their purchase behaviours in brand selection (Romaniuk and Sharp, 2016).

Switching brands in purchases reflects the uncertainty associated with a consumer's brand selection. To understand and predict the brand selection of a consumer, this research also adapted Shannon entropy to measure the brand-switching behaviour of the consumer. Shannon entropy is defined as a quantitative measure of uncertainty represented by the probability distribution and has been widely used to measure consumer behaviours (Kapur *et al.*, 1984; Maassen and Uffink, 1988; Singh, 2000). The higher the entropy value is, the higher the uncertainty of a problem will be, and thus the more information will be needed for problem solving. According to Hirsh *et al.* (2012), Shannon entropy can be used to quantify the uncertainty associated with a given perceptual or behavioural experience. In addition, Chen (2005) argues that entropy theory offers a unified understanding of the human mind. Thus, this research uses the adapted Shannon entropy to quantify the uncertainty of consumers' purchase behaviour, given certain behavioural experiences. Understanding the brand-switching behaviour of consumers in terms of the uncertainty associated with their purchase behaviour may allow retailers to understand consumers' minds and personalities.

To measure the uncertainty of consumer behaviours to understand their minds and personalities, in this research, the probability mass function of brand selection in the Shannon entropy measure is calculated by using transitional probability. The transitional probability used in this research is adapted from the core concept of a Markov chain. This is the probability that a consumer will change their choice from brand A to brand B in consecutive transactions. Instead of using the probability calculated by dividing the total number of purchases by the total number of purchases with the same brand, using transitional probabilities for entropy calculation enables people to clearly understand whether consumers consistently purchase one brand over all consecutive transactions. Based on our knowledge of the measurement of repeat purchase behaviours, the adapted Shannon entropy measure has not been used to measure the uncertainty of purchase behaviours given certain behavioural experiences in prior studies. The adapted Shannon entropy algorithm for measuring the brand-switching behaviour of a consumer is:

$$\text{Brand Switching} = -\sum_{i=0}^{n}\left(\left(P(X_n)\right) \times \log_2^{\left(P(X_n)\right)}\right) = -\sum_{i=0}^{n}\left(\left(\frac{SWa-b}{SW}\right) \times \left(\log_2^{\left(\frac{SWa-b}{SW}\right)}\right)\right) \quad \textbf{(3.8)}$$

$P(X_n)$ --- The transitional probability

$SWa - b$ --- The total number of transactions switching from brand A to brand B

SW --- The total number of transaction switches = the total number of transactions -1

n --- The total number of forms of transaction switches in the product category

$$\text{Normalized Brand Switching} = \frac{-\sum_{i=0}^{n}\left(\left(P(X_n)\right)\times\log_2^{\left(P(X_n)\right)}\right)}{-\sum_{i=0}^{n}\left(\left(\frac{1}{n}\right)\times\log_2^{\left(\frac{1}{n}\right)}\right)} = \frac{-\sum_{i=0}^{n}\left(\left(\frac{SWa-b}{SW}\right)\times\left(\log_2^{\left(\frac{SWa-b}{SW}\right)}\right)\right)}{-\sum_{i=0}^{n}\left(\left(\frac{1}{n}\right)\times\log_2^{\left(\frac{1}{n}\right)}\right)} \quad \textbf{(3.9)}$$

Based on Formula 3.9, the adapted Shannon entropy value will be normalized. This value varies between zero and one (including zero and one). If consumers consistently purchase the same brand in all transactions, they only have one type of transaction switch (switch from brand A to brand A). In this case, the total number of transaction switches from brand A to brand A equals the total number of transaction switches. Their transitional probability equals one, and their brand switch value equals zero. Thus, they have repeat purchase behaviours and are expected to carry out exploitation activities in purchases, based on their existing knowledge and learning in the product category. The uncertainty of their purchase behaviours is expected to be low, and they are expected to be conservative. In other words, their future purchase behaviours are expected to be certain and predictable. On the contrary, the more forms of transaction switches there are (switch from brand A to brand B), the smaller the transitional probability of each form of transaction switch will be, and the higher the brand-switching value will be (i.e. the normalized brand-switching value will be closer to one). In that case, the higher the uncertainty of the purchase behaviour is, the lower the repeat purchase probability is, the more exploration activities are expected to be carried out by the consumer, and thus the more difficult it is to predict the consumer's purchase behaviours. In other words, the higher the brand-switching value, the higher the uncertainty level of consumer behaviours and the lower the possibility that the consumer is conservative.

3.6 Analysis Process of the Research

The purpose of this research is to segment consumers and discover their behavioural patterns in terms of their brand selection behaviours in relation to promotions. The inductive reasoning approach is used in this research to lead to the conclusions. Figure 3.2 demonstrates the analysis process in a product market.

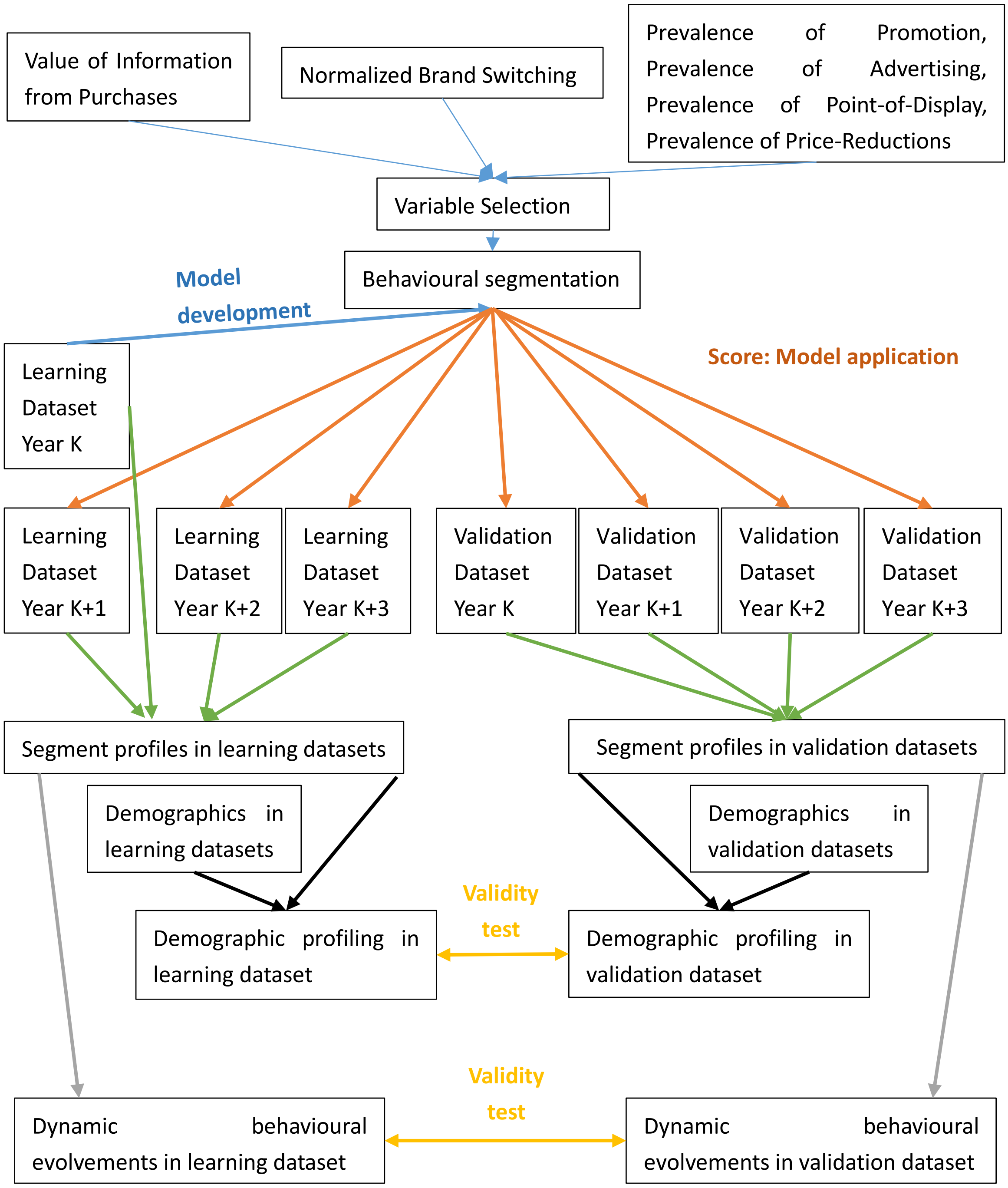

Figure 3.2: Analysis process in a product market

As presented in Chapter 3, six algorithms are developed and used to measure an individual consumer's brand selection behaviour in relation to promotions. Before segmenting consumers based on their quantified purchase behaviour, the behavioural variables are selected to avoid producing distorted results from a high degree of collinearity among the variables in the segmentation. In this research, segmentation model is developed by dealing with a learning dataset in the first consecutive year in a product market. The rest of the datasets created in the product market are then scored by implementing the developed segmentation model. The behavioural profile of each segment in a dataset is generated based on the characteristics of consumers in the segment in terms of their brand selection behaviours in relation to promotions. In validating the behavioural segmentation and supporting marketers to effectively target consumers with expected purchase behaviours, this paper profiles the identified behavioural segments by using the demographic variables in both of the learning and validation datasets. By comparing the membership of each consumer over the years, the dynamic behavioural evolvements in the consumer purchase lifecycle are identified in both the learning and validation datasets. The results of the demographic profiling and behavioural evolvement identification generated in the learning datasets are validated by those results generated in the validation datasets. In general, the analysis of a product market consists of four steps: behavioural segmentation, segment profiling, demographic profiling, and the identification of dynamic behavioural evolvements. After analysing the purchase behaviours of consumers in each of the selected product markets, a comparative analysis across selected product markets is conducted to find out the commonalities and differences in consumer purchase behaviours across product markets in the final step of this research. These six analysis steps are presented in the following sub-sections.

3.6.1 Step 1: variable selection

To segment consumers via clustering analysis, the quantified behavioural variables used in the clustering analysis should not be collinear (Sambandam, 2003; Sarstedt and Mooi, 2014). Collinearity is defined as a high level of correlation between two variables (Sambandam, 2003). Multicollinearity refers to a high degree of correlation among more than two variables. Variables with a high degree of collinearity represent the same concept (Sambandam, 2003; Sarstedt and Mooi, 2014). In clustering analysis, it is essential to select variables that represent sufficiently unique concepts regarding a specific managerial objective to identify distinct market segments (Sarstedt and Mooi, 2014). The use of highly correlated variables is likely to produce distorted results because the concept is represented multiple times in the data (the number of times is determined by the number of correlated variables in the clustering analysis) and gets multiple weights of all the other variables (Sambandam, 2003). The clustering solution thus is likely to be skewed in the direction of the concept that is overrepresented by the highly correlated variables (Sambandam, 2003; Sarstedt and Mooi, 2014).

In this research, six variables, which are the Prevalence of Promotion, Prevalence of Advertising, Prevalence of Point-of-Display, Prevalence of Price-Reduction, the Value of Information from Purchases, and the Normalized Brand Switching, are created to quantify a consumer's brand choice behaviour in response to the promotional mix. In order to avoid the generation of distorted results by using the quantified behavioural variables in the clustering analysis, correlation analysis among the six variables is conducted in each selected product category. In Step 2, consumers are segmented into behavioural groups based on the selected behavioural variables.

3.6.2 Step 2: behavioural segmentation

Grouping consumers with similar wants and needs is a fundamental marketing activity (Sarstedt and Mooi, 2014). Retailers can then target the right consumers for building relationships with individual consumers at effective costs (Bottomley and Nairn, 2004; Nairn and Bottomley, 2003). In marketing, researchers and marketers often segment consumers and markets based on practical grounds, industry practice, and wisdom, which involve high degrees of subjectivity (Sarstedt and Mooi, 2014). Compared to these commonly used segmentation approaches, clustering analysis is widely used in searching for patterns in complex data and segmenting consumers based on data, which is less subjective. In this research, clustering analysis is implemented to identify homogenous groups of consumers in terms of their brand selection behaviours in relation to promotions. The use of clustering analysis instead of predictive modelling may allow marketers to identify the trade-offs between the maximization of immediate purchase value from taking advantage of promotions and the extension of market knowledge from trying alternatives in consumer purchase decision making. Consumers with similar characteristics in brand selection behaviours in relation to promotions are classified into the same behavioural segment with the support of SAS Enterprise Miner. SAS Enterprise Miner is a powerful data-mining software for streamlining the data-mining process. It can be used to support the creation of highly accurate predictive and descriptive models by analysing vast amounts of numerical and textual data (SAS Institute Inc., 2009).

In this research, the behavioural segmentation model is generated by dealing with the learning dataset of the first selected year. The generated behavioural segmentation model is then implemented to score the rest of the learning and validation datasets in a product market. In Step 3, the generated behavioural segments in each dataset are profiled on the basis of the brand selection behaviour in relation to promotions for the purpose of differentiation and definition. This research typifies a type of brand selection behaviour in relation to promotions with a group of consumers.

3.6.3 Step 3: segment profiling

For the purpose of differentiating behavioural segments via generating segment profiles, a scatter diagram that presents the membership status of each consumer over the years is used in combination with two series of bar charts generated by SAS Enterprise Miner. In a scatter diagram, the membership of a consumer in a year is presented with a colour and a shaped spot. Consumers in the same behavioural group are represented with the same colour. When a consumer's segment membership changes from one year to another, the spot that represents his/her behaviour changes from one colour (the original membership) to another (the new membership). When the membership of a consumer remains the same over the years, the colour that represents the consumer's behavioural segment remains unchanged. In general, the scatter diagram allows people to visualize the distribution of behavioural segments, which helps them to understand the behavioural profile of each segment.

The two series of bar charts generated from SAS Enterprise Miner provide a comprehensive image of the behavioural profile of a segment. A series of bar charts that present the distribution of the behavioural variables in a behavioural segment relative to that in the population is used to find out the characteristics of the behavioural segment in terms of the brand selection behaviour in relation to promotions. Inferred from the scatter diagram in a product market, the weights of behavioural variables in determining the behavioural segment differ across segments. Another series of bar charts show the weight of each variable in determining a behavioural segment. The visualization of the variable weights together with the associated characteristics of the variable in a segment not only allows people to understand and predict the potential purchase behaviours of the consumers in the segment, but also helps people to understand how consumers make trade-offs between market knowledge extension and immediate purchase value maximization.

In general, combining the scatter diagram and the two series of bar charts to profile and define behavioural segments may allow people to better understand consumers and their associated decision-making process in purchases. In Step 4, demographic profiling is used as an approach to validate the behavioural segmentation in this research.

3.6.4 Step 4: demographic profiling

Validating behavioural segmentation is essential for retailers to successfully develop coherent marketing programmes (Nairn and Bottomley, 2003). Criterion-related validity is determined by assessing whether clusters differ across external variables that are theoretically related to them (Bottomley and Nairn, 2004; Nairn and Bottomley, 2003). As explained in the literature review, the demographics of a consumer are suggested to be related to both promotion proneness and dynamic choice behaviours. Demographics are thus used to profile each behavioural segment to assess the criterion-related validity. In order to profile behavioural segments and find out whether the generated segments differ across demographics, the Segment Profile node in SAS Enterprise Miner is used to automate the profiling process.

For each behavioural segment, the associated demographic profile in a year generated from the learning dataset in the year is validated by using the profile generated from the validation dataset. In order to find out the influence of demographics on consumer purchase behaviours over the years, the demographic profiles of a behavioural segment over four years are compared. The demographics of a behavioural segment that remain the same over four years are regarded as the stable variables for predicting purchase behaviours, regardless of market experiences.

Like demographics, the market experiences of consumers also influence their purchase behaviours in their purchase lifecycles. In Step 5, this research identifies and uncovers the dynamic behavioural evolvement patterns, routes, and approaches in the consumer purchase lifecycle.

3.6.5 Step 5: identification of dynamic behavioural evolvements

Under uncertainty, consumers' past experiences in purchases affect their current choices due to the change of their information set from market learning (Luo *et al.*, 2015; Yang *et al.*, 2015; Erdem and Keane, 1996; Heilman *et al.*, 2000). In order to find out how consumers' purchase behaviours evolve in their purchase lifecycles, their associated membership across two consecutive years is compared in this step. The dynamic behavioural evolvement patterns and routes discovered from the learning datasets is validated by using those identified in the validation datasets. The identified dynamic behavioural evolvement patterns, routes, and approaches allow marketers to understand and predict how consumers make trade-offs between the maximization of immediate purchase value and the extension of market knowledge in the consumer purchase lifecycle. It thus might help marketers to tailor their marketing strategies based on consumers' needs and wants in the associated purchase stage.

3.6.6 Step 6: comparative analysis across product markets

The last step of the data analysis in this research is a comparative analysis across the selected product markets in four aspects. Firstly, the proportion and the number of brands tried by consumers are compared across product markets to find out the exploration conditions of consumers in different product markets. Secondly, the typical purchase behaviours across product markets are compared to find out how consumers differ in their purchase behaviours across product markets. Thirdly, the demographic profiles of behavioural segments are compared across the selected product markets to identify the commonalities and differences. Fourthly, the dynamic behavioural evolvement routes identified in each of the selected product markets are compared to find out how the routes differ across product markets. The insights generated from the comparative analysis may allow marketers to make predictions about the purchase behaviours of consumers in a product market, based on the characteristics of the product market. In the next chapter, the numerical studies in this research are presented.

3.7 Conclusion

Overall, this research develops six sets of data-mining algorithms to quantify a consumer's brand selection behaviour in relation to promotions. As the Prevalence of Promotion in purchases can reflect and be reflected by a consumer's promotion proneness, it is used to quantify the consumer's psychological propensity to accept promotions. The Prevalence of Promotion refers to the percentage of purchases on promotion out of the total number of purchases in a certain period. The higher the Prevalence of Promotion, the more prone the consumer is to promotions. Consumers with high values in the Prevalence of Promotion are more likely to be attracted by promotions and to select brands on promotion. On the contrary, consumers with low values in the Prevalence of Promotion are less sensitive to promotions and are inclined to make purchases even without promotions.

By the same token, the Prevalence of Advertising, the Prevalence of Point-of-Display, and the Prevalence of Price-Reduction are used to quantify a consumer's proneness to advertising, point of display, and price reduction, respectively. The values of these three behavioural variables indicate a consumer's psychological propensity to accept a particular type of promotion, rather than proneness to any type of promotion.

In purchases, consumers update their information sets via either continuously purchasing their preferred brands or exploring different brands in a product market. In their purchase lifecycles, their exploration and exploitation activities influence their current purchase decisions due to their updated market information set. As the purpose of exploration in purchases is to extend market knowledge, the Value of Information from Purchases may determine the possibility that a consumer will engage in exploration activities in their current purchase. In this research, the Value of Information from Purchases is used to quantify a consumer's dynamic choice behaviour (i.e. exploration and exploitation behaviours in purchases).

In this research, the other way to understand a consumer's brand choice is to understand how he/she switches brands in purchases. To quantify the brand-switching behaviour of a consumer, Shannon entropy is adapted and used to measure the uncertainty associated with the consumer's brand selection. Transitional probability, adapted from the core concept of a Markov chain, is used to calculate the probability mass function in the entropy measurement. For comparison purposes, the value of brand switching for each individual consumer is normalized, ranging between zero and one.

To answer the research questions, this research consists of six analysis steps. Step 1 presents the process of selecting behavioural variables for behavioural segmentation. Step 2 introduces the behavioural segmentation based on the brand selection behaviour in relation to promotions. Step 3 provides a description of profiling the generated behavioural segments based on consumer purchase behaviours. Step 4 presents the demographic profiling in this research. The approach used for identifying dynamic behavioural evolvements in the consumer purchase lifecycle is presented in Step 5. In Step 6, a comparative analysis of the findings in the selected product markets is discussed.

Overall, this chapter presented the behavioural measurements and the analysis steps in this research. In Chapter 4, the implementation of the behavioural measurements in the numerical studies is discussed.

CHAPTER 4: NUMERICAL STUDIES

4.1 Introduction

Following the description of behavioural measurements and the analysis process in Chapter 3, Chapter 4 presents the application of the developed behavioural measurements in the US market in four sections. Section 4.2 describes the data used in this research in four sub-sections. Firstly, a general description of the dataset is provided. Then, the markets for analysis are selected and the associated datasets used for analysis are described. In this research, the salty snack, yogurt, and toilet tissue markets are selected for analysis. The required data and the associated data-preparation process in those three product markets are presented in Sections 4.2.2, 4.2.3, and 4.2.4, respectively. To understand the brand selection conditions in the selected three product markets, Section 4.3 discusses the number and the proportion of brands explored by consumers in each of the product markets. Section 4.4 presents the handling of the data by using the developed algorithms to quantify the brand selection behaviour in relation to promotions. To conduct behavioural segmentation, the behavioural variables are selected. Section 4.5 discusses the process and results of the variable selection in this research.

4.2 IRI Marketing Data

4.2.1 Overview of the IRI marketing dataset

In this research, IRI marketing data is used to analyse consumer purchase behaviours (Bronnenberg *et al.*, 2008; Kruger and Pagni, 2013). The IRI marketing dataset is one of two current major point-of-sale or store-scanner data sources (Bronnenberg *et al.*, 2008; Kruger and Pagni, 2013; Perloff and Denbaly, 2007). It was constructed primarily for marketing purposes and is widely used by retailers, manufacturers, and farm commodity groups in marketing research (e.g. Bauner and Wang, 2014; Bronnenberg and Mela, 2004; Chevalier and Kashyap, 2011; Gupta, 1988; Hovhannisyan and Bozic, 2014; Hovhannisyan and Gould, 2011; Huang *et al.,* 2006; Sinapuelas and Robinson, 2012).

Compared to store loyalty card datasets, the IRI marketing dataset has four outstanding advantages in academic usage. Firstly, the IRI marketing dataset has high accessibility for academic usage. Unlike store loyalty card datasets, the IRI marketing dataset is available to academic researchers to study important research topics in marketing and economics (Bronnenberg *et al.*, 2008).

Secondly, the information on household demographics available in the IRI marketing dataset is much richer than that available in store loyalty card datasets (Perloff and Denbaly, 2007). In the IRI marketing dataset, information on 26 valid household demographic variables is provided every year (Kruger and Pagni, 2013). The provision of comprehensive demographic characteristics on a yearly basis enables researchers to conduct demographic-related research for data lasting several years.

Thirdly, the IRI marketing dataset contains more-complete records of consumer purchases than those in store loyalty card datasets. The purchase records in the IRI marketing dataset are collected by consumers themselves via scanning all purchases from all retail stores after each shopping trip. However, store loyalty card datasets only contain records of purchases made in the stores of the associated retailer. The IRI marketing dataset consists of household-based scanner data and is therefore more complete than store loyalty card datasets in terms of the data collection fields (Perloff and Denbaly, 2007).

Fourthly, the IRI marketing dataset is potentially subject to fewer measurement errors than store loyalty card datasets are (Perloff and Denbaly, 2007). In purchases, consumers may infrequently use loyalty cards or use someone else's card for convenience. Both of these card usage behaviours can result in errors when measuring consumer purchase behaviours via dealing with their purchase records. However, as the transactional data in the IRI marketing dataset is collected by consumers themselves after each shopping trip, with the instruction of IRI group, the measurement errors resulting from the data collection approach are limited. In general, the data collection approach in the IRI marketing dataset makes it more suitable to be used in measuring consumer purchase behaviours than store loyalty card datasets are.

Specifically, the IRI marketing dataset consists of delivery store datasets, store datasets, panel datasets, and panel demographic datasets in 31 frequently purchased consumer goods categories from 2001 to 2011 (Kruger and Pagni, 2013). The wide coverage of product categories enables the analysis of store choice and purchase behaviours across categories, and market basket effects (Bronnenberg, *et al.*, 2008). The long time horizon covered in the IRI marketing dataset, on the one hand, enables researchers to discover how price elasticities vary over the lifecycle of a product; on the other hand, it could afford insights into how consumers behave in brand selection in their purchase lifecycles (Luo *et al.,* 2015). In general, the wide breadth of the IRI dataset enables people to discover knowledge of marketing strategy beyond a limited number of categories, markets, and years (Bronnenberg *et al.*, 2008).

Delivery store data provides information about the stores. It does not vary by product categories but varies by years. Stores in the IRI marketing dataset are masked by using IRI_KEY for the purpose of identification across the various tables. In a delivery store data file, the type of outlet, the estimated annualized sales in millions, the market name, an open and close week, and the masked retailer are associated with each IRI_KEY. From the delivery store data, the stores in the retail market can be identified.

Unlike the delivery store dataset, the store dataset is at the store week UPC level and varies across product categories and years. The store dataset consists of product sales, pricing, and promotion data (i.e. retail features, displays, and retailer coupons) for all items sold by 124 retailers in 50 US markets (Bronnenberg *et al.*, 2008). According to Bronnenberg *et al.* (2008), the large number of stores covered in the dataset enables people to explore spatial competition across stores and channel choice across store formats. In addition, the wide coverage of the US market in the store dataset allows people to engage in exploring such issues as product roll-out, differences in retailers, and consumer behaviours across markets. In other words, the broad array of markets covered in the dataset is essential and required for estimating and understanding spatial and market effects on retailers and consumers.

Like the store dataset, the panel dataset varies across product categories and time. Panel data is the transactional records of panellists. Each piece of panel data consists of a unique panellist ID number, the IRI week the transactional record was produced, the total number of units purchased by the household in the transaction, the outlet and the retail store the transaction occurred in, the total dollars paid in the transaction, and the identification number of the product item purchased by the household. In the IRI marketing dataset, panel data is provided for two behavioural markets, which are Eau Claire (Wisconsin) and Pittsfield (Massachusetts). Consumers' purchase behaviours in these two behavioural markets can thus be simulated by dealing with the panel dataset. In prior research, the panel data in the IRI marketing dataset has been used to explore such issues as how loyalty patterns shift over time, how brand penetration is influenced by marketing, commonalities in behaviour across categories, and store switching (Bronnenberg *et al.*, 2008). Due to the provision of panel demographic data each year, researchers can associate their findings in consumer behaviour with demographic characteristics. This enables people to better understand the identified consumer behaviours in terms of the associated demographic characteristics.

For example, Huang *et al.* (2006) used the IRI marketing dataset to examine how a grocery store's sales activity affects its customers' choices across brands, controlling for consumer characteristics. They predicted the switching behaviours of consumers by using household demographics and the frequency with which stores conduct sales: temporary reductions in price from the usual or modal price. They found that as the sales frequency increases for a given brand, households are more likely to be loyal to that brand or switch between that brand and others but are less likely to be loyal to other brands.

In this research, the IRI marketing dataset is used to analyse the demographic-related purchase behaviours of consumers in purchasing frequently purchased consumer goods. In the IRI marketing dataset, no consumer was identified as making purchases across geographic markets. However, the majority of the consumers made their purchases with different retailers in the same geographic market (e.g. around 81% of consumers purchased salty snacks from different retailers in Pittsfield). As the consumers always made purchases in only one geographic market but across different retailers, the transactional records generated from all retailers in a geographic market are used for analysis. In this research, the Pittsfield market is selected for analysis. This is because the transactional data generated in Pittsfield is from more retailers than that in the Eau Claire market (i.e. seven retailers in Pittsfield provide transactional data and six retailers in Eau Claire provide the data). Pittsfield is the largest city of Berkshire County, Massachusetts, US. In 2010, the population in Pittsfield reached 44,737. The large population in Pittsfield provides retailers and manufacturers with an opportunity to increase their sales and profits via attracting and obtaining consumers. The purchase behaviours of consumers in Pittsfield are processed and modelled to help retailers and manufacturers to better understand the consumers and thus provide attractive strategies for the consumers.

Even though the IRI marketing dataset consists of data ranging from 2001 to 2011, the transactional records in the panel dataset from 2008 to 2011 cannot be associated with the product features provided in the store dataset. In this research, the data ranging from 2004 to 2007 is thus selected for analysis. As consecutive transactional records are required to calculate the behavioural variables for behavioural modelling, the products that were frequently and massively purchased by a large number of consumers from 2004 to 2007 are selected for analysis. In order to find out the varieties of the demographic-related behavioural findings across product markets with different number of brands, salty snack, yogurt, and toilet tissue are selected from 31 product categories. The selected three product markets have a sufficient number of purchases made by a large number of consumers for the purpose of analysis and differ in the number of brands available in the Pittsfield market. The following three sub-sections provide comprehensive description about the salty snack, yogurt, and toilet tissue markets, respectively.

4.2.2 Salty snack market

Snack foods play a major part of Americans' diets in everyday life. The total sales of the snack category in the US increased from $41.1 billion in 2010 to $47.5 billion in 2015 (Statista, 2016). Among the snack foods, yogurt and salty snacks had the highest volume sales growth in 2013. In this sub-section, the background and data selection of the salty snack market are provided. Information about the yogurt market is provided in the following sub-section.

In North America, over 60% of consumers enjoyed crisps as a snack in 2014 (Statista, 2016). For example, $11.2 billion of potato crisps were consumed in the US in 2015. According to American consumers, the purpose of consuming snacks is either to satisfy hunger or to replace a meal. The diet preference for salty snacks resulted in a 2.3% increase in the sales volume of salty snacks in 2013. In 2014, the worth of the salty snack market in the US reached $28.2 billion (Trefis Team, 2014). Facing the huge and increased demand for salty snacks in the US, a large number of salty snack brands have been introduced to compete for consumers (Statista, 2016). In Pittsfield, 79 salty snack brands were available for consumers to select from in 2004. In 2005, eight new salty snack brands were introduced in the Pittsfield market. In 2006, 11 new brands of salty snacks were introduced; in 2007, eight new salty snack brands were introduced. In general, consumers had the opportunity to select salty snacks from 98 brands by 2007 and from 106 brands by 2008. The Pittsfield salty snack market is a dynamic product market due to the introduction of new brands over the years.

To understand the brand selection behaviours of consumers in response to promotions in Pittsfield, this research applies the developed behavioural measurements to process the point-of-sale data from 2004 to 2007 in the IRI marketing dataset. The dataset for processing consists of consumers' salty snack transactional records, the marketing mix information associated with each brand, and the demographic characteristics associated with each consumer. It is generated by merging the panel dataset, store dataset, and demographic dataset in the Pittsfield market. In Pittsfield, 1,467 consumers have salty snack purchase records in the four consecutive years from 2004 to 2007. To quantify a consumer's brand selection behaviour in relation to promotions, sufficient transactional records are needed for each consumer. In this study, consumers who had no fewer than 12 transactional records each year are selected for analysis. In total, 840 consumers who made 158,566 purchases in Pittsfield from 2004 to 2007 are thus selected. One out of those 840 consumers provided invalid demographic information to retailers and thus is excluded from further analysis. In this study, the final dataset for processing consists of 839 consumers with their associated

158,365 purchases from 2004 to 2007.

We take a 60% random sample to obtain 503 consumers who made 22,633 purchases in 2004 to form ‘learning dataset 2004’. The processed ‘learning dataset 2004’ is used to generate a segmentation model via clustering analysis with the support of SAS Enterprise Miner. For the purpose of identifying the behavioural evolvements and evaluating the ability of demographics in reflecting purchase behaviours over time, the remaining 24,118 purchases in 2005, 23,613 purchases in 2006, and 23,627 purchases in 2007 made by those 503 consumers are used to form ‘learning dataset 2005’, ‘learning dataset 2006’, and ‘learning dataset 2007’, respectively. These three learning datasets are then scored by implementing the segmentation model generated from ‘learning dataset 2004’.

The remaining 336 consumers made 64,374 purchases from 2004 to 2007 (15,698 purchases in 2004, 16,841 purchases in 2005, 16,286 purchases in 2006, and 15,549 purchases in 2007). For the purpose of validating the results generated in the learning datasets, four validation datasets, which are ‘validation dataset 2004’, ‘validation dataset 2005’, ‘validation dataset 2006’, and ‘validation dataset 2007’, are created in this study. Each of the four validation datasets consists of the purchases made by the 336 consumers in the associated year. For example, ‘validation dataset 2004’ consists of 15,698 purchases made by the 336 consumers in 2004. Like the learning datasets for 2005, 2006, and 2007, these four validation datasets are scored by implementing the segmentation model generated from ‘learning dataset 2004’.

4.2.3 Yogurt market

The US yogurt market is a highly competitive, expanding market (Statista, 2016). The US is among the top 11 yogurt-consuming countries (Durankiev, 2015). According to a survey conducted from 2014 to 2015, 56.38% of US households eat or drink yogurt in their daily lives (Experian, 2016). The per capita consumption of yogurt in the US presented an increasing trend from 2000 to 2013 (US Department of Agriculture and Economic Research Service, 2016). In 2013, the US yogurt per capita consumption amounted to about 27.5 half pints. The increasing trends also applied to the volume sales of yogurt in the US from 2012 to 2014. In 2014, US yogurt volume sales came to 3.36 billion pints (USDEC, 2016). In general, the sales of yogurt in the US increased from $6.2 billion in 2011 to over $7.7 billion in 2015 (Frozen and Refrigerated Buyer, 2016).

Facing such a big market with high potential, many brands of yogurt have been introduced to capture the business opportunities via competing for consumers in the market. In the Pittsfield market, 16 brands were available for consumers to choose from in 2004. Similar to the salty snack market, the yogurt market is also a dynamic market due to the release of new brands over the years. By 2006, 18 brands of yogurt had been released to the market and were available for purchase in Pittsfield. The number of brands released to the yogurt market in Pittsfield gradually increased to 21 by 2007 and to 24 by 2008.

To understand the behaviour of US households in purchasing yogurt, the transactional records associated with product features and consumers' demographic characteristics from 2004 to 2007 in the Pittsfield market are processed. Following the data-preparation process in the salty snack market, the panel dataset, store dataset, and demographic dataset from 2004 to 2007 in the Pittsfield yogurt market are merged. In Pittsfield, 1,045 consumers made purchases of yogurt in the continuous four years from 2004 to 2007. Among those 1,045 consumers, some consumers have a very limited number of transactional records to be used for quantifying their purchase behaviours and thus cannot be selected for analysis. As the yogurt market in the US is still an infant market (Statista, 2016), a very limited number of consumers make a large amount of purchases of yogurt per year. In other words, if we select consumers with a large number of yogurt purchases per year, a very limited number of consumers will meet the requirements and be selected for analysis. In this research, consumers who had no fewer than six transactional records per year in the Pittsfield yogurt market are selected. In total, 708 consumers in the market satisfy the selection requirement and thus are selected for analysis. As one out of the 708 consumers provided invalid demographic information to retailers, that consumer is excluded from further analysis. In general, 707 consumers with their associated 132,233 transactional records from 2004 to 2007 form the final dataset for processing in the Pittsfield yogurt market.

For the purpose of model development and validation, the 707 selected consumers are randomly divided into two groups to the ratio of 6:4. In total, 421 consumers with 17,182 transactional records for yogurt in 2004 are selected to create ‘learning dataset 2004’. The generated ‘learning dataset 2004’ is processed by applying the developed data-mining algorithms in this research. The consumers in the dataset are then segmented with the support of SAS Enterprise Miner to generate the segmentation model. To identify the behavioural evolvements in the consumer purchase lifecycle and to evaluate the ability of demographics in predicting purchase behaviours, ‘learning dataset 2005’, ‘learning dataset 2006’, and ‘learning dataset 2007’ are created via selecting the purchase records of those 421 consumers in 2005, 2006, and 2007, respectively. ‘Learning dataset 2005’ consists of 20,542 transactions made by these 421 consumers in 2005. ‘Learning dataset 2006’ includes 20,348 transactional records for yogurt created by these consumers in 2006. The 19,324 transactions made by these consumers in 2007 form ‘learning dataset 2007’. By the same token, these consumers’ purchase behaviours from 2005 to 2007 are quantified by using the algorithms provided in Chapter 3. In each year from 2005 to 2007, these 421 consumers are segmented on the basis of their quantified purchase behaviours by using the generated segmentation model in the yogurt market.

For validation purposes, the yogurt transactions made by the remaining 286 consumers in 2004, 2005, 2006, and 2007 are used to create ‘validation dataset 2004’, ‘validation dataset 2005’, ‘validation dataset 2006’, and ‘validation dataset 2007’, respectively. The four created validation datasets consist of 12,192 transactions made in 2004, 14,197 transactions made in 2005, 14,177 transactions made in 2006, and 14,271 transactions made in 2007, respectively. These 286 consumers are also segmented based on their quantified purchase behaviours by implementing the segmentation model generated in ‘learning dataset 2004’ in the yogurt market.

4.2.4 Toilet tissue market

Unlike the yogurt market, the toilet tissue market in the US is a mature market with high product penetration (Kalil, 2008). As the largest tissue market in the world, the US tissue market has good growth opportunities due to the continued growth in the per capita consumption of tissue (Kalil, 2008; Lindahl, 2008). As the biggest sub-sector of the tissue market, toilet tissue accounts for 45% of the consumption of tissue in the US (Kalil, 2008). In the US, the household penetration rate of toilet tissue is close to 100% (Lindahl, 2008). In such a mature and big market, fierce competition is unsurprising. Unlike consumers in Western Europe, consumers in the US prefer national brands than private brands in the toilet tissue market. According to Lindahl (2008), private brands hold a fairly weak position and only account for around 13% of the value share in the US toilet tissue market.

In this research, the purchase behaviours of consumers in the Pittsfield toilet tissue market are analysed. The panel dataset, store dataset, and demographic dataset from 2004 to 2007 in the toilet tissue category are merged to generate a dataset that consists of the transactional records associated with product features and consumers' demographic characteristics. In Pittsfield, 1,274 consumers have purchase records in the continuous four years from 2004 to 2007. Like the panel selection in the yogurt market, the panel selection in the toilet tissue market is also limited by the number of transactions used to quantify purchase behaviour of a consumer and the number of consumers selected for analysis. By making trade-offs between these two constraints, consumers who made at least five purchases in each of the selected four years are selected for analysis in this research. In Pittsfield, 544 consumers satisfy the requirement and are selected for further analysis. The final dataset for processing in the toilet tissue market consists of 32,798 transactional records of the selected 544 consumers from 2004 to 2007 in Pittsfield.

For the purpose of model development, 60% of the 544 consumers in Pittsfield are randomly sampled to create the learning datasets. In total, 327 consumers with their associated 20,254 transactional records are thus selected to form the learning datasets. Like the learning datasets created in the salty snack and yogurt markets, four learning datasets are created in the Pittsfield toilet tissue market. 'Learning dataset 2004' consists of 4,652 transactional records created by those 327 consumers in 2004. This dataset is used to generate the segmentation model in the toilet tissue market based on the quantified purchase behaviours of consumers. To identify the behavioural evolvements in the consumer purchase lifecycle and the demographic profiles of behavioural segments for targeting purpose, 'learning dataset 2005', 'learning dataset 2006', and 'learning dataset 2007' are created and formed by 5,143 transactional records in 2005, 5,095 transactional records in 2006, and 5,364 transactional records in 2007. The selected 327 consumers in each of these three learning datasets are segmented based on the quantified purchase behaviours via implementing the segmentation model generated in 'learning dataset 2004'.

For the purpose of validation, the rest of the 217 consumers associated with their 12,544 transactional records from 2004 to 2007 form the four validation datasets. 'Validation dataset 2004' consists of 2,909 transactional records of those 217 consumers in 2004; 3,147 transactional records created in 2005 are included in 'validation dataset 2005'. 'Validation dataset 2006' and 'validation dataset 2007' consist of 3,191 and 3,297 transactional records, respectively. The selected 217 consumers in those four validation datasets are segmented based on their quantified purchase behaviours by applying the generated segmentation model in the toilet tissue market.

4.3 Brand Selection Conditions Across Product Markets

After introducing the data in the selected three product markets, this section provides general information about the brand selection conditions in each of product market. It provides a market-based overview of the competitive situation of a product market, and the proportion and the number of brands explored by consumers in the product market. In brand selection, consumers optimize their purchase behaviours via balancing the exploration and exploitation activities to maximize purchase utility (Macready and Wolpert, 1998). Exploring a product market via trying alternative brands enables consumers to extend their market knowledge and thus discover a better choice that beats their current best choice (Audibert *et al.*, 2008; Lavie *et al.*, 2010). Even though the exploration activities have big potential rewards, they also involve potential risks and costs. Understanding the brand selection conditions in each product market may allow people to better understand a typical consumer's purchase behaviour in the product market. Details about the brand selection conditions in each product market are provided in Appendix A. A summary of the brand selection conditions in those three product markets is provided in Table 4.1.

Table 4.1: Summary of the brand selection conditions in the salty snack, yogurt, and toilet tissue markets

	Year	Salty snack	Yogurt	Toilet tissue
The number of brands available in Pittsfield	2004	79	16	12
	2005	87	18	13
	2006	98	21	13
	2007	106	24	14
The minimum number of brands tried by a consumer	2004	1	1	1
	2005	1	1	1
	2006	2	1	1
	2007	2	1	1
The maximum number of brands tried by a consumer	2004	19	9	10
	2005	19	10	10
	2006	21	11	10
	2007	24	13	10
The average number of brands tried by a consumer in Pittsfield	2004	5.76	4	3.14
	2005	7.9	5.21	3.95
	2006	9.32	5.95	4.41
	2007	10.58	6.5	4.71
The average proportion of explored brands over the total number of brands	2004	0.072911	0.25	0.261667
	2005	0.090805	0.289444	0.303846
	2006	0.095102	0.283333	0.339231
	2007	0.099811	0.270833	0.336429

Table 4.1 shows that the number of brands available for selection was highest in the salty snack market and lowest in the toilet tissue market. The average number of brands tried by consumers was highest in the salty snack market and lowest in the toilet tissue market. These differences across product markets indicate that the **average number of brands** explored by consumers in a product market is **positively** related to the number of brands available for selection in the product market. This suggests that consumers in a competitive product market with a large number of brands for selection are likely to try more brands to extend their market knowledge than those in a product market with a smaller number of brands for selection.

Consumers in Pittsfield were found to only explore a proportion of the brands available in the market, rather than trying all available brands to obtain full market knowledge. The comparison of the frequency distribution of the proportion of explored brands in the salty snack, yogurt, and toilet tissue markets in each consecutive years from 2004 to 2007 is presented in Appendix B. Similar comparative results were identified regarding the frequency distribution of the proportion of explored brands across the four consecutive years. Figure 4.1 shows the comparison of the proportion of explored brands in the salty snack, yogurt, and toilet tissue markets from 2004 to 2007.

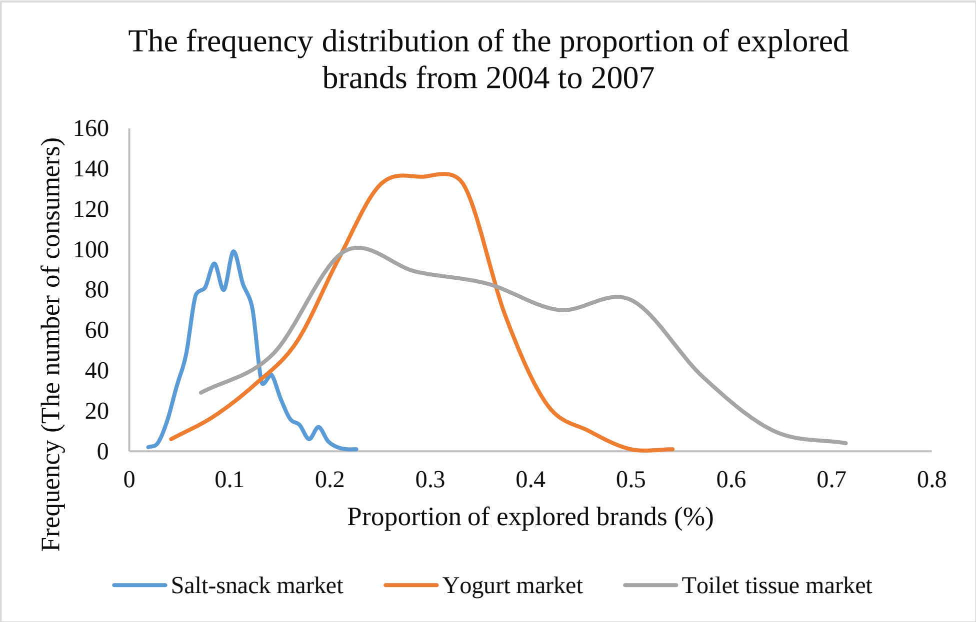

Figure 4.1: Comparison of the proportion of explored brands in the salty snack, yogurt, and toilet tissue markets from 2004 to 2007

In the Pittsfield salty snack market, 0.2% of consumers bought only one brand exclusively from 2004 to 2005. The minimum number of brands tried by a consumer in the salty snack market from 2004 to 2007 is two. In this market, no one had tried more than 24% of the brands available. Most consumers in the salty snack market had tried around 6–12% of the brands available in the market. On average, 10% of the brands available in the salty snack market had been explored by consumers. These statistics indicate that most consumers in the salty snack market practise multi-brand purchasing and only few are 100% loyal. Therefore, these majority of consumers are loyal switchers instead of brand loyals or brand switchers in the Pittsfield salty snack market. In Pittsfield yogurt and toilet tissue markets, the same conclusions could be draw from similar statistic findings. In the Pittsfield yogurt market, 0.8% of consumers bought only one brand exclusively from 2004 to 2007. In this product market, the proportion of explored brands ranged from 4% to 54%. Most of the consumers in the yogurt market had explored 20–33% of brands. On average, 27% of the brands available in the yogurt market had been explored by consumers. In the Pittsfield toilet tissue market, 5% of consumers bought only one brand exclusively from 2004 to 2005. Most of the consumers had explored 20–50% of brands. On average, 34% of the brands available in the toilet tissue market had been explored by consumers.

In general, no one was identified as having full market knowledge from trying all brands in a product market. The average proportion of brands explored by consumers was smallest in the salty snack market and largest in the toilet tissue market. These differences across product markets indicate that the **average proportion of brands** explored by consumers in a product market is **negatively** related to the number of brands available for selection in the product market. This suggests that consumers in a competitive product market with a large number of brands for selection are likely to explore a smaller proportion of brands than those in a product market with a smaller number of brands for selection.

Trying a new brand in a product market enables consumers to increase their $\frac{1}{N}$ market knowledge (i.e. N represents the number of brands available for purchase in the product market). The proportion of brands explored by a consumer represents the market knowledge that the consumer obtained from their past purchases. To obtain the same amount of market knowledge, consumers in a product market with a large number of brands need to spend more efforts on exploration than those in a product market with a smaller number of brands. Consumers in a product market with a large number of brands for selection are thus more likely to have less market knowledge than those in a product market with a small number of brands for selection, even though the consumers in a product market with a large number of brands might have tried more brands to extend their market knowledge.

After reviewing the data and the three selected product markets, the next section presents the method of implementing the developed behavioural measurements in dealing with the transactional data to quantify a consumer's brand selection behaviour in relation to promotions.

4.4 Algorithm Implementation for Processing Transactional Data

As presented in Chapter 3, six sets of behavioural measurements are used to quantify a consumer's brand selection behaviour in relation to promotions. Four of them are used to measure a consumer's responsiveness to promotions and the other two are used to quantify the brand selection behaviour of a consumer. This section consists of two sub-sections. Section 4.4.1 presents the method of dealing with transactional data in quantifying the reactions of a consumer to promotions. Section 4.4.2 provides the algorithm implemented for the data processing in measuring the brand selection behaviour of a consumer.

4.4.1 Data processing of the Prevalence of Promotion

In the IRI marketing dataset, the promotional status of each item, such as the availability of advertising, point of display, and price reduction, are provided in the store dataset. Advertisements, points of display, and/or price reductions are used to promote a product every week in a retail store. Consumers thus have an opportunity to take advantage of promotions at every purchase. As the aim of the research is to segment consumers based on their reactions to the promotional mix, a new variable labeled as 'promotion acceptance'is created to represent consumers' reactions to the promotional mix. Consumers' reactions are coded as '1' when they had responded to at least one type of the promotional mix in a transaction and coded as '0' when they had not respond to any type of the promotional mix. For a consumer, the total number of purchases on promotion in a period is the total number of purchases that coded as '1' in 'promotion acceptance' in the period. The total number of purchases in the period is the total number of transactional records existing in the period in the dataset. The promotion proneness of a consumer in the period is reflected by the quotient of the total number of purchases on promotion over the total number of purchases made by the consumer in the period.

To accelerate the calculation process, this research uses Microsoft Visual Basic for Applications (VBA) to automate the calculation of behavioural variables. The use of VBA in data processing significantly reduces the repetitive computation and increases the efficiency in data preparation. The VBA program used in calculating the Prevalence of Promotion is provided and explained in Appendix C.

In this research, the Prevalence of Advertising, the Prevalence of Point-of-Display, and the Prevalence of Price-Reduction are quantified by processing the advertising feature data, point-of-display feature data, and price-reduction feature data, respectively. Rather than creating promotion acceptance, instead, advertising acceptance, point-of-display acceptance, and price-reduction acceptance are created and used for calculating the number of purchases with advertising, on point of display, and with price reduction, respectively. Like the Prevalence of Promotion, these three behavioural variables are calculated by using the adapted VBA program explained in Appendix C.

4.4.2 Data processing of the measurements of brand selection behaviours

In this research, consumers' transactional data is used and processed to measure their dynamic choice behaviours. The COLUPC in the panel dataset, which is the combination of the UPC system, generation, vendor, and item fields (Kruger and Pagni, 2013), is processed. As a brand has a unique code of 'vendor' in the panel dataset, the vendor information in a consumer's purchase records is extracted and processed to calculate the number of brands that had been purchased by the consumer (i.e. n in Formula 3.7).

To find out the number of brands available in a product market (i.e. 'N' in Formula 3.7), the information on 'IRI_KEY', 'WEEK', and 'VEND' in the store dataset and the information on 'IRI_KEY' and 'Market_Name' in the delivery store dataset are processed. 'IRI_KEY' is the masked store number in a market (Kruger and Pagni, 2013). There are several retail stores in a retail market. In the IRI marketing dataset, no cross-market purchases occurred, while a significant number of consumers made purchases across retail stores in the same market (e.g. around 81% consumers made their purchases of salty snacks in different retail stores in Pittsfield). This means that the consumers always made purchases in only one retail market but across different retail stores. The consumers thus had the opportunity to purchase any of the brands available in the retail market. In a dynamic product market, new brands may be introduced and some existing brands may be withdrawn every year. In that case, '*N*' is the total number of brands introduced to a retail market in the consumer purchase lifecycle. For example, we assume that a product market has ten brands available for a consumer to select in a year. After a certain period, a new brand is introduced and an existing brand is withdrawn from the product market. In that case, the consumer has 11 brands available for selection in their purchase lifecycle, as 11 brands are introduced and have existed in the product market in the purchase lifecycle. The use of the total number of brands introduced to a retail market in consumer purchase lifecycle as the value of '*N*' for calculating the Value of Information from Purchases eliminates the possibility of any biases of the measure from the changes of number of brands over years.

With the given '*n*' and '*N*', the Value of Information from Purchases can be generated by applying Formula 3.7. To automate the calculation process, this research uses the VBA program provided and explained in Appendix D to process the transactional records of consumers.

Similar to the data processing of the Value of Information from Purchases, the 'vend' information in both the panel dataset and the store dataset is used to calculate the Normalized Brand Switching. The VBA program for automating the calculation of the Normalized Brand Switching is provided and explained in Appendix E.

4.5 Variable Selection

In all three selected product markets, the Prevalence of Promotion, the Prevalence of Advertising, the Prevalence of Point-of-Display, and the Prevalence of Price-Reduction are significantly and highly correlated with each other ($r>0.7$, $p<0.001$). This means that consumers who are inclined to accept a type of promotion may also be inclined to react to other types of promotions. As the advertising, point of display, and price reduction discussed in this research are in-store promotions, the high and significant correlation among these behavioural variables indicates that consumer purchase behaviour in relation to in-store promotions is not dependent on the type of in-store promotion. This finding is inconsistent with some findings in prior research (e.g. Bawa *et al.*, 1997; Blattberg and Neslin, 1990; Lichtenstein *et al.*, 1995, 1997). This finding supports the notion that consumers' reactions to promotions do not vary across different types of in-store promotions.

The high and significant correlation among the four behavioural variables suggests that they represent the same concept, which is a consumer's reactions to promotions. Segmenting consumers based on these four behavioural variables thus might produce a skewed solution in the direction of promotion proneness. In this research, the Prevalence of Promotion is selected and used in clustering analysis for the following two reasons. Firstly, the Prevalence of Promotion presents the highest degree of correlation with the Prevalence of Advertising, the Prevalence of Point-of-Display, and the Prevalence of Price-Reduction. Secondly, the Prevalence of Promotion represents and reflects a consumer's reactions to advertising, point of display, and price reduction. It is calculated in terms of whether a consumer responds to any types of promotion in a transaction. However, the Prevalence of Advertising, the Prevalence of Point-of-Display, and the Prevalence of Price-Reduction only represent a consumer's reaction to an associated type of promotion.

According to the correlation statistics, which is shown in Appendix F, the Prevalence of Promotion is not highly correlated with the Value of Information from Purchases ($r<0.23$). Particularly in the salty snack and toilet tissue markets, no significant correlation was found to exist between the Prevalence of Promotion and the Value of Information from Purchases ($r<0.06$, $p>0.22$). This is consistent with the finding in prior research that promotion proneness and dynamic choice behaviour are not related (Ailawadi *et al.*, 2001; Martínez and Montaner, 2006). These two behavioural variables thus represent two unique concepts and can be used as criteria to segment consumers at the same time.

The Normalized Brand Switching and the Prevalence of Promotion are weakly correlated ($r<0.27$). However, the Normalized Brand Switching and the Value of Information from Purchases were found to be highly and significantly correlated ($r>=0.49$, $p<0.001$). This means that these two variables of brand selection represent a similar concept and cannot be used together for clustering analysis. In this research, the Value of Information from Purchases is selected for segmenting consumers together with the Prevalence of Promotion for the following three reasons. First, the measurement of the Value of Information from Purchases is developed based on reliable and confident theoretical foundations. Second, the calculation of the Value of Information from Purchases is simpler than that of the Normalized Brand Switching. It is easier for marketers in retailing to understand and use the developed algorithms of the Value of Information from Purchases to process a large amount of data. Third, compared to the Value of Information from Purchases, the Normalized Brand Switching has a slightly higher degree of correlation with the Prevalence of Promotion. Using the Normalized Brand Switching in the clustering analysis together with the Prevalence of Promotion thus has a slightly higher risk of generating distorted results than using the Value of Information from Purchases.

The Prevalence of Promotion and the Value of Information from Purchases are selected from the six behavioural variables to segment consumers with the support of SAS Enterprise Miner. This research segments consumers into four behavioural groups based on their characteristics in those two variables. The Prevalence of Promotion and the Value of Information from Purchases in learning dataset 2004 are selected as inputs for the clustering analysis to generate the segmentation model. In SAS Enterprise Miner, PROC FASTCLUS, which is designed to find good clusters (but not necessarily the best possible clusters) with only a few passes over the dataset, is used to perform the clustering (Cerrito, 2005; SAS Institute Inc., 1999). The variables used in the clustering analysis are transformed when their distributions are not close to normal distribution (i.e. highly skewed and/or with high kurtosis). Before performing k-means clustering, both input variables are standardized to ensure all inputs have similar measurement scales. K-means clustering is highly sensitive to the initial seeds, whose values determine the eventual assignment of the data to clusters (Khan, 2012). This research limits the maximum number of clusters to four and sets the software to identify the initial clusters. As the data in learning and validation datasets clump together rather than separate, full replacement is used, which is the preferred method in this case, to generate well-separated initial seeds for the clustering analysis (Collica, 2011).

Full replacement, also named the farthest-point heuristic based initialization method, selects initial seeds that are very well separated (He, 2006; Khan and Ahmad, 2013; SAS Institute Inc., 2011). Summarized from He (2006) and SAS Institute Inc. (2011), the implementation of the full replacement algorithm selects the first complete case as the first seed. The next complete case that is separated from the first seed as far as possible becomes the second seed. Subsequent seeds are selected to maximize the distance to the nearest of all centroids (seeds) picked so far, as long as the maximum number of seeds is not exceeded. If a case is complete but fails to qualify as a new seed, this case is then considered to replace one of the old seeds. An old seed is replaced if the distance between the case and the closest seed is greater than the minimum distance between seeds. The seed that is replaced is selected from the two seeds that are closest to each other. The seed that is replaced is the one of these two seeds that has the shortest distance to the closest of the remaining seeds when the other seed is replaced by the current observation.

4.6 Conclusion

In this research, the developed behavioural measurements are implemented to deal with the IRI marketing dataset. In order to automate the data processing, this research uses a VBA program to deal with the transactional data in the IRI marketing dataset. The IRI marketing dataset is widely used in marketing research due to its high accessibility for academic usage, rich household demographic information, complete consumer purchase records, low measurement errors, wide coverage of product categories, and long time horizon. To implement the behavioural measurements, this research selects three product categories in Pittsfield, MA, US, which are the salty snack, yogurt and toilet tissue markets. The three selected product markets have a sufficient number of purchases made by a large number of consumers, which allows marketers to analyse consumer purchase behaviours via implementing the developed behavioural measurements. However, these selected product markets differ in the number of brands available for consumers to select from in the Pittsfield market.

In each of the selected product markets, consumers who had made sufficient number of purchases from 2004 to 2007 are selected for analysis. In the salty snack market, 839 consumers with their associated 158,365 purchases from 2004 to 2007 are selected. In the yogurt market, 707 consumers with their associated 132,233 transactional records from 2004 to 2007 form the final dataset for processing. In the toilet tissue market, 32,798 transactional records of 544 consumers from 2004 to 2007 in Pittsfield are selected for analysis. For the purpose of model development, 60% of the selected consumers in each product market are randomly selected to form learning datasets on a yearly basis. 'Learning dataset 2004', 'learning dataset 2005', 'learning dataset 2006', and 'learning dataset 2007' are thus created in each product market. The transactional records created by the remaining 40% of consumers form four validation datasets on a yearly basis. 'Validation dataset 2004', 'validation dataset 2005', 'validation dataset 2006', and 'validation dataset 2007' are thus created to validate the analysis results.

Comparing the brand selection conditions across the three product markets, it was found that the average proportion of brands explored by consumers in a market is negatively associated with the number of brands available for selection in the product market, and the number of brands explored by consumers in a product market is positively related to the number of brands available for selection in the product market.

In this research, we found that consumers' reactions to promotions do not vary across different types of in-store promotions. To segment consumers based on their brand selection behaviours in relation to promotions, the Prevalence of Promotion and the Value of Information from Purchases are selected as input variables in clustering analysis. The empirical results of the behavioural segmentation are presented and explained in Chapter 5.

CHAPTER 5: ANALYSIS OF BEHAVIOURAL SEGMENTS

5.1 Introduction

After reviewing the conditions of brand exploration in the selected product markets, this chapter presents the behavioural profiles of the identified behavioural segments in each product market. To differentiate and understand the identified behavioural segments, each behavioural segment is profiled on the basis of the characteristics in the Prevalence of Promotion (see Section 3.2.2) and the Value of Information from Purchases (see Section 3.4.2.2). A scatter diagram (i.e. Figure 5.1, 5.10, and 5.19) is used to visualize the distribution of behavioural segments for each of the years 2004–2007 in the learning and validation datasets combined in a product market. In the scatter diagram, behavioural segments are distinguished by using different colours. The membership of consumers in different years is represented and differentiated by using different shapes in the diagram. Consumers within a behavioural segment present similar brand selection behaviours in relation to promotions, which show marked differences from the purchase behaviours of those outside of the segment. In this research, a type of brand selection behaviour in relation to promotions is typified with a group of consumers.

To profile and define the generated behavioural segments in a product market, three types of histogram are used in this research. These histograms demonstrate the characteristics of behavioural segments in the Prevalence of Promotion, the Value of Information from Purchases, and the Market Knowledge respectively. The blue-shaded region of the histograms represents the distribution of the given segment in terms of a behavioural variable. The red outline represents the population in terms of the behavioural variable. The differences in the distribution of behavioural variables in each cluster versus the overall population can be identified from these histograms to generate the behavioural profiles of the segments. In order to analyse whether the segments identified differ in terms of their sensitivity to different types of promotions, the Prevalence of Advertising, the Prevalence of Point-of-display, and the Prevalence of Price-Reduction are used to profile each behavioural segment. To better understand the decision making of each group of consumers, the weights of the behavioural variables in determining the behavioural segment are visualized in a bar chart. The relative weight of a behavioural variable in the segment determination indicates the importance of the behavioural variable in consumer decision making. Understanding the weights of behavioural variables in determining a behavioural segment enables people to understand how consumers in the behavioural segment make purchase decisions via making trade-offs between extending market knowledge and maximizing immediate purchase value.

This section consists of four sub-sections. The first three sub-sections present the behavioural profiles of consumer segments in the salty snack, yogurt, and toilet tissue markets, respectively, with the support of the figures discussed above. The last sub-section discusses the results in comparing the behavioural segments generated in those three product markets. The findings in the comparative analysis aim to help marketers to understand the similarities and differences in consumer purchase behaviours across product markets.

5.2 Salty Snack Market

As can be seen in Figure 5.1, consumers in different segments exhibited marked differences in the Prevalence of Promotion and the Value of Information from Purchases.

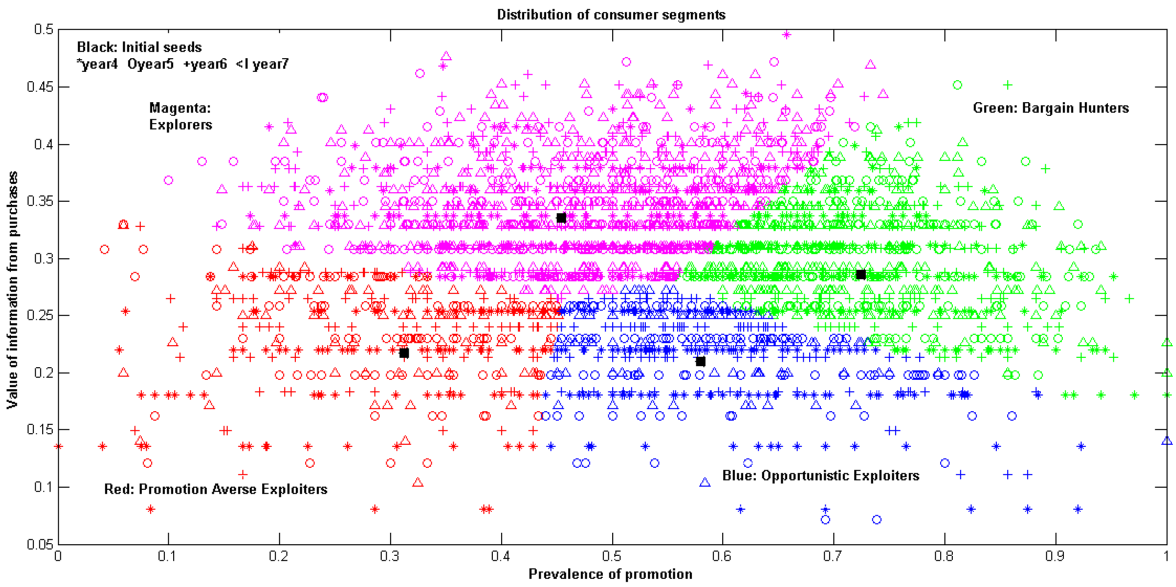

Figure 5.1: Distribution of behavioural segments from 2004 to 2007 in the salty snack market

Red segment

Consumers in the ‘Red’ segment had low values in the Prevalence of Promotion. They also had low values in the Value of Information from Purchases. This latter condition occurred either when consumers lacked market knowledge or when consumers had high levels of market knowledge (see Section 3.4.2.2). As can be seen in Figure 5.2, consumers in the ‘Red’ segment appeared to have a much lower market knowledge compared to the overall set of consumers in the market. Because of this low value in the Market Knowledge, these consumers were not able to differentiate among brands to obtain a high value of information from their purchases (see Section 3.4.2.2).

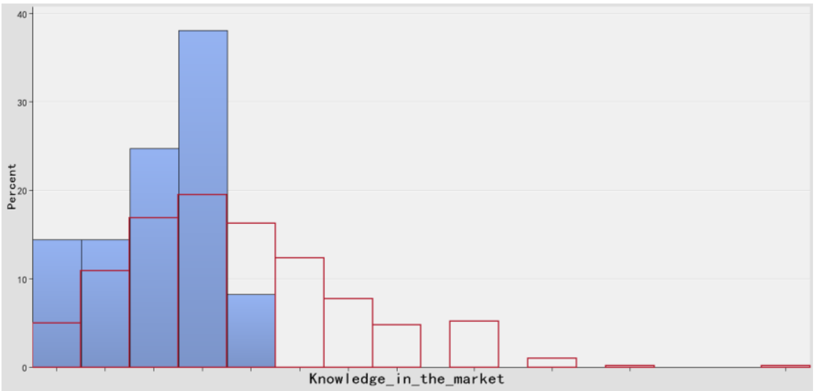

Figure 5.2: The Market Knowledge of consumers in the ‘Red’ segment (i.e. segment 1)

In determining this behavioural segment, as can be seen in Figure 5.3, the Prevalence of Promotion had a much higher weight than the Value of Information from Purchases. This indicates that a low Prevalence of Promotion played a more important role than a low Value of Information from Purchases in determining the membership of consumers in the ‘Red’ segment. The avoidance of paying for promotions is thus suggested to play a more important role than the avoidance of risks from trying alternatives in the purchase decision making of the consumers in the ‘Red’ segment. These consumers were thus even less likely to be motivated to maximize immediate purchase value via taking advantage of promotions than to extend market knowledge via trying alternatives. This might be because the extension of market knowledge may allow consumers with limited market knowledge to improve their capability in achieving an increased information value from purchases.

Figure 5.3: Variable weights in determining the 'Red' segment (i.e. segment 1)

Due to the avoidance of paying for promotions and the avoidance of risks from trying alternatives, we would expect these consumers to be inclined to repeatedly purchase a subset of their familiar big brands or preferred brands, regardless of promotions (Heilman *et al.*, 2000). In this study, the consumers in the 'Red' segment are labelled as 'Promotion-averse Exploiters'.

Green segment

Consumers in the 'Green' segment had the highest values in the Prevalence of Promotion. With the same value in the Value of Information from Purchases, we would expect consumers in this segment to have the highest probability to buy promoted salty snacks in the Pittsfield market (see Section 3.2). In determining this behavioural segment, as can be seen in Figure 5.4, the Prevalence of Promotion dominated the Value of Information from Purchases. This indicates that a high value in the Prevalence of Promotion played a dominant role in determining the membership of consumers in the 'Green' segment. The decisions made by consumers in this segment are suggested to be predominantly influenced by whether a product was promoted. This means that the maximization of immediate value from shopping for bargains played a dominant role in the purchase decision making of these consumers. In this study, the consumers in the 'Green' segment are labelled as 'Bargain Hunters'. They were most likely to adapt their purchase decisions in accordance with promotions.

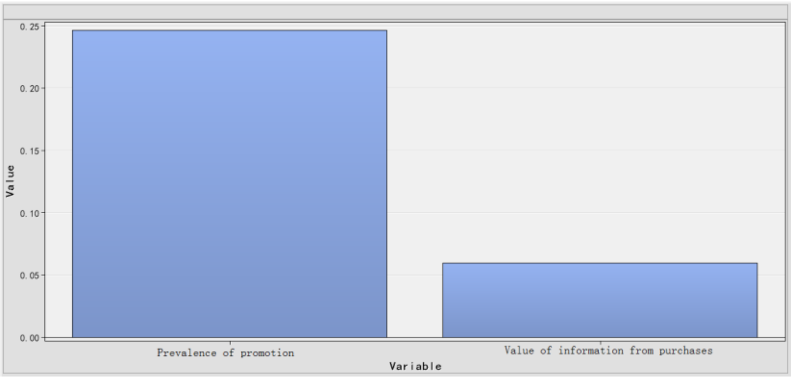

Figure 5.4: Variable weights in determining the 'Green' segment (i.e. segment 3)

Magenta and Blue segments

As can be seen in Figure 5.5, consumers in the 'Magenta' and 'Blue' segments had medium values in the Prevalence of Promotion. Consumers in the 'Blue' segment had relatively higher values in the Prevalence of Promotion than those in the 'Magenta' segment.

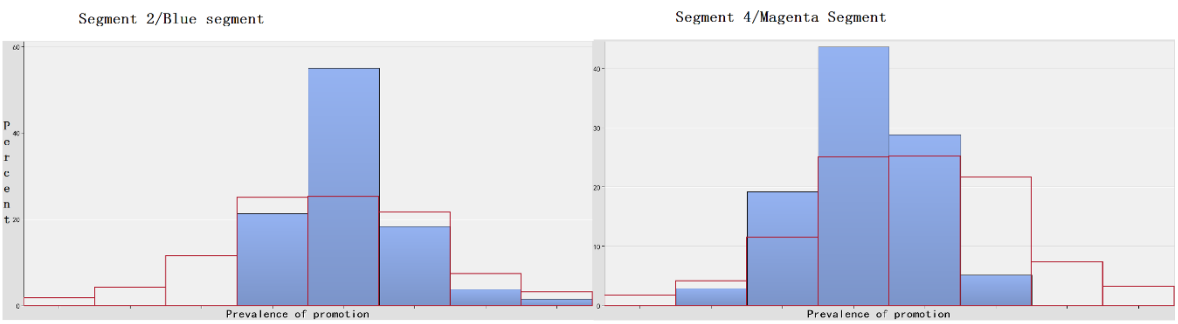

Figure 5.5: The Prevalence of Promotion of the 'Blue' and 'Magenta' segments (i.e. segment 2 and 4)

In determining the membership of consumers in these two behavioural segments, the Value of Information from Purchases had a higher weight than the Prevalence of Promotion. Particularly, as can be seen in Figure 5.6, the Value of Information from Purchases dominated the Prevalence of Promotion in determining the 'Magenta' segment.

Figure 5.6: Variable weights in determining the 'Magenta' segment (i.e. segment 4)

Among the four identified behavioural segments, consumers in the 'Magenta' segment had the highest values in the Market Knowledge. Figure 5.7 shows that the Value of Information from Purchases in this segment was much higher than that in the population. As can be seen in Figure 5.2, with the same value in the Prevalence of Promotion, consumers in the 'Magenta' segment had the highest values in the Value of Information from Purchases. The dominant weight and high value of the Value of Information from Purchases in the 'Magenta' segment thus indicate that the decisions made by consumers in the segment were predominantly influenced by whether a brand was new for information extension. Motivated by a high Value of Information from Purchases, these knowledgeable consumers would be expected to be inclined to further explore the salty snack market by trying alternative brands to extend their market knowledge from purchases (see Section 3.4.2.2). In this research, the consumers in the 'Magenta' segment are thus labelled as 'Explorers'. The extension of market knowledge played a dominant role in the decision making of those Explorers. They were more likely to be motivated by new brands rather than by promotions to make purchases.

Figure 5.7: The characteristics of ‘Magenta’ segment (i.e. segment 4) consumers in the Value of Information from Purchases

As can be seen in Figure 5.8, the Market Knowledge and the Value of Information from Purchases in the ‘Blue’ segment were lower than those in the population. This indicates that consumers in the ‘Blue’ segment consistently purchased a subset of their familiar or preferred brands.

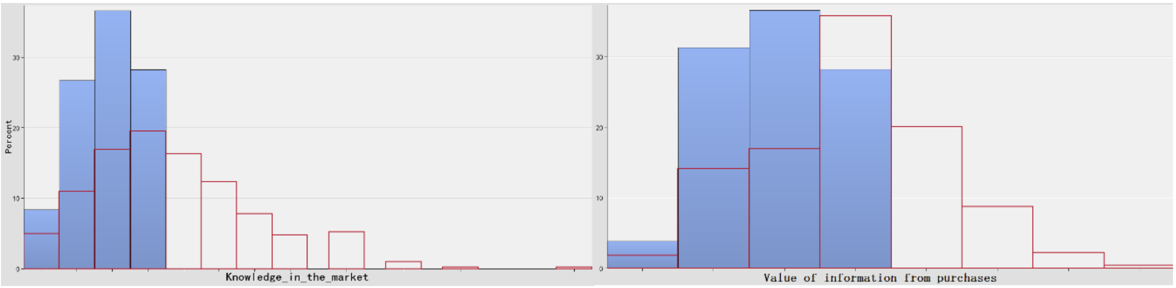

Figure 5.8: Characteristics of ‘Blue’ segment (i.e. segment 2) consumers in the Market Knowledge and the Value of Information from Purchases

Figure 5.9 shows that the Value of Information from Purchases had a slightly higher weight than the Prevalence of Promotion in determining the ‘Blue’ segment. This indicates that a low Value of Information from Purchases played a slightly more important role than a high Prevalence of Promotion in determining the membership of consumers in the ‘Blue’ segment. The avoidance of risks from trying alternatives is thus suggested to play a slightly more important role than the maximization of immediate purchase value from taking advantage of promotions in the purchase decision making of the consumers in the ‘Blue’ segment. These consumers therefore were more likely to consistently purchase a subset of their familiar or preferred brands than to take advantage of promotions to make purchases. In other words, they were less likely to extend their market knowledge via trying alternatives than to maximize their immediate purchase value via buying promoted brands. In this study, these consumers are labelled as ‘Opportunistic Exploiters’.

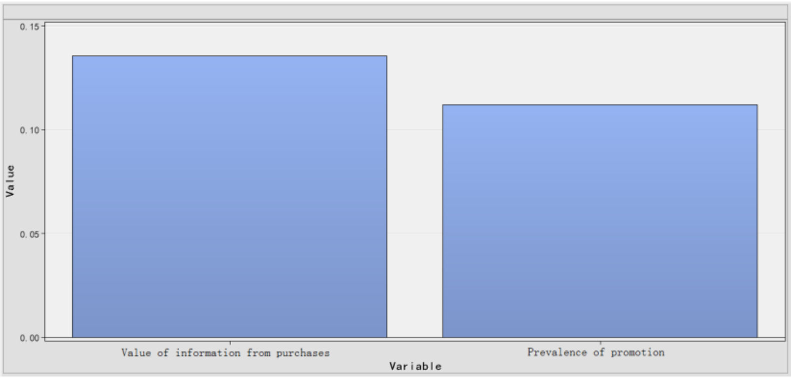

Figure 5.9: Variable weights in determining the ‘Blue’ segment (i.e. segment 2)

The characteristics of consumers in each behavioural segment are summarized in Table 5.1. In salty snack market, the distributions of a behavioural segment in terms of the Prevalence of Promotion, the Prevalence of Advertising, the Prevalence of Point-of-display, and the Prevalence of Price-Reduction are similar. This finding indicates that the identified four behavioural segments do not differ in terms of their sensitivity to different types of in-store promotions even though they differ in terms of their sensitivity to promotions. This finding further confirms that consumer purchase behaviours in relation to promotions are not dependent on the type of in-store promotion in Pittsfield salty snack market.

Table 5.1: Behavioural segments in the Pittsfield salty snack market

Segment	**Prevalence of Promotion**	**Value of Information from Purchases**	**Typical behaviours and associated purposes**

Promotion-averse Exploiters	Low	Low	Purchase familiar or preferred brands regardless of promotions to avoid risks from trying alternatives
Bargain Hunters	High	Varies	Shopping for bargains to maximizing immediate purchase value
Explorers	Medium-low	High	Extending market knowledge particularly by taking advantage of promotions
Opportunistic Exploiters	Medium-high	Low	Make use of promotions to repeatedly buy familiar or preferred brands to minimize risks from trying alternatives

5.3 Yogurt Market

As can be seen in Figure 5.10, consumers in the yogurt market were evenly distributed across the four behavioural segments.

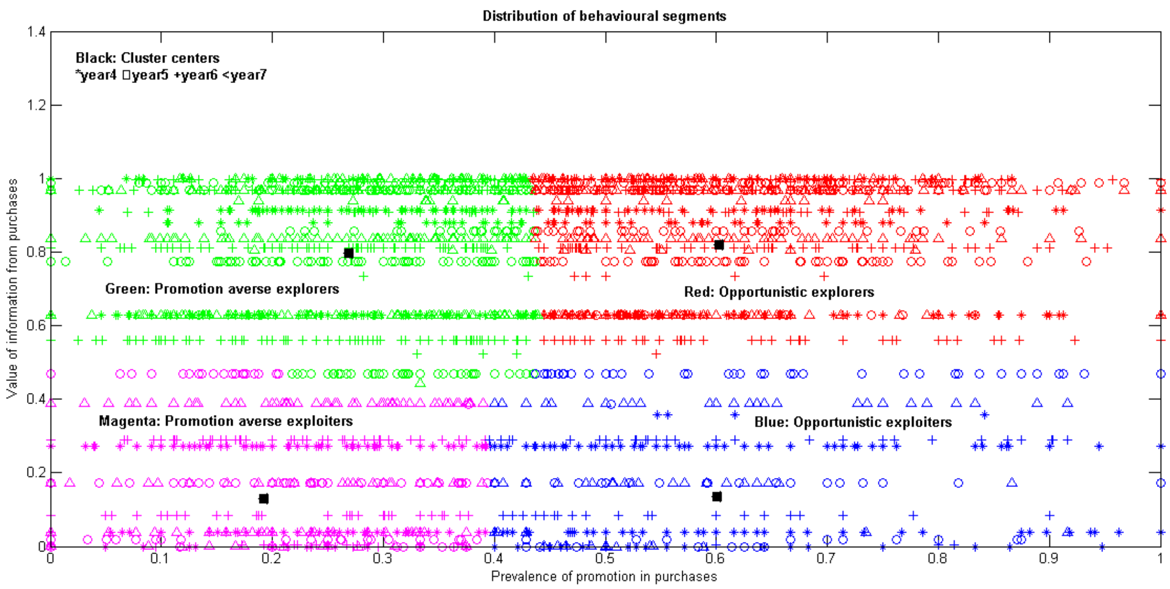

Figure 5.10: The distribution of behavioural segments from 2004 to 2007 in the Yogurt market

<u>Red segment</u>

Consumers in the ‘Red’ segment had high values in both the Prevalence of Promotion and the Value of Information from Purchases. As can be seen in Figure 5.11, consumers in this segment had a medium amount of market knowledge compared to the overall set of consumers in the market. Due to this medium level of market knowledge, these consumers were able to differentiate some brands available in the yogurt market to obtain a high value of information from their purchases (see Section 3.4.2.2).

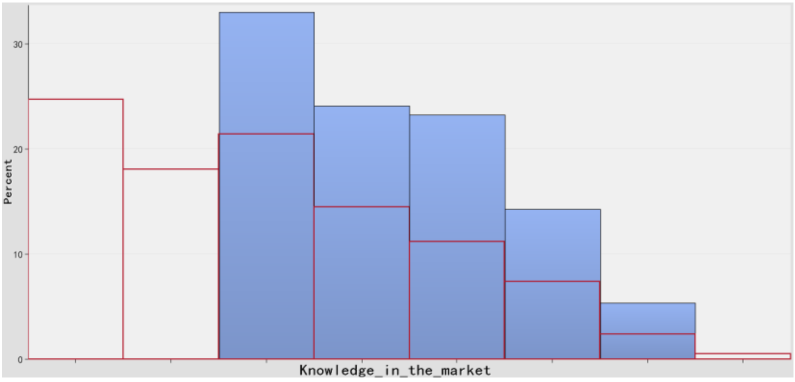

Figure 5.11: The Market Knowledge of consumers in the ‘Red’ segment (i.e. segment 1)

In determining the ‘Red’ segment, as can be seen in Figure 5.12, the Prevalence of Promotion had a higher weight than the Value of Information from Purchases. This indicates that a high Prevalence of Promotion played a more important role than a high Value of Information from Purchases in determining the membership of consumers in the ‘Red’ segment. The purchase decisions made by consumers in this segment are thus suggested to be predominantly influenced by whether a product was on promotion. This means that the maximization of immediate purchase value from taking advantage of promotions played a more important role in the purchase decision making of these consumers than the extension of market knowledge from trying alternatives. The consumers in this segment were more likely to be motivated by promotions to maximize their immediate purchase value than by new brands to extend their market knowledge. In general, we would expect these consumers to be inclined to take advantage of promotions to explore the yogurt market via trying alternatives (see Sections 3.2.2 and 3.4.2.2). In this research, these consumers are labelled as ‘Opportunistic Explorers’.

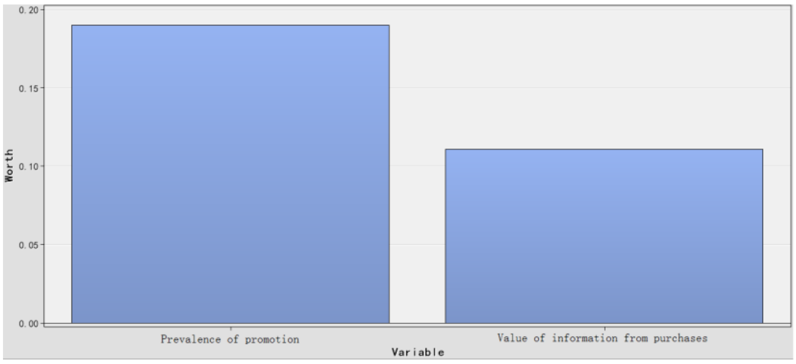

Figure 5.12: Variable weights in determining the 'Red' segment (i.e. segment 1)

<u>Blue segment</u>

Consumers in the 'Blue' segment also had high values in the Prevalence of Promotion in purchases. However, they had low values in the Value of Information from Purchases. As can be seen in Figure 5.13, consumers in the 'Blue' segment appeared to have either very limited market knowledge or a very high volume of market knowledge. Motivated by the low Value of Information from Purchases due to the lack of market knowledge, these consumers would be expected to be inclined to consistently purchase a subset of their familiar big brands or their preferred brands (Heilman *et al.*, 2000). On the contrary, motivated by the low Value of Information from Purchases due to a high level of market knowledge, these consumers would be expected to be loyal to their preferred brands (see Section 3.4.2.2). In this study, the consumers in the 'Blue' segment are labelled as 'Opportunistic Exploiters'.

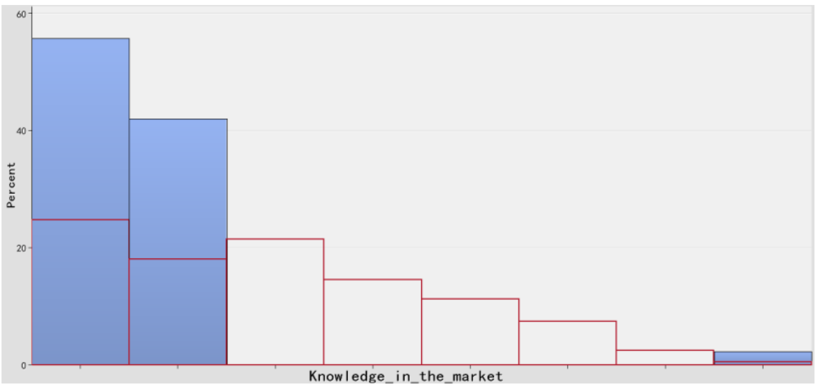

Figure 5.13: The Market Knowledge of consumers in the ‘Blue’ segment (i.e. segment 2)

In determining the ‘Blue’ segment, as can be seen in Figure 5.14, the Value of Information from Purchases had a slightly higher weight than the Prevalence of Promotion. This indicates that a low Value of Information from Purchases played a slightly more important role than a high Prevalence of Promotion in determining the membership of consumers in the ‘Blue’ segment. The avoidance of risks from trying alternatives is thus suggested to play a slightly more important role than the maximization of immediate purchase value in the decision making of these Opportunistic Exploiters. These Opportunistic Exploiters were thus less likely to be motivated by new brands to extend their market knowledge than by promotions to maximize their immediate purchase value.

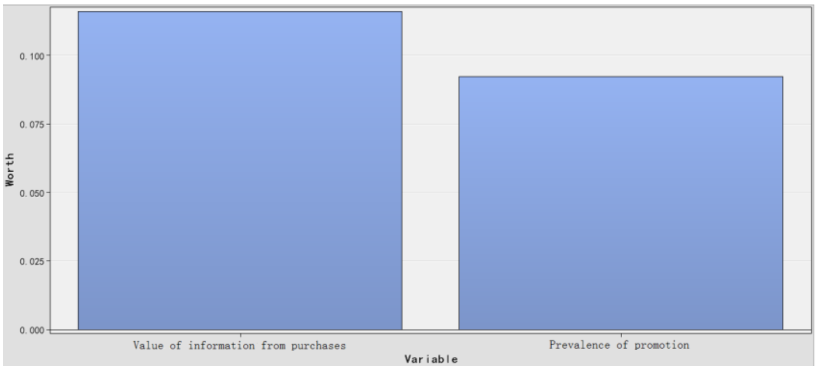

Figure 5.14: Variable weights in determining the ‘Blue’ segment (i.e. segment 2)

<u>Green segment</u>

Consumers in the ‘Green’ segment had low values in the Prevalence of Promotion and high values in the Value of Information from Purchases. As can be seen in Figure 5.15, these consumers had a medium level of market knowledge, which allowed them to obtain a high value of information from their purchases (see Section 3.4.2.2). Motivated by the high Value of Information from Purchases, these consumers would be expected to be inclined to extend their market knowledge via trying alternative brands (see Section 3.4.2.2).

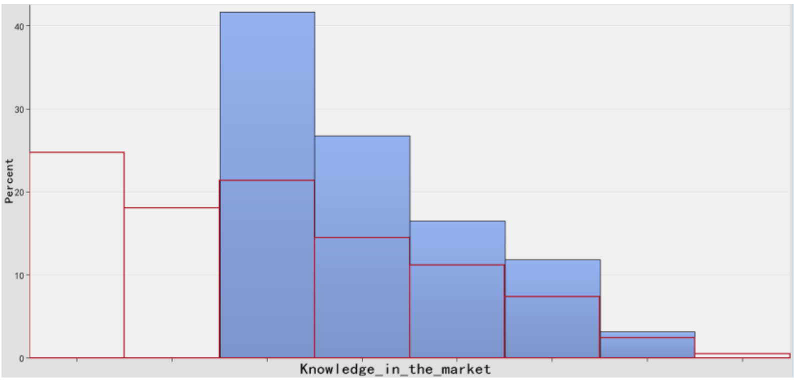

Figure 5.15: The Market Knowledge of consumers in the 'Green' segment (i.e. segment 3)

In determining the 'Green' segment, the Prevalence of Promotion had a slightly higher weight than the Value of Information from Purchases, as demonstrated in Figure 5.16. This indicates that a low Prevalence of Promotion played a slightly more important role than a high Value of Information from Purchases in determining the membership of consumers in the 'Green' segment. The avoidance of paying for promotions is thus suggested to play a slightly more important role than the extension of market knowledge in the purchase decision making of the consumers in the 'Green' segment. These consumers were thus less likely to be motivated by promotions to maximize their immediate purchase value than by new brands to extend their market knowledge. We would expect these consumers to extend their market knowledge by trying alternatives, regardless of promotions (see Sections 3.2.2 and 3.4.2.2). In this study, these consumers are labelled as 'Promotion-averse Explorers'.

Figure 5.16: Variable weights in determining the 'Green' segment (i.e. segment 3)

Magenta segment

Consumers in the ‘Magenta’ segment had low values in both the Prevalence of Promotion and the Value of Information from Purchases. Figure 5.17 shows that consumers in this segment appeared to have much lower market knowledge compared to the overall set of consumers in the market. The lack of market knowledge made these consumers unable to obtain a high value of information from their purchases (see Section 3.4.2.2).

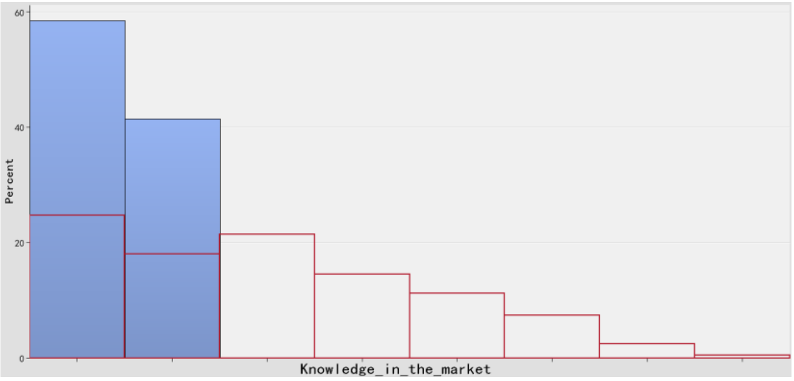

Figure 5.17: The Market Knowledge of consumers in the ‘Magenta’ segment (i.e. segment 4)

In determining the ‘Magenta’ segment, as can be seen in Figure 5.18, the Value of Information from Purchases had a slightly higher weight than the Prevalence of Promotion. This indicates that a low Value of Information from Purchases played a slightly more important role than a low Prevalence of Promotion in determining the membership of consumers in the ‘Magenta’ segment. The avoidance of risks from trying alternatives is thus suggested to play a slightly more important role than the avoidance of paying for promotions in the purchase decision making of the consumers in the ‘Magenta’ segment. These consumers were thus slightly less likely to be motivated by new brands to extend their market knowledge than by promotions to maximize their immediate purchase value. In general, we would expect these consumers to be inclined to consistently purchase a subset of their familiar big brands or their preferred brands, regardless of promotions. In this study, consumers in the ‘Magenta’ segment are labelled as ‘Promotion-averse Exploiters’.

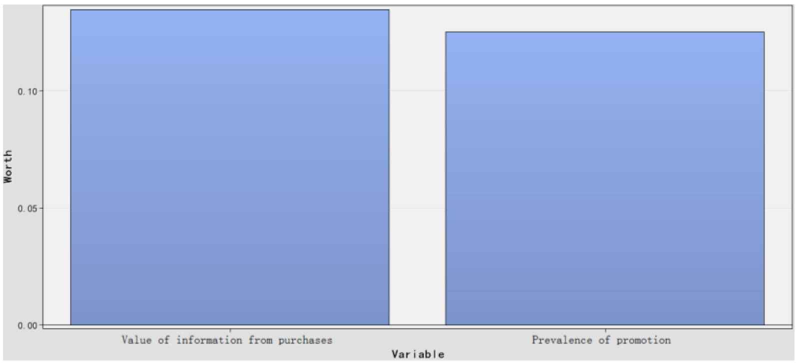

Figure 5.18: Variable weights in determining the 'Magenta' segment (i.e. segment 4)

The characteristics of consumers in each behavioural segment in the yogurt market are summarized in Table 5.2. In yogurt market, the distributions of a behavioural segment in terms of the Prevalence of Promotion, the Prevalence of Advertising, the Prevalence of Point-of-display, and the Prevalence of Price-Reduction are similar. This finding indicates that the identified four behavioural segments do not differ in terms of their sensitivity to different types of in-store promotions even though they differ in terms of their sensitivity to promotions. This finding further confirms that consumer purchase behaviours in relation to promotions are not dependent on the type of in-store promotion in Pittsfield yogurt market.

Table 5.2: Behavioural segments in the Pittsfield yogurt market

Segment	**Prevalence of Promotion**	**Value of Information from Purchases**	**Typical behaviours and associated purposes**
Opportunistic Explorers	High	High	Make use of promotions to extend market knowledge
Opportunistic Exploiters	High	Low	Make use of promotions to repeatedly buy familiar or preferred brands to minimize risks from trying alternatives
Promotion-averse Explorers	Low	High	Trying different brands to extend market knowledge, regardless of promotions
Promotion-averse Exploiters	Low	Low	Purchase familiar big brands or preferred brands regardless of promotions to avoid risks from trying alternatives

5.4 Toilet Tissue Market

Figure 5.19 shows that the purchase behaviours of consumers in the toilet tissue market were almost evenly distributed across the four behavioural segments.

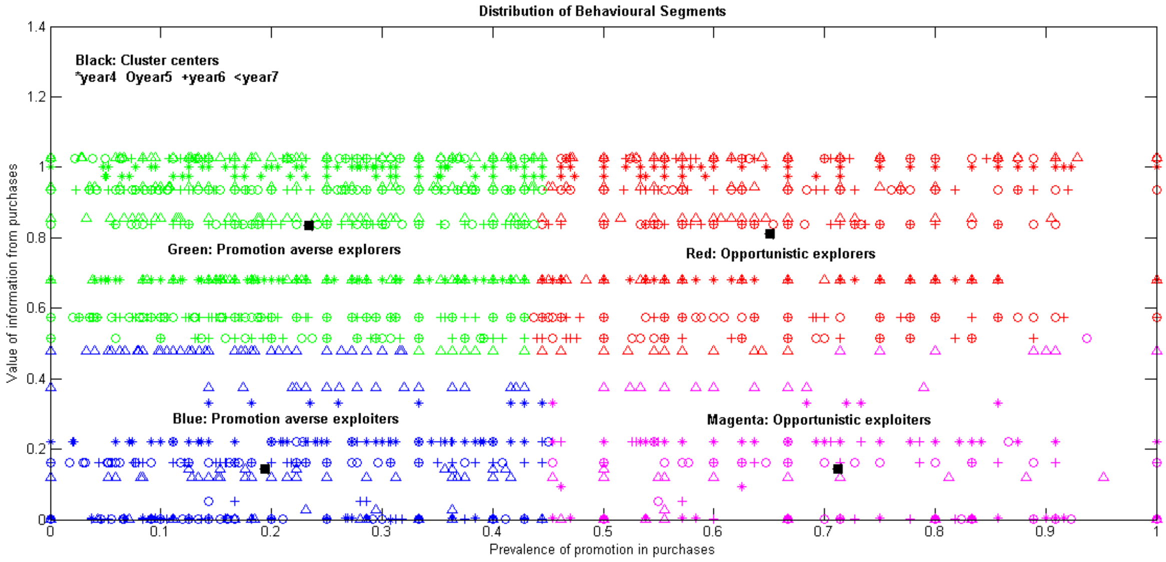

Figure 5.19: Distribution of behavioural segments from 2004 to 2007 in the toilet tissue market

<u>Red segment</u>

Consumers in the 'Red' segment had high values in both the Prevalence of Promotion and the Value of Information from Purchases. Figure 5.20 shows that consumers in this segment had a medium amount of market knowledge compared to the overall set of consumers in the toilet tissue market.

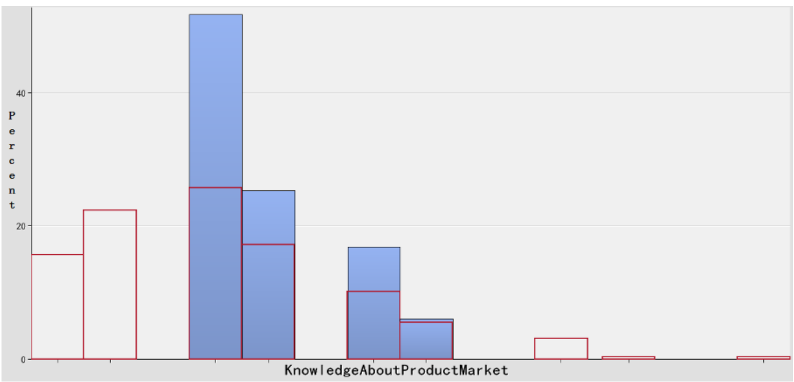

Figure 5.20: The Market Knowledge of consumers in the ‘Red’ segment (i.e. segment 1)

In determining the ‘Red’ segment, Figure 5.21 shows that the Prevalence of Promotion had a higher weight than the Value of Information from Purchases. This indicates that a high Prevalence of Promotion played a more important role than a high Value of Information from Purchases in determining the membership of consumers in this ‘Red’ segment. Whether a product was promoted is thus suggested to play a predominant role in the decision making of the consumers in the ‘Red’ segment, rather than whether the product was new to them. Consumers in this segment were more likely to be motivated to maximize their immediate purchase value by taking advantage of promotions than to extend their market knowledge by trying alternatives. In this research, the consumers in the ‘Red’ segment are labelled as ‘Opportunistic Explorers’.

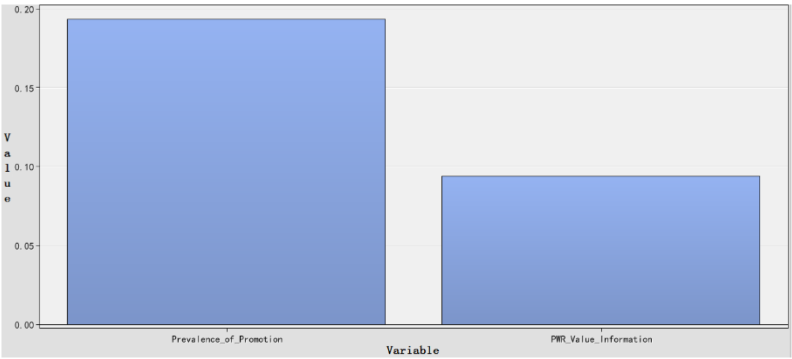

Figure 5.21: Variable weights in determining the ‘Red’ segment (i.e. segment 1)

<u>Blue segment</u>

Contrasting with Opportunistic Explorers, consumers in the ‘Blue’ segment had low values in both the Prevalence of Promotion and the Value of Information from Purchases. As can be seen in Figure 5.22, consumers in the ‘Blue’ segment appeared to have either very limited market knowledge or a high level of market knowledge. We would thus expect these consumers to be inclined to either consistently purchase their familiar big brands or be loyal to a subset of their preferred brands, regardless of promotions (see Section 3.4.2.2).

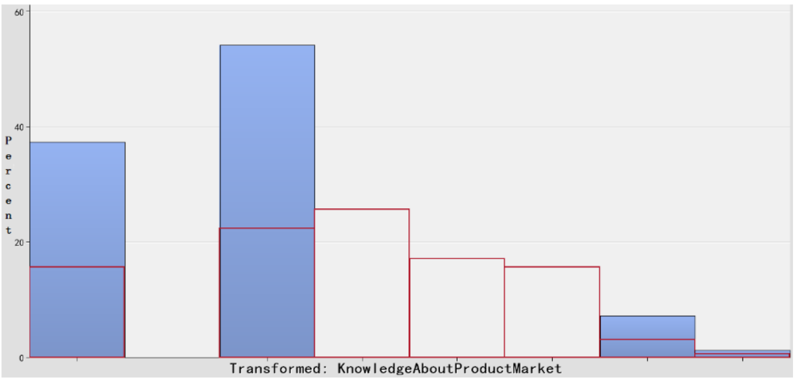

Figure 5.22: The Market Knowledge of consumers in the ‘Blue’ segment (i.e. segment 2)

In determining the ‘Blue’ segment, as can be seen in Figure 5.23, the Value of Information from Purchases had a higher weight than the Prevalence of Promotion. This indicates that a low Value of Information from Purchases played a more important role than a low Prevalence of Promotion in determining the membership of consumers in the ‘Blue’ segment. The avoidance of risks from trying alternatives is thus suggested to play a more important role than the avoidance of paying for promotions in the decision making of consumers in the ‘Blue’ segment. These consumers were thus even less likely to be motivated by new brands to further extend their market knowledge than by promotions to maximize their immediate purchase value. In this research, the consumers in the ‘Blue’ segment are labelled as ‘Promotion-averse Exploiters’.

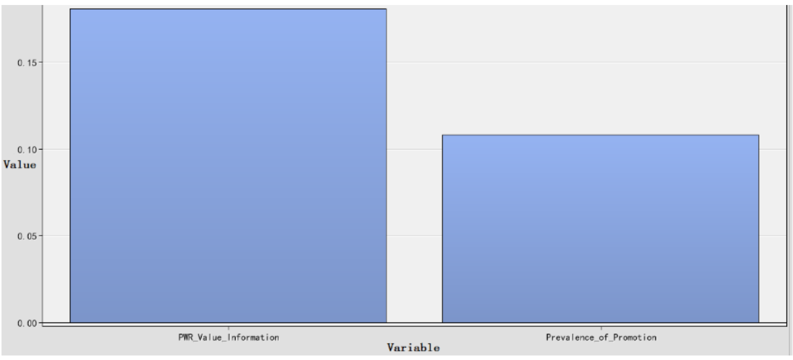

Figure 5.23: Variable weights in determining the ‘Blue’ segment (i.e. segment 2)

Green segment

Consumers in the 'Green' segment also had low values in the Prevalence of Promotion. However, these consumers had high values in the Value of Information from Purchases. Figure 5.24 shows that these consumers had a medium level of market knowledge compared to the overall set of consumers in the toilet tissue market.

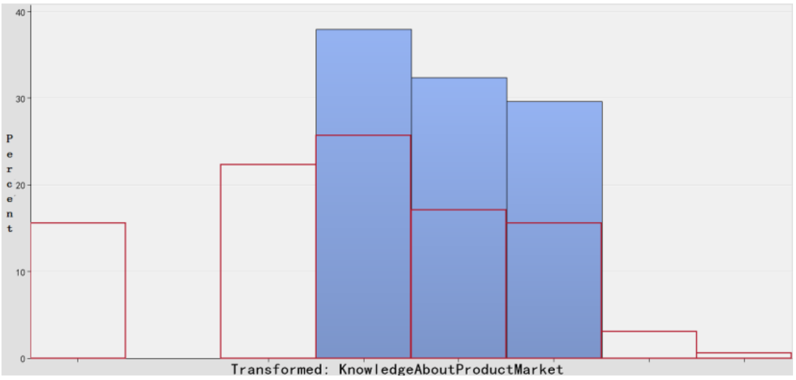

Figure 5.24: The Market Knowledge of consumers in the 'Green' segment (i.e. segment 3)

In determining the 'Green' segment, Figure 5.25 shows that the Prevalence of Promotion had a slightly higher weight than the Value of Information from Purchases. This indicates that a low Prevalence of Promotion played a slightly more important role than a high Value of Information from Purchases in determining the membership of consumers in the Green segment. The avoidance of paying for promotions is thus suggested to play a slightly more important role than the extension of market knowledge in the decision making of consumers in the 'Green' segment. These consumers were thus more likely to be motivated by new brands to further extend their market knowledge than by promotions to maximize their immediate purchase value. They would be expected to be inclined to extend their market knowledge via trying alternatives, regardless of promotions. In this study, the consumers in the 'Green' segment are labelled as 'Promotion-averse Explorers'.

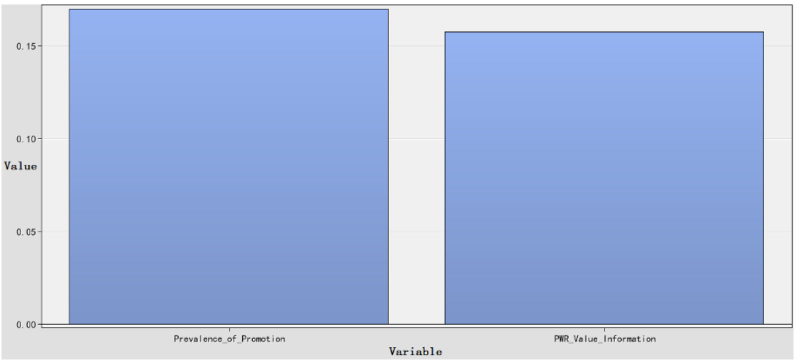

Figure 5.25: Variable weights in determining the ‘Green’ segment (i.e. segment 3)

Magenta segment

Consumers in the ‘Magenta’ segment had high values in the Prevalence of Promotion and low values in the Value of Information from Purchases. As can be seen in Figure 5.26, the consumers in the ‘Magenta’ segment also appeared to have either limited market knowledge or a high level of market knowledge.

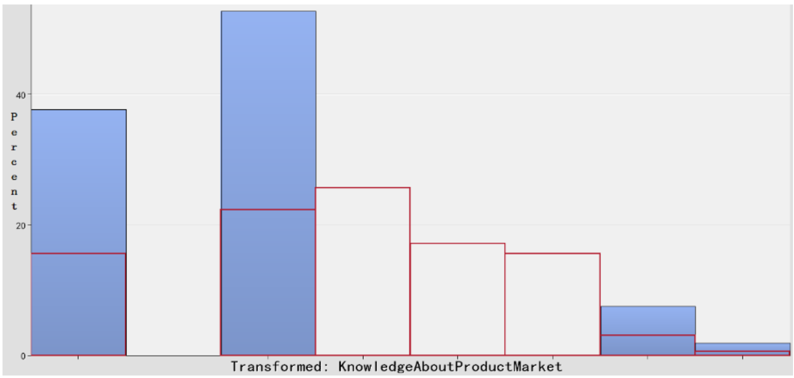

Figure 5.26: The Market Knowledge of consumers in the ‘Magenta’ segment (i.e. segment 4)

In determining the ‘Magenta’ segment, Figure 5.27 shows that the Prevalence of Promotion had a higher weight than the Value of Information from Purchases. This indicates that a high Prevalence of Promotion played a more important role than a low Value of Information from Purchases in determining the membership of consumers in the ‘Magenta’ segment. Whether a product was promoted is thus suggested to play a more important role than the avoidance of risks from trying alternatives in the purchase decision making of consumers in the 'Magenta' segment. These consumers were thus more likely to be motivated by promotions to maximize their immediate purchase value than by new brands to extend their market knowledge. They would be expected to be inclined to take advantage of promotions to consistently purchase a subset of their familiar or preferred brands. In this study, these consumers are labelled as 'Opportunistic Exploiters'.

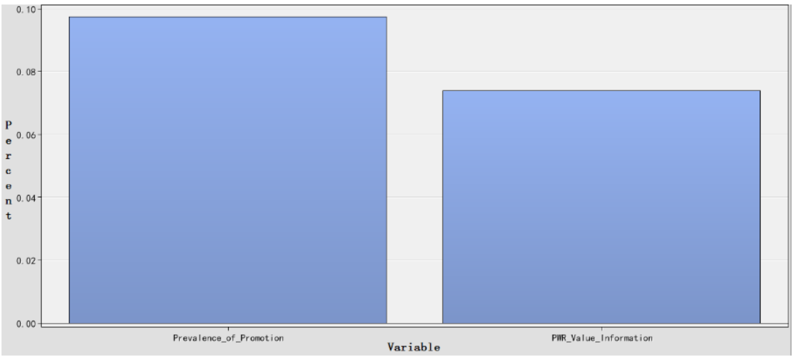

Figure 5.27: Variable weights in determining the 'Magenta' segment (i.e. segment 4)

The characteristics of consumers in each behavioural segment in the toilet tissue market are summarized in Table 5.3. In toilet tissue market, the distributions of a behavioural segment in terms of the Prevalence of Promotion, the Prevalence of Advertising, the Prevalence of Point-of-display, and the Prevalence of Price-Reduction are similar. This finding indicates that the identified four behavioural segments do not differ in terms of their sensitivity to different types of in-store promotions even though they differ in terms of their sensitivity to promotions. This finding further confirms that consumer purchase behaviours in relation to promotions are not dependent on the type of in-store promotion in Pittsfield toilet tissue market.

Table 5.3: Behavioural segments in the Pittsfield toilet tissue market

Segment	**Prevalence of Promotion**	**Value of Information from Purchases**	**Typical behaviours and associated purposes**
Opportunistic Explorers	High	High	Make use of promotions to extend market knowledge
Opportunistic	High	Low	Make use of promotions to

Exploiters			repeatedly buy familiar or preferred brands to minimize risks from trying alternatives
Promotion-averse Explorers	Low	High	Trying different brands to extend market knowledge, regardless of promotions
Promotion-averse Exploiters	Low	Low	Purchase familiar or preferred brands regardless of promotions to avoid risks from trying alternatives

5.5 Market Comparison

After presenting the characteristics of the behavioural segments in terms of the Prevalence of Promotion and the Value of Information from Purchases in the salty snack, yogurt, and toilet tissue markets, this section compares the behavioural segments across the product markets to find out how the typical purchase behaviours differ across these product markets. For the purpose of comparison, Table 5.4 summarizes the characteristics of the behavioural segments across the product markets. The predominant motivator in Table 5.4 refers to the motivator that is supposed to be most able to motivate consumers in the segment to make purchases. It is generated based on the trade-off between the extension of market knowledge and the maximization of immediate purchase value in consumer purchase decision making (see Sections 5.2, 5.3, and 5.4).

Table 5.4: Comparison of behavioural segments across product markets

Product market	**Behavioural segment**	**Relative weight of behavioural variable in determining a segment**		**Predominant motivator**
		Prevalence of Promotion	**Value of Information from Purchases**	
Salty snack market	Promotion-averse Exploiters	0.76	0.24	New brands
	Opportunistic Exploiters	0.45	0.55	Promotion
	Bargain Hunters	0.8	0.2	Promotion
	Explorers	0.27	0.73	New brands
Yogurt market	Promotion-averse Exploiters	0.48	0.52	Promotion
	Opportunistic	0.44	0.56	Promotion

	Exploiters			
	Opportunistic Explorers	0.63	0.37	Promotion
	Promotion-averse Explorers	0.53	0.47	New brands
Toilet tissue market	Promotion-averse Exploiters	0.37	0.63	Promotion
	Opportunistic Exploiters	0.57	0.43	Promotion
	Opportunistic Explorers	0.67	0.33	Promotion
	Promotion-averse Explorers	0.52	0.48	New brands

Table 5.4 shows that the behavioural segments identified in the yogurt and toilet tissue markets are similar to each other but differ from those identified in the salty snack market. This means that typical brand selection behaviours in relation to promotions were similar across the yogurt and toilet tissue markets but could not be generalized to the salty snack market. Consumers in the salty snack market behaved differently from those in the yogurt and toilet tissue markets in terms of the trade-offs in their purchase decision making.

Compared to the Promotion-averse Exploiters in the yogurt and toilet tissue markets, these consumers in the salty snack market placed far more weight on the Prevalence of Promotion than the Value of Information from Purchases in their purchase decision making. This shows that the Promotion-averse Exploiters in the salty snack market were less likely to be motivated to pay for promotions than to extend their market knowledge via trying alternatives (see Sections 5.2, 5.3, and 5.4). This means that the Promotion-averse Exploiters in the salty snack market were more likely to be inclined to try new brands than those in the yogurt and toilet tissue markets. The Promotion-averse Exploiters in the yogurt and toilet tissue markets were more likely to be motivated to make purchases by promotions, rather than by new brands in the markets.

Opportunistic Exploiters were the only group of consumers who placed almost equal weights on the Prevalence of Promotion and the Value of Information from Purchases in their decision making in all three product markets. These Opportunistic Exploiters were more likely to be motivated to pay for promotions than to extend their market knowledge via trying alternatives.

Among the three product markets, hunting for bargains in purchases was only identified as a typical purchase behaviour in the salty snack market. In the yogurt and toilet tissue markets, the purchase behaviour of Opportunistic Explorers was most similar to the purchase behaviour of Bargain Hunters in the salty snack market (see Sections 5.2, 5.3, and 5.4). Among the four typical types of consumers in the yogurt and toilet tissue markets, Opportunistic Explorers placed the highest weight on the Prevalence of Promotion in their purchase decision making. This means that these Opportunistic Explorers were more likely to be motivated to pay for promotions to maximize the immediate purchase value than the other consumers in the yogurt and toilet tissue markets. Compared to Bargain Hunters, those Opportunistic Explorers placed a higher weight on the Value of Information from Purchases in their purchase decision making. This means that extending market knowledge played a more important role in the decision making of these Opportunistic Explorers than that of the Bargain Hunters. These Opportunistic Explorers were thus more likely to be inclined to extend their market knowledge via trying alternatives than the Bargain Hunters.

Among the consumers in the salty snack market, the Explorers were the group of consumers who placed the highest weight on the Value of Information from Purchases in their purchase decision making. These Explorers were thus most likely to be motivated to buy new brands to extend their market knowledge. This purchase behaviour was more similar to the purchase behaviour of Promotion-averse Explorers in the yogurt and toilet tissue markets than to that of other consumers in those two product markets. Compared to the Explorers in the salty snack market, the Promotion-averse Explorers in the yogurt and toilet tissue markets placed lower weight on the Value of Information from Purchases in their purchase decision making. This means that the extension of market knowledge via trying alternatives played a less important role in the purchase decision making of the Promotion-averse Explorers in the yogurt and toilet tissue markets than in the decision making of Explorers in the salty snack market. Whether a product was new to consumers had a more significant influence on the purchase decision making of the Explorers in the salty snack market than that of the Promotion-averse Explorers in the yogurt and toilet tissue markets. The Explorers in the salty snack market were thus more likely to be inclined to buy new brands regardless of promotions than the promotion-averse explorers were.

In general, the typical brand selection behaviours in relation to promotions differed across product markets. These differences might be related to the market conditions in each product market. The yogurt and toilet tissue product markets had a similar number of brands for selection. However, the number of available brands in these two product markets differed significantly from that in the salty snack market.

In this research, similar typical purchase behaviours of consumers were identified across the yogurt and toilet tissue markets. However, the identified typical purchase behaviours of consumers in these two product markets presented a clear difference from those in the salty snack market. These findings suggest that the typical purchase behaviours of consumers are likely to be similar across product markets with a similar number of brands available for selection.

CHAPTER 6: ANALYSIS OF DEMOGRAPHIC PROFILING

6.1 Introduction

To validate the behavioural segmentation, criterion-related validity is assessed in this research by using consumers' demographics to profile their associated behavioural segment in each product market. The purpose of the criterion-related validity is to assess whether the behavioural segments differ across consumers' demographics that are theoretically related to them. In this study, ten out of 12 demographic variables that can well characterize a behavioural segment are selected and used to profile the segment. The demographic profile of a behavioural segment in a dataset is generated by comparing the distribution of each demographic variable in the behavioural segment to the distribution of the demographic variable in the overall population. The demographic profile of a behavioural segment is a basic description of the common demographic characteristics of the consumers within the segment (Collica, 2011). In this study, the demographic profile of a behavioural segment identified in a learning dataset is validated by using that in the corresponding validation dataset. The identified common demographic characteristics of the consumers within a behavioural segment in both the learning and validation datasets in a year form the demographic profile of the behavioural segment in the year.

The generated demographic profile of each behavioural segment in year 2004 is demonstrated in a table (i.e. Table 6.1, 6.6, and 6.12) in the 'Assessment results of criterion-related validity' section in each product market. The distinctive demographic characteristics that can be used for differentiating between two behavioural segments are identified and summarized in a table (i.e. Table 6.2, 6.7, and 6.13) for each product market. The information in the table demonstrates how well the identified behavioural segments differ across consumers' demographics. It indicates the validity of the behavioural segmentation in each product market.

In prior research, it has been suggested that consumers' purchase behaviours can be identified by using their demographic characteristics (Bawa and Ghosh, 1999; Bell *et al.*, 1999; Blattberg *et al.*, 1978; Kwon and Kwon, 2007; Lichtenstein *et al.*, 1997; Teunter, 2002; Urbany *et al.*, 1996). In this research, the capability of demographics in targeting consumers with given brand selection behaviours in relation to promotions is examined via profiling the generated behavioural segments by using demographics. In a product market, consumers not only differ in demographic characteristics but also differ in their purchase experiences. A reliable and valid demographic profile is thus needed to be able to target consumers in a behavioural segment regardless of their purchase experiences. In this research, a demographic profile of each behavioural segment in the four consecutive years from 2004 to 2007 is generated and compared in each product market. The behaviour-related demographic profile to target consumers in a behavioural segment consists of the demographic characteristics that remain unchanged in profiling the behavioural segment across the four consecutive years. These stable demographic variables are suggested to have significant influences on the decision making of the consumers in the associated behavioural segment. The generated behaviour-related demographic profiles may help marketers to target consumers with expected purchase behaviours in a short time.

In order to find out the effectiveness of the generated behaviour-related demographic profiles in targeting, the improved performances in identifying a group of consumers with expected purchase behaviours using the demographic profiles are measured. The improved performances of targeting are quantified as the weighted difference in percentages between a group of consumers associated with the expected demographic characteristics and a group of consumers in the population. US census data is used in this research to determine the weight of the improved performances of targeting each sub-group of consumers. Figures are produced and provided to visualize the improved performances. In these figures, the blue line represents the percentage distribution of consumers in a behavioural segment in association with the characteristics of a demographic variable. The orange line in the figures represents the percentage of those consumers in the population. The gap between the blue line and the orange line represents the difference in percentages between consumers in the behavioural segment in association with the characteristics of the demographic variable and those consumers in the population. If there is a gap above the orange line and under the blue line, this represents a positive difference, which represents an improved performance in targeting consumers in the behavioural segment using the demographic variable.

In the US retail market, retailers compete for millions of consumers. A slight increase in targeting performances will make a huge difference to retailers in attracting and obtaining consumers by using tailored marketing strategies. The findings in this study thus have significant implications in retail marketing. Even though the methodology employed in this research does not allow us to reach a firm conclusion on whether these results are statistically significant, these results are thought to capture non-random variation. It is because significant improvements in targeting consumers with given purchase behaviours by using demographic variables are identified and validated in different datasets across four consecutive years.

Overall, this section consists of four sub-sections. The first three sub-sections present the demographic profiling in the salty snack, yogurt, and toilet tissue markets. The last sub-section compares the results of the demographic profiling across the three product markets to find out how the capability of demographics in targeting consumers with given brand selection behaviours in relation to promotions differs across product markets.

6.2 Salty Snack Market

6.2.1 Assessment results of criterion-related validity

The demographic profiles of behavioural segments in year 2004 are shown in Table 6.1.

Table 6.1: Demographic profiles of behavioural segments in year 2004 in the Pittsfield salty snack market

Segment	Promotion-averse Exploiters	Opportunistic Exploiters	Bargain Hunters	Explorers
Combined household income (per year)	Low income	Lower-middle class	Upper-middle class	High income
Family size	Small or very large family size (1 person, 3 people, or no fewer than six people)	Two people	N/A	N/A
Age of male	55-64	65+	35-54	35-54
Education level reached by male	N/A	N/A	Graduated high school, postgraduate work, technical school, completed grade school, some college	N/A
Occupation of male	Machine operator, clerical	Retired	Professional or technical, labourer	Sales, private household worker, manager or administrator
Male working hours	N/A	Retired,	Full time	Full time
Age of female	N/A	N/A	N/A	35-54
Education level reached by female	Low level of education, i.e. some and graduated high school	Technical school	Graduated from college	N/A
Occupation of female	Clerical, manager or administrator, retired	Manager or administrator	Unemployed	Professional or technical
Female working hours	N/A	N/A	Unemployed	Full time
Children group	N/A	Family size > 0 yet no children	N/A	Children in [6-11) & [12-17), child in [6-11), child in [12-17), children in [0-5), [6-11) & [12-17)
Marital status	N/A	N/A	Married	Separated

Each behavioural segment in 2004 was profiled by at least six demographic variables. We found that Promotion-averse Exploiters in 2004 belonged to low-income households with either small or very large family sizes. The males of the households were young seniors in the age between 55 and 64 years old who worked as machine operators or clerical staff. The females of the households were not well educated and were most likely to work as clerical staff, managers, or administrators or to be retired.

Opportunistic Exploiters were also profiled as low income and working class with small family sizes in 2004. Specifically, the Opportunistic Exploiters were retired working-class consumers with a fair income and education, without the presence of children. Compared to Promotion-averse Exploiters' households, Opportunistic Exploiters' households had a higher combined household income, an older and retired male in the household, and a better-educated and more-professional female in the household. The higher income and education level make these Opportunistic Exploiters less restricted by their shopping budgets in reacting to in-store promotions, and they have a higher capability to process promotional messages than Promotion-averse Exploiters do (Teunter, 2002). Opportunistic Exploiters who were more than 65 years old and who were retired had fewer time constraints and greater price knowledge than Promotion-averse Exploiters did (Urbany *et al.*, 1996). These Opportunistic Exploiters were thus expected to have more time to conduct extensive searches about promotions to reduce their purchase costs than the Promotion-averse Exploiters (Urbany *et al.*, 1996; Blattberg *et al.*, 1978; Teunter, 2002). In general, Opportunistic Exploiters and Promotion-averse Exploiters in the salty snack market differ across several demographic variables, which are summarized in Table 6.2. The differences in the demographic characteristics between these two groups of consumers explain why they behave differently in brand selection in relation to promotions (see Section 5.2).

Table 6.2: Summary of the demographic variables used for differentiating behavioural segments in the salty snack market

	Opportunistic Exploiters	**Bargain Hunters**	**Explorers**
Promotion-averse Exploiters	Combined household income, education level reached by female, family size, occupation of female, occupation of male, age of male	Combined household income, education level reached by female, occupation of female, occupation of male, age of male	Combined household income, occupation of male, occupation of female, age of male

Opportunistic Exploiters		Combined household income, education level reached by female, male working hours, occupation of female, occupation of male, age of male	Combined household income, children group, male working hour, occupation of female, occupation of male, age of male
Bargain Hunters			Combined household income, female working hour, occupation of female, occupation of male, marital status

Bargain Hunters were profiled as well-educated, middle-aged (i.e. in the age between 35 and 54 years old), upper-middle-class people with full-time and high-autonomy work. These were married couples with an unemployed wife. Compared to Promotion-averse Exploiters and Opportunistic Exploiters, Bargain Hunters were younger and richer couples with better-educated but unemployed wives and higher work autonomy of the husband. Young consumers make more decisions at the point of purchase due to the motivations from in-store promotions (Inman *et al.*, 2004). This might be the reason why the middle-aged Bargain Hunters were more sensitive to in-store promotions than the Promotion-averse Exploiters and Opportunistic Exploiters were. The households with better-educated females had higher capabilities in processing promotion and brand information (Teunter, 2002). This may explain why the Bargain Hunters were more likely to shop for bargains and to extend their market knowledge via trying alternatives than the Promotion-averse Exploiters and Opportunistic Exploiters were. In addition, households with unemployed females did not have time pressure and could allocate more time for shopping (Teunter, 2002), which made these Bargain Hunters be more likely to increase their unplanned purchases motivated by promotions than Promotion-averse Exploiters and Opportunistic Exploiters. In general, Bargain Hunters present different demographic characteristics from Promotion-averse Exploiters and Opportunistic Exploiters and thus behave differently in purchases.

Explorers were profiled as middle-aged, high-income people. Both the males and females of the households were working full time and had high work autonomy. Even though these households had at least one child, they were separated couples. Compared to the other three groups of consumers, Explorers had the highest combined household income. They thus had the least restrictions on shopping budgets for extending their market knowledge via trying alternatives (Mann and Rashmi, 2010; Teunter, 2002). Like Bargain Hunters, Explorers were younger and had higher work autonomy than Promotion-averse Exploiters and Opportunistic Exploiters. These Explorers also differed from Opportunistic Exploiters in their children group status and male working status. Children, who are the main consumers in the salty snack market, are inclined to accept new things and are vulnerable to TV advertisements. Satisfying the requests of children may require households to buy different brands. This might be the reason why Explorers came from households with children but Opportunistic Exploiters did not. Compared to Explorers, Opportunistic Exploiters had a lower occupation status (i.e. retired) and thus were more likely to be loyal to their preferred brands (Mann and Rashmi, 2010).

Even though the demographic profile of Explorers was more similar to that of Bargain Hunters than those of the other two groups of consumers, Explorers were also identified to differ from Bargain Hunters in the occupations and marital statuses of households (see Sections 2.5.1.7 and 2.5.2.7). Compared to Explorers, Bargain Hunters had fewer time restrictions in searching for promotions, as both husband and wife held jobs that required a high degree of commitment (Heilman *et al.,* 2000; Schaninger and Allen, 1981). However, these dual-career families had higher incomes than Bargain Hunters did, allowing them to explore the salty snack market.

Concluding the findings of the demographic profiling for the year 2004, the behavioural segments generated in the salty snack market differ in consumers' demographic characteristics that are theoretically related to the behavioural segments. The behavioural segmentation in this research was thus proven to be valid, based on the criterion-related validity assessment.

6.2.2 Behaviour-related demographic profile for targeting

For the purpose of targeting consumers based on their behaviour-related demographics, Table 6.3 is provided to show the comparative results of the demographic profiles across the four consecutive years from 2004 to 2007 in the Pittsfield salty snack market.

Table 6.3: Demographic profiles of behavioural segments over the years in the salty snack market

Segment	Demographics	Year2004	Year2005	Year2006	Year2007
Promotion-averse Exploiters	**Combined household income (per year)**	**Low income**	**Low** or very high **income**	**Low income**	**Low income**
	Family size	Small or very large family size (1person, 3 people or no fewer than six people)	Small family size, i.e. one person	Small family size: 1-2 people	N/A
	Age of male	55-64	N/A	N/A	N/A
	Education level reached by male	N/A	Low education, i.e. some high school; graduated high school	Low education, i.e. some high school	Low education, i.e. some high school
	Occupation of male	Machine operator, clerical	Retired	Retired	N/A
	Male working hours	N/A	Retired	Retired	N/A
	Age of female	N/A	55-64	55-64	55-64
	Education level reached by female	Low level of education, i.e. some and graduated high school	N/A	N/A	Low education, i.e. some high school
	Occupation of female	Clerical, manager or administrator, retired	Manager or administrator, retired	Retired, clerical, manager or administrator	N/A
	Female working hours	N/A	N/A	N/A	Homemaker

	Children group	N/A	N/A	Family size > 0, yet not children	N/A
	Marital status	N/A	Not married, i.e. single, widowed	Not married, i.e. widowed	Not married, i.e. single
Opportunistic Exploiters	**Combined household income (per year)**	**Lower-middle class**	**Lower-middle class**	**Lower-middle class**	**Lower-middle class**
	Family size	Two people	Two people	N/A	N/A
	Age of male	65+	N/A	N/A	N/A
	Education level reached by male	N/A	N/A	Technical school, some college	Some high school, technical school
	Occupation of male	**Retired**	**Retired**	**Retired**	**Retired**
	Male working hours	**Retired**	**Retired**	**Retired**, unemployed	**Retired**
	Age of female	N/A	N/A	N/A	65+, (25-34)
	Education level reached by female	Technical school	N/A	Technical school	N/A
	Occupation of female	Manager or administrator	Retired	Retired	Retired
	Female working hours	N/A	Retired	Retired	Retired
	Children group	Family size > 0, yet not children	Family size > 0, yet no children	N/A	Family size > 0, yet no children
	Marital status	N/A	N/A	N/A	N/A

Bargain Hunters	**Combined household income (per year)**	**Higher-middle class**	**Higher-middle class**	**Higher-middle class**	**Higher-middle class**
	Family size	N/A	N/A	N/A	N/A
	Age of male	35-54	35-44	65+	N/A
	Education level reached by male	**Graduated high school**, postgraduate work, technical school, some college	**Graduated high school**	**Graduated high school**	**Graduated high school,** some college
	Occupation of male	Professional or technical, Labourer	Labourer, professional or technical, unemployed, clerical	Clerical	Unemployed, clerical
	Male working hours	Full time	Full time	N/A	N/A
	Age of female	N/A	N/A	65+	65+
	Education level reached by female	Fair education, i.e. graduated from college	N/A	N/A	Some high school, technical school
	Occupation of female	**Unemployed**	**Unemployed**	**Unemployed**	**Unemployed**
	Female working hours	**Unemployed**	**Unemployed**	**Unemployed**	**Unemployed**
	Children group	N/A	Child in [12-17),children in [0-5) and [12-17), children in [6-11) and [12-17)	N/A	Child in [0-5), child in [6-11), children in [0-5) and [12-17)

	Marital status	Married	N/A	N/A	N/A
Explorers	**Combined household income (per year)**	**High income**	**High** or very low **income**	**High income**	**High income**
	Family size	N/A	N/A	Five people	Three people or four people
	Age of male	**35-54**	**45-54**	**35-54**	**35-54**
	Education level reached by male	N/A	High education, i.e. some college, graduated from college	High education, i.e. graduated from college, postgraduate work	High education, i.e. graduated from college
	Occupation of male	Sales, private household worker, **manager or administrator**	Professional or technical, **manager or administrator**, sales	Labourer, **manager or administrator**	Sales, professional or technical, **manager or administrator**, labourer
	Male working hour	**Full time**	**Full time**	**Full time**	**Full time**
	Age of female	35-54	35-54	35-54	N/A
	Education level reached by female	N/A	N/A	N/A	N/A
	Occupation of female	**Professional or technical**	Manager or administrator, **professional or technical**	**Professional or technical**	**Professional or technical**
	Female working hour	**Full time**	Part time, **full time**	**Full time**	**Full time**

	Children group	Children in [6-11) &[12-17), child in [6-11), child in [12-17),children in [0-5), [6-11) and [12-17)	N/A	N/A	Child in [12-17)
	Marital status	Separated	N/A	N/A	N/A

As can be seen in Table 6.3, the characteristics of combined household income remained stable over the four years in each behavioural group. This finding suggests that combined household income was an appropriate behaviour-related demographic variable in differentiating and targeting Promotion-averse Exploiters, Opportunistic Exploiters, Bargain Hunters, and Explorers. Marketers could thus predict consumers' brand selection behaviours in relation to promotions based on their combined household incomes to tailor marketing strategies. Figure 6.1 visualizes the improved performance in targeting Promotion-averse Exploiters using combined household income in learning dataset 2004. The visualizations of the improved performance in all eight datasets are provided in Appendix G.

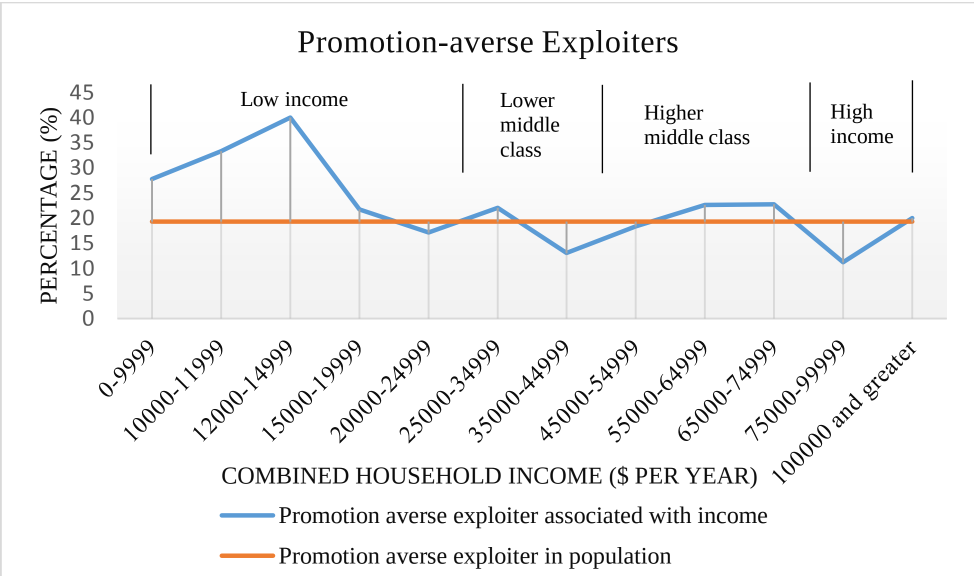

Figure 6.1: Improved performance in targeting Promotion-averse Exploiters using combined household income in learning dataset 2004 in salty snack market

According to the distribution of combined household income in the US (DeNavas-Walt *et al.*, 2005, 2006, 2007, 2008; US Census Bureau, 2007), the consumers are regrouped into four classes for the purpose of segment profiling. The new income groups are presented in Figure 6.1. It shows that the percentage of Promotion-averse Exploiters in the low-income group was much higher than that in the population. This finding supports the notion that low-income consumers are more likely to be Promotion-averse Exploiters. This might be due to their limited budgets for shopping (see Sections 2.5.1.1 and 2.5.2.1).

As the low-income consumers consist of five combined household income groups, the weighted increase in accuracy is used to quantify the performance in identifying Promotion-averse Exploiters by targeting low-income consumers. The weights are generated by using the income distribution data in the US census. For example, the consumers whose combined household incomes were between $0 and $9,999 per year accounted for around 30.63% of low-income consumers in 2004 (DeNavas-Walt *et al.*, 2005). Thus, 30.63% is used as the weight for measuring the improved performance in targeting the very low-income group. In this study, 27.78% of consumers whose combined household incomes were between $0 and $9,999 per year were Promotion-averse Exploiters. However, in learning dataset 2004, 19.28% of the consumers were Promotion-averse Exploiters. When targeting consumers whose combined household incomes were between $0 and $9,999 per year, the accuracy of targeting the right Promotion-averse Exploiters increases by 8.5% (i.e. 27.78% - 19.28% = 8.5%). This means that targeting consumers whose combined household incomes are between $0 and $9,999 per year would enable marketers to target 8.5% more Promotion-averse Exploiters. By the same token, the weights and increased unit targeting performances of the rest of the low-income sub-groups can be generated, which are illustrated in Table 6.4.

Table 6.4: Performance improvement from targeting low-income consumers in 2004

Low-income group ($ per year)	Promotion-averse Exploiters in income group (%)	Promotion-averse Exploiters in population (%)	The unit performance improvement (%)	Weight	Performance improvement from targeting each low-income group (%)	Performance improvement from targeting low-income consumers (%)
0–9,999	27.78	19.28	8.50	0.3063	2.60	2.60 + 1.09 + 3.28 + 0.55 + (-0.50) = 7.02
10,000–11,999	33.33	19.28	14.05	0.0775	1.09	
12,000–14,999	40.00	19.28	20.72	0.1585	3.28	
15,000–19,999	21.74	19.28	2.46	0.2254	0.55	
20,000–24,999	17.14	19.28	-2.14	0.2324	-0.50	

The performance improvement from targeting a low-income sub-group is quantified by multiplying the unit performance improvement in the low-income sub-group with the associated weight of the sub-group. The performance improvement from targeting low-income consumers is the sum of the performance improvement from targeting all five low-income sub-groups in identifying Promotion-averse Exploiters. The results generated in the learning dataset 2004 suggest a 7.02% increase in the probability that a consumer with a low income is a Promotion-averse Exploiter compared to a consumer in the population.

By the same token, the performance improvements from targeting low-income consumers in 2005, 2006, and 2007 are also quantified and equal 0.53%, 3.28%, and 7.63%, respectively. In the market, low-income consumers may have different experiences. To quantify the improved targeting performances regardless of market experiences, the percentages of the increased targeting performances are averaged over the four years. On average, there is a 4.62% (i.e. (7.02% + 0.53% + 3.28% + 7.63%) / 4 = 4.62%) increase in the probability that a consumer with a low income is a Promotion-averse Exploiter compared to a consumer in the population.

Opportunistic Exploiters were lower-middle class with a retired male in the household. A consumer whose combined household income was between $25,000 and $44,999 per year was at least 4.47% more likely to be an Opportunistic Exploiter compared to a consumer in the population. To target Opportunistic Exploiters, the occupation of the male in the household could also be used. A consumer with a retired male in the household was at least 8.64% more likely to be an Opportunistic Exploiter. This might be because retired consumers have fewer time constraints for shopping and are older (see Sections 2.5.1.3, 2.5.1.4, 2.5.2.3, and 2.5.2.4).

Bargain Hunters were higher-middle class with poorly educated males and unemployed wives in the households. The profile of Bargain Hunters suggests that traditional families were more likely to be Bargain Hunters. Targeting households whose combined household incomes are between $45,000 and $54,999 per year would enable marketers to achieve a 4.53% increase in accuracy in successfully identifying Bargain Hunters. In addition, a consumer with a male in the household who had graduated from high school was 3.2% more likely to be a Bargain Hunter. When the females in the households were unemployed, it was at least 9.1% more likely that the consumers would be Bargain Hunters. This might be because the unemployed wife had more time for searching for promotions (see Section

2.5.1.4).

Explorers were high-income households. The male household members were full-time managers or administrators and were between 45 and 54 years old. The female household members were full-time professional or technical staff. Targeting households whose combined household incomes are between $75,000 and $99,999 per year would enable marketers to identify at least 10.95% more Explorers than targeting all households. Compared to the population, a consumer with a full-time working male member in the household was at least 3.14% more likely to be an Explorer. In addition, targeting consumers from households where the male members are managers or administrators would enable marketers to identify at least 4.7% more Explorers than targeting all households. The age of males in households was also a significant factor in identifying Explorers. Figure 6.2 shows the percentages of Explorers in different age groups of males in households in learning dataset 2004. The visualizations of the improved performance in targeting Explorers using the ages of males in households in all eight datasets are provided in Appendix H.

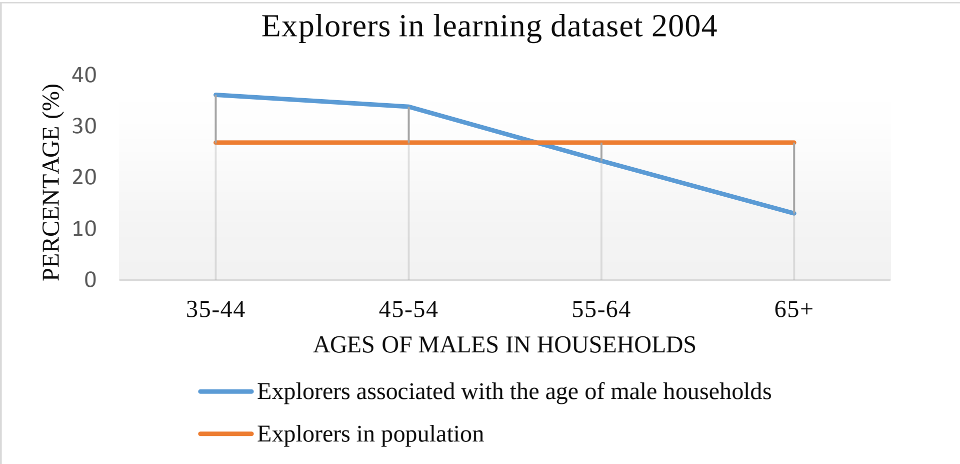

Figure 6.2: Improved performance in targeting Explorers using ages of males in households in learning dataset 2004

A consumer from a household with a male aged between 35 and 44 years old was at least 4.64% more likely to be an Explorer. When targeting consumers from households with male members between 45 and 54 years old, there is a 4.51% increase in the probability that a consumer is an Explorer. Targeting households with male members between 35 and 54 years old would enable marketers to identify at least 4.56% more Explorers (US Census Bureau, 2007, 2007, 2009, 2009). The occupational characteristics of female households also could be used to target Explorers. A consumer from a household with a full-time working female was at least 4.08% more likely to be an Explorer than consumers in the rest of the population were. Consumers from households where females were employed in professional or technical work were at least 4.93% more likely to be Explorers.

The results generated in the learning datasets are validated by using the four validation datasets. A summary of the improved performances by using demographics to identify associated purchase behaviours in both the learning and validation datasets is presented in Table 6.5.

Table 6.5: Improved performances in targeting using demographic variables in salty snack market

	Learning dataset				**Validation dataset**			
Stable demographics	Promotion -averse Exploiters	Opportunistic Exploiters	Bargain Hunters	Explorers	Promotion -averse Exploiters	Opportunistic Exploiters	Bargain Hunters	Explorers
Combined household income (per year)	$0–$24,999 (4.62%)	$25,000–$44,999 (5.13%)	$45,000–$54,999 (7.71%)	$75,000–$99,999 (11.08%)	$0–$24,999 (7.46%)	$25,000–$44,999 (4.47%)	$45,000–$54,999 (4.53%)	$75,000–$99,999 (10.95%)
Occupation of male		Retired (8.92%)		Manager or administrator (7.16%)		Retired (8.64%)		Manager or administrator (4.72%)
Male working hour		Retired (9.28%)		Full time (4.02%)		Retired (8.64%)		Full time (3.14%)
Education level reached by male			Graduated high school (4.50%)				Graduated high school (3.17%)	
Age of male				35-44 (8.97%); 45-54 (7.73%); 35-54 (8.36%)				35-44 (4.64%); 45-54 (4.51%); 35-54 (4.56%)
Occupation of female			Unemployed (11.52%)	Professional or technical (4.97%)			Unemployed (7.49%)	Professional or technical (8.03%)
Female working hour			Unemployed (9.11%)	Full time (4.08%)			Unemployed (19.51%)	Full time (8.14%)

Consistent with the findings of Narasimhan (1984), an inverse U-shaped relationship between combined household income and promotion proneness was identified in the salty snack market. The relationship between combined household income and exploration behaviour was found to be positive in this research, which supports the findings of prior research (e.g. Farley, 1964; Leszczyc and Timmermans, 1997; Mann and Rashmi, 2010; Rogers, 1995; Tate, 1961). In general, demographic variables could be used to target a group of consumers with expected brand selection behaviours in relation to promotions in the salty snack market. There was an increase in the probability that a consumer with a demographic characteristic would exhibit a particular purchase behaviour. Identifying consumers' purchase behaviours based on their associated demographic characteristics was suggested and confirmed to be feasible and valid in the salty snack market.

6.3 Yogurt Market

6.3.1 Assessment results of criterion-related validity

The demographic profiles of each behavioural segment in year 2004 in the Pittsfield yogurt market are shown in Table 6.6.

Table 6.6: Demographic profiles of behavioural segments in year 2004 in the Pittsfield yogurt market

Segment	Opportunistic Explorers	Opportunistic Exploiters	Promotion-averse Explorers	Promotion-averse Exploiters
Children Group	N/A	N/A	Children in [0-5)&[6-11)	N/A
Combined Household Income (per year)	$12,000 to $19,999; $55,000 to $64,999; $25,000 to $34999	$20,000 to $24,999; $45,000 to $54,999; $0 to $11,999	$45,000 to $54,999; $100,000 and greater; $35,000 to $44,999; $75,000 to $99,999; $15,000 to $19,999	$55,000 to $74,999; $0 to $9,999
Education Level Reached by Female	Graduated from college, some high school[1]	Graduated high school	Some college, postgraduate work	Some college
Education Level Reached by Male	Graduated from college, postgraduate work	N/A	Technical school	N/A
Family Size	Three to four people	One person, three people, or six or more people[2]	No fewer than four people	N/A
Female Working Hours	N/A	Retired	Part time <35hrs./wk, full time >35hrs./wk	Homemaker
Male Working Hours	Part time <35hrs./wk	N/A	N/A	N/A
Marital Status	N/A	Widowed, single	N/A	N/A
Occupation of Female	Professional or technical, cleaning, food, health service worker	Retired, professional or technical[3]	Clerical, operative (machine operatore), manager or administrator, private household worker	Clerical, sales, private household worker
Occupation of Male	Manager or administrator, unemployed, cleaning, food, health service worker	Clerical	Sales, manager or administrator	Labourer, sales[4]
Age of Female	25-34	35-44	N/A	N/A
Age of Male	N/A	N/A	N/A	55-64

[1] The greyed characteristic of female education level is not as important as the other characteristics of female education level in profiling Opportunistic Explorers.
[2] The greyed characteristic of family size is not as important as the other characteristics of family size in profiling Opportunistic Exploiters.
[3] The greyed characteristic of female occupation is not as important as the other characteristics of female occupation in profiling Opportunistic Exploiters.
[4] The greyed characteristic of male occupation is not as important as the other characteristics of male occupation in profiling Promotion-averse Exploiters.

Each behavioural segment was profiled by at least six demographic variables in 2004. Opportunistic Explorers in the yogurt market were profiled as belonging to relatively low-income households with three to four family members. The males of the households were well educated and working part time in administrative, managerial, cleaning, food, or health service roles or were unemployed. The females of the households were well-educated young consumers who were working as professional or technical staff or as cleaning, food, or health service workers.

The Opportunistic Exploiters had even lower combined household incomes than the Opportunistic Explorers did. This might be because their more-limited budgets for shopping may not allow these Opportunistic Exploiters to take risks to try new brands (see Section 2.5.2.1). In this research, Opportunistic Exploiters were profiled as consumers from low-income households with either small or very large family sizes. The marital status of Opportunistic Exploiters was either widowed or single. The females of the households were in the middle age between 35 and 44 years old or in retirement. The education level reached by them was graduating from high school. The males of the households were engaged in routine work, such as clerical work. Compared to the Opportunistic Explorers, the Opportunistic Exploiters had a lower combined household income, poorer education level, smaller family size, and older age. Besides, the Opportunistic Exploiters also differed from the Opportunistic Explorers in their occupations. The differences in the stated demographics between Opportunistic Exploiters and Opportunistic Explorers explain why Opportunistic Exploiters were less likely to extend their market knowledge via trying alternatives than Opportunistic Explorers were (see Section 2.5.2). The demographic variables that can be used to differentiate between the two behavioural segments are listed in Table 6.7.

Table 6.7: Summary of the demographic variables used for differentiating behavioural segments in the yogurt market

	Opportunistic Exploiters	**Promotion-averse Explorers**	**Promotion-averse Exploiters**
Opportunistic Explorers	Combined household income, education level reached by female, family size, occupation of female, occupation of male, age of female	Combined household income, education level reached by female, education level reached by male, family size, occupation of female	Combined household income, education level reached by female, occupation of female, occupation of male
Opportunistic Exploiters		Combined household income, education	Combined household income,

		level reached by female, family size, female working hours, occupation of female, occupation of male	education level reached by female, female working hours, occupation of female, occupation of male
Promotion-averse Explorers			Combined household income, female working hours, occupation of female, occupation of male

Promotion-averse Explorers were profiled as consumers in a big family with a relatively high combined household income. At least two small children were in the household. The females of the households were well educated and engaged in either full-time or part-time routinized work. The males of the households had graduated from technical school and were working in sales, management, or administration. Compared to Opportunistic Explorers, Promotion-averse Explorers had higher combined household incomes, larger family sizes, more-routinized work, poorer education levels of males in the households, and higher education levels of females in the households. In other words, Promotion-averse Explorers and Opportunistic Explorers differed across these demographic variables. Compared to Opportunistic Exploiters, Promotion-averse Explorers had higher combined household incomes and larger family sizes. Consumers in these two behavioural segments also differed in the demographic characteristics of the females in the households. Consumers with better-educated working females in their households were more likely to be Promotion-averse Explorers than Opportunistic Exploiters.

Promotion-averse Exploiters had combined household incomes either between $55,000 and $74,999 per year or between $0 and $9,999 per year. The females of the households had some college education and were engaged in routinized work, like clerical, sales, and homemaking work. The males of the households were young seniors in the age between 55 and 64 years old who were working as labourers or sales staff. As exploiters, Promotion-averse Exploiters were likely to have higher combined household incomes and higher education levels of females in the households than Opportunistic Exploiters. Besides, these two groups of exploiters also differed across the occupations of both females and males in the households. Compared to Opportunistic Explorers, Promotion-averse Exploiters had higher combined household incomes, lower education levels of females in the households, and more-routinized work. The combined household incomes, education level reached by females in the households, and occupations of males and females thus could be used to differentiate between these two behavioural segments. The demographic characteristics of the Promotion-averse Exploiters were relatively more similar to those of Promotion-averse Explorers than those of the other two behavioural segments. Compared to Promotion-averse Explorers, Promotion-averse Exploiters had relatively lower combined household incomes. Those two behavioural segments also differed in the characteristics of the occupations of both males and females and the working hours of females in the households.

In general, the findings of the demographic profiling in the year 2004 show that the behavioural segments generated in the yogurt market differ across consumers' demographics that are theoretically related to them. The assessment results of criterion-related validity thus support the notion that the behavioural segmentation in the Pittsfield yogurt market was valid.

6.3.2 Behaviour-related demographic profile for targeting

In order to target consumers with expected purchase behaviours based on their behaviour-related demographics, Table 6.8 is produced to show the demographic profiles of behavioural segments across the four consecutive years from 2004 to 2007 in the Pittsfield yogurt market.

Table 6.8: Demographic profiles of behavioural segments over the years in the yogurt marke

Segment	Demographic	Year 2004	Year 2005	Year 2006	Year 2007
	Children group	N/A	N/A	N/A	N/A
	Combined household income	$12,000 to $19,999; $55,000 to $64,999; $25,000 to $34,999	$25,000 to $34,999; $65,000 to $74,999	$25,000 to $34,999; $15,000 to $19,999; $10,000 to $14,999; $35,000 to $44,999	$20,000 to $24,999; $15,000 to $19,999; $12,000 to $14,999
	Education level reached by female	Graduated from college, some high school	N/A	Graduated high school	N/A
	Education level reached by male	Graduated from college, postgraduate work	Postgraduate work, some college	N/A	Some high school, graduated high school, technical school
	Family size	Three or four people	Three or four people	N/A	Three people or six or more people
Opportunistic Explorers	**Female working hours**	N/A	N/A	N/A	Unemployed, part time <35hrs/wk, retired
	Male working hours	Part time <35hrs/wk	Unemployed	Retired, homemaker	Unemployed, part time <35hrs/wk
	Marital status	N/A	Divorced	Divorced	N/A
	Occupation of female	Professional, technical, cleaning, food, health service	Cleaning, food, health service worker	Retired, unemployed	Retired, manager, administrator
	Occupation of male	Manager, administrator, unemployed, cleaning, food, health service	Sales, unemployed	Retired, operative (machine operator)	Professional, technical, cleaning, food, health service worker, unemployed, private household worker
	Age of female	25–34	N/A	45–54, 65+	45–54, 65+
	Age of male	N/A	25–34, or 35-54	N/A	45–54

	Children group	N/A	Child in [12-17), or children in [0-5).[6-11)&[12-17)	Child in [12-17)	N/A
	Combined household income	$20,000 to $24,999; $45,000 to $54,999; $0 to $11,999	$0 to $9,999; $45,000 to $54,999; $65,000 to $74,999	$20,000 to $24,999	$0 to $11,999
	Education level reached by female	Graduated high school	Graduated high school	Technical school, some high school	N/A
	Education level reached by male	N/A	N/A	Some college	N/A
	Family size	One person, three people, or six or more people	One person or six or more people	N/A	Two people
Opportunistic Exploiters	**Female working hours**	Retired	N/A	Part time <35hrs/wk	Retired
	Male working hours	N/A	Part time <35hrs/wk	N/A	Retired
	Marital status	Widowed, single	N/A	N/A	N/A
	Occupation of female	Retired, professional, technical	Operative (machine operator), private household worker, manager, administrator	N/A	Retired
	Occupation of male	Clerical	Clerical, cleaning, food, health service worker	Operative (machine operator), labourer, clerical, professional, technical	Retired
	Age of female	35–44	N/A	45–54	55–64
	Age of male	N/A	55–64	55–64	65+
Promotion-	**Children**	Children in [0-5)&[6-11)	Children in [6-11)&[12-17)	N/A	Child in [0-5), child in [6-11),

Averse Explorers	**group**				children in [0-5)&[6-11)
	Combined household income	**$45,000 to $54,999**; $100,000 and greater; $35,000 to $44,999; **$75,000 to $99,999**; $15,000 to $19,999	**$75,000 to $99,999;** $100,000 and greater; $15,000 to $19,999; **$45,000 to $54,999**; $10,000 to $11,999	**$45,000 to $54,999**; **$75,000 to $99,999;** $65,000 to $74,999	**$75,000 to $99,999; $45,000 to $54,999**
	Education level reached by female	Some college, postgraduate work	N/A	Postgraduate work, some college, graduated from college	Graduated from college
	Education level reached by male	Technical school	N/A	N/A	N/A
	Family size	No fewer than four people	Two people or six or more people	Three people, no fewer than five people	N/A
	Female working hours	**Part time <35hrs/wk, full time >35hrs/wk**	**Part time <35hrs/wk, full time >35hrs/wk**	**Part time <35hrs/wk, full time >35hrs/wk,** student	**Part time <35hrs/wk, full time >35hrs/wk**
	Male working hours	N/A	Full time >35hrs/wk	Unemployed, part time <35hrs/wk, full time >35hrs/wk	Full time >35hrs/wk, homemaker
	Marital status	N/A	N/A	N/A	N/A
	Occupation of female	Clerical, operative (machine operator), manager, administrator, private household worker	Clerical, professional, technical	Professional, technical, cleaning, food, health service	Professional, technical, sales, craftsman, cleaning, food, health service worker
	Occupation of male	Sales, manager, administrator	Professional, technical, sales, private household worker	Sales, unemployed, operative (machine operator), craftsman, manager, administrator,	Manager, administrator, private household worker, labourer

				private household worker	
	Age of female	N/A	N/A	N/A	25–44
	Age of male	N/A	45–54	45–54	N/A
Promotion-Averse Exploiters	**Children group**	N/A	Children in [6-11)&[12-17)	Family size >0, yet no children, children in [0-5),[6-11)&[12-17)	Children in [0-5)&[12-17), children in [6-11)&[12-17)
	Combined household income	$55,000 to $74,999; $0 to $9,999	$55,000 to $64,999; $20,000 to $24,999; $75,000 to $99,999	$20,000 to $24,999	$35,000 to $44,999
	Education level reached by female	Some college	Some college	N/A	Some college
	Education level reached by male	N/A	N/A	Graduated from college	Graduated from college
	Family size	N/A	N/A	One person or two people	N/A
	Female working hours	**Homemaker**	**Homemaker,** unemployed	**Homemaker**	**Homemaker**
	Male working hours	N/A	N/A	N/A	full time >35hrs/wk
	Marital status	N/A	N/A	Single	N/A
	Occupation of female	Clerical, sales, private household worker	Unemployed	Unemployed, operative (machine operator)	Unemployed, labourer, operative (machine operator)
	Occupation of male	Labourer, sales	Labourer, professional, technical, manager, administrator, private household worker, unemployed	Professional, technical, manager, administrator, private household worker	Professional, technical, labourer

	Age of female	N/A	N/A	N/A	N/A
	Age of male	55–64	25–44, 55–64	N/A	25–34

In profiling Opportunistic Exploiters and Opportunistic Explorers, no demographic characteristics remained unchanged across the four consecutive years. This means that no demographic variable had significant influences on the purchase decision making of Opportunistic Explorers and Opportunistic Exploiters. It is thus difficult to successfully target Opportunistic Explorers and Opportunistic Exploiters by using demographic variables.

Unlike opportunists, promotion-averse consumers could be targeted by using demographic variables. Promotion-averse Explorers came from high-income households with either part-time or full-time working wives. Their high combined household incomes allowed the Promotion-averse Explorers to allocate higher budgets to shopping, which may have made them less conscious of and less sensitive to price changes (Ailawadi *et al.*, 2001; Ainslie and Rossi, 1998; Kim *et al.*, 1999). The limited constraints in shopping budgets may also induce Promotion-averse Explorers to extend their market knowledge via trying alternatives (Mann and Rashmi, 2010). Working women normally have more time constraints, which do not allow them to spend more time on shopping for searching for promotions (Blattberg *et al.*, 1978; Inman *et al.*, 2004). In general, the characteristics of combined household income and female working status explained the purchase behaviours of Promotion-averse Explorers and could be used to target these consumers, regardless of their purchase experiences. Appendix I visualizes the improved performances in targeting Promotion-averse Explorers using combined household income across the four years from 2004 to 2007 in the learning and validation datasets. Figure 6.3 presents the visualized performance improvement in the learning dataset 2004 for the purpose of explanation.

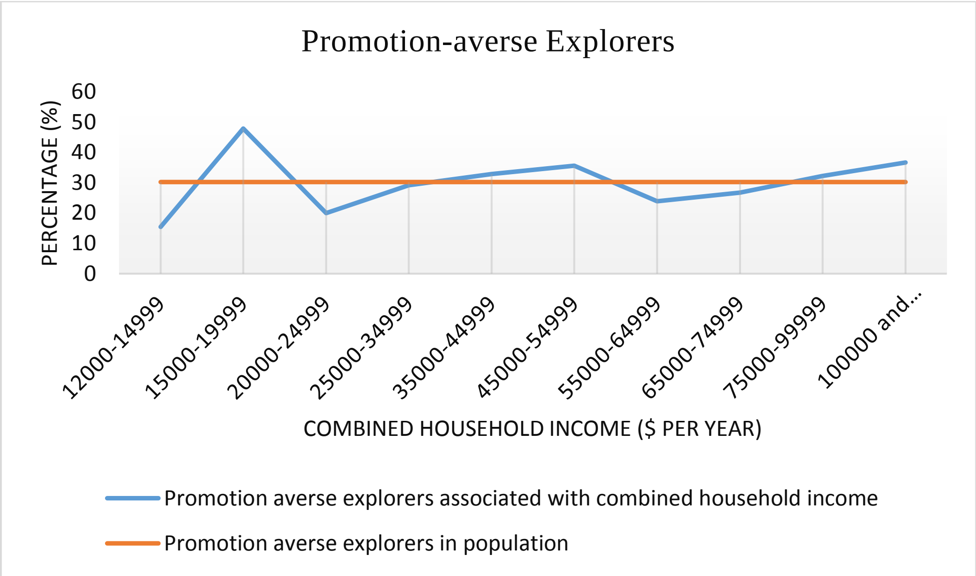

Figure 6.3: Improved performance in targeting Promotion-averse Explorers by using

combined household incomes in learning dataset 2004

As can be seen in Figure 6.3, consumers in five combined household income groups had a higher percentage of Promotion-averse Explorers than those in the population in 2004. However, Table 6.8 and Appendix I show that only the consumers who came from the households with the combined household incomes between $45,000 and $54,999 per year and between $75,000 and $99,999 per year were more likely to be Promotion-averse Explorers in the four consecutive years. There is an average 4.75% (i.e. (5.39% + 2.15% + 6.76% + 4.69%) / 4 = 4.75%) increase in the probability that a consumer with a combined household income between $45,000 and $54,999 per year is a Promotion-averse Explorer compared to a consumer in the population. A consumer with a combined household income between $75,000 and $99,999 per year was on average 5.32% (i.e. (1.98% + 3.66% + 1.17% + 14.47%) / 4 = 5.32%) more likely to be a Promotion-averse Explorer than a consumer in the population was. Targeting households in either of these two combined household income groups was thus found to enable marketers to improve performances in identifying Promotion-averse Explorers.

To assess the improved performance in identifying Promotion-averse Explorers via targeting households in both of these combined household income groups, simply summing the improved performances in targeting households in each income group would double the improved performances in targeting the two income groups. In this research, the performance improvement in targeting an income group is weighted by using the percentage of the income group in the targeted income groups. Income distribution data from the US census is used to generate the weights in assessing the performance improvement in targeting. In the US, households whose combined incomes were between $45,000 and $54,999 per year accounted for around 8.77% of households in the population in 2004, while households whose combined incomes were between $75,000 and $99,999 per year accounted for around 11% of households in the population (DeNavas-Walt *et al.*, 2005). When targeting these two income groups, households whose incomes were between $45,000 and $54,999 per year accounted for around 44.36% (i.e. 8.77% / (8.77%+11%) = 44.36%) of the households in the targeted groups. The households in the other targeted income group accounted for around 55.64% (i.e. 1 - 44.36% = 55.64%) of households in the targeted groups. In other words, 44.36% of the targeted households had incomes between $45,000 and $54,999 per year and the rest had incomes between $75,000 and $99,999 per year. The generated 44.36% and 55.64% are then used as weights in calculating the weighted improved performance in targeting via multiplying the increased percentage of Promotion-averse Explorers in the associated income group.

In 2004, 35.56% of Promotion-averse Explorers came from households whose combined incomes were between $45,000 and $54,999 per year, compared to 30.17% in the population. When targeting that income group, the accuracy of targeting Promotion-averse Explorers increases by 5.39% (i.e. 35.56% - 30.17% = 5.39%). This means that targeting households whose combined incomes are between $45,000 and $54,999 per year would enable marketers to target 5.39% more Promotion-averse Explorers. By the same token, the increased percentage of Promotion-averse Explorers in the other income group could be calculated and used to quantify the improved performance in targeting. The performance improvement from targeting these two income groups is the sum of the weighted performance improvement from targeting each of the income groups. Table 6.9 demonstrates the calculation process for the performance assessment in 2004.

Table 6.9: Calculation process for the performance improvement in targeting two income groups in 2004

<table>
<tr><th>Income group ($ per year)</th><th>Promotion-averse Explorers in income group (%)</th><th>Promotion-averse Explorers in population (%)</th><th>The unit performance improvement (%)</th><th>Weight</th><th>Performance improvement from targeting each income group (%)</th><th>Performance improvement from targeting the two income groups (%)</th></tr>
<tr><td>45,000-54,999</td><td>35.56</td><td>30.17</td><td>5.39</td><td>0.44</td><td>2.37</td><td rowspan="2">2.37 + 1.10 = 3.47</td></tr>
<tr><td>75,000 – 99,999</td><td>32.14</td><td>30.17</td><td>1.97</td><td>0.56</td><td>1.10</td></tr>
</table>

The results of the performance assessment indicate a 3.47% increase in the probability that a household in the targeted income groups is a Promotion-averse Explorer compared to a household in the population in 2004. By the same token, the performance improvements from targeting these two income groups in 2005, 2006, and 2007 are assessed and quantified, which equal 2.99%, 3.56%, and 10.38%, respectively. As these Promotion-averse Explorers differed in their market experiences, the improved performances in targeting are averaged over the four consecutive years to measure the performance improvement in targeting regardless of consumer market experiences. Therefore, there is a 5.10% (i.e. (3.47% + 2.99% + 3.56% + 10.38%) / 4 = 5.10%) increase in the probability that a consumer from the targeted household income groups is a Promotion-averse Explorer compared to a consumer in the population.

Besides combined household income, Promotion-averse Explorers could also be profiled by using female working hours. Appendix J visualizes the improved performance in targeting Promotion-averse Explorers using female working hours across the four years from 2004 to 2007 in the learning and validation datasets. As the findings in Table 6.8 and Appendix J show, consumers from households with either part-time or full-time employed females were more likely to be Promotion-averse Explorers. Targeting households with part-time employed females would enable marketers to improve the performance in identifying Promotion-averse Explorers by around 4.62% on average (i.e. (4.21% + 8.12% + 5.93% + 0.23%) / 4 = 4.62%). There is an average 1.82% (i.e. (0.05% + 0.08% + 2.95% + 4.18%) / 4 = 1.82%) increase in the probability that a consumer from a household with a full-time employed female is a Promotion-averse Explorer compared to a consumer in the population. Figure 6.4 presents the visualized performance improvement in the learning dataset 2004 for the purpose of explanation.

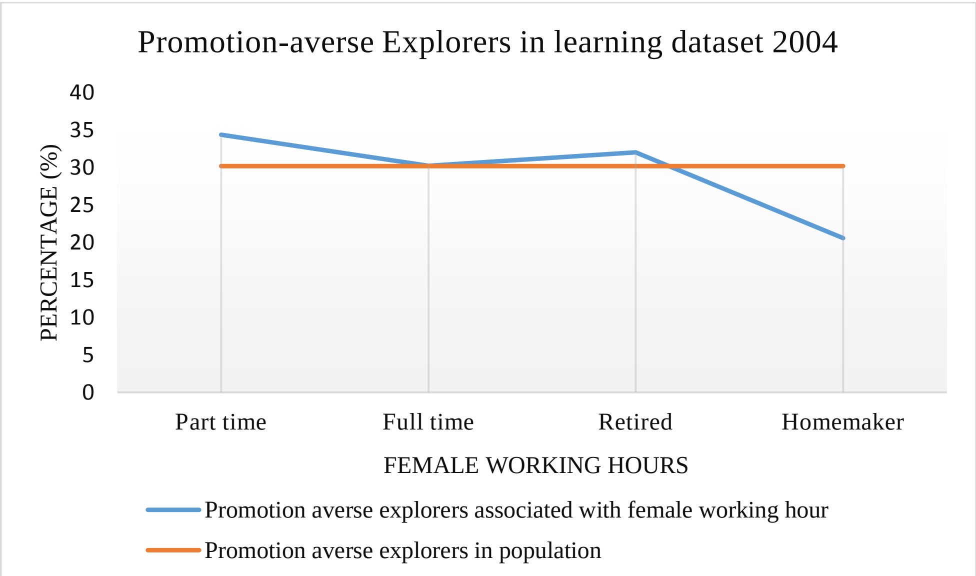

Figure 6.4: Improved performance in targeting Promotion-averse Explorers using female working hours in learning dataset 2004

According to labour force statistics in the US, the proportion of part-time vs. full-time employed females is 34.05% to 65.95% (Mislinski, 2016; US Bureau of Labor Statistics, 2016). In the performance assessment, these two proportions are used as weights to quantify the weighted improved performance in identifying Promotion-averse Explorers via targeting either full-time or part-time employed female households. Table 6.10 demonstrates the calculation process for this performance improvement in learning dataset 2004.

Table 6.10: Calculation process for the performance assessment in learning dataset 2004

Female working hours	Promotion-averse Explorers in female working group (%)	Promotion-averse Explorers in population (%)	The unit performance increase (%)	Weight	Performance improvement from targeting each female working group (%)	Performance improvement from targeting the two female working groups (%)
Part time	34.38	30.17	4.21	0.34	1.43	1.43+ 0.033 = 1.463
Full time	30.22	30.17	0.05	0.66	0.033	

The generated results indicate that targeting households with part-time employed female and households with full-time employed females would enable marketers to improve the performance in identifying Promotion-averse Explorers by 1.46% in 2004. By the same token, the performance improvements in targeting these two groups of consumers in 2005, 2006, and 2007 are assessed, which equal 2.82%, 3.97%, and 2.84%, respectively. The average improved performance in the four consecutive years from 2004 to 2007 was 2.77% (i.e. (1.46% + 2.82% + 3.97% +2.84%) / 4 = 2.77%). This means that targeting consumers in these two female working-hour groups increased the probability of identifying Promotion-averse Explorers by 2.77% on average.

The characteristics of female working hours could also be used to identify Promotion-averse Exploiters. The increased probability that a household with a female homemaker was a Promotion-averse Exploiter was 10.03% in 2004, 9.13% in 2005, 8.00% in 2006, and 12.78% in 2007. A consumer from a household with a female homemaker was therefore 9.99% (i.e. (10.03% + 9.13% + 8.00% + 12.78%) / 4 = 9.99%) more likely to be a Promotion-averse Exploiter on average.

The results generated in the learning datasets are validated by using the four validation datasets. A summary of the improved performances in identifying consumers with certain purchase behaviours using demographics is presented in Table 6.11.

Table 6.11: Improved performances in targeting using demographic variables in the yogurt market

	Learning dataset		Validation dataset	
Stable demographics	Promotion-averse Explorers	Promotion-averse Exploiters	Promotion-averse Explorers	Promotion-averse Exploiters
Combined household income ($ per year)	45,000–54,999 (4.75%); 75,000–99,999 (5.32%); 45,000–54,999 and 75,000–99,999 (5.10%)		45,000–54,999 (12.96%); 75,000–99,999 (5.51%); 45,000–54,999 and 75,000–99,999 (8.71%)	
Female working hours	Part time (4.62%); Full time (1.82%); Part time and full time (2.77%)	Homemaker (9.98%)	Part time (6.93%); Full time (3.08%); Part time and full time (4.39%)	Homemaker (8.99%)

In general, demographic variables could be used to target Promotion-averse Explorers and Promotion-averse Exploiters in the yogurt market. In terms of these Promotion-averse Explorers and Promotion-averse Exploiters, there was an increase in the probability that a consumer with the identified demographic characteristic would have the expected purchase behaviour. However, no valid demographic profiles were identified to target Opportunistic Explorers and Opportunistic Exploiters in the yogurt market. Demographic variables thus could not be used to target opportunists in the yogurt market. Identifying consumers' purchase behaviours based on their associated demographic characteristics is suggested to be feasible and valid for some but not all consumers in the yogurt market.

6.4 Toilet Tissue Market

6.4.1 Assessment results of criterion-related validity

The demographic profiles of behavioural segments in year 2004 in the Pittsfield toilet tissue market are shown in Table 6.12.

Table 6.12: Demographic profiles of behavioural segments in year 2004 in the Pittsfield toilet tissue market

Segment	Opportunistic Explorers	Promotion-averse Exploiters	Promotion-averse Explorers	Opportunistic Exploiters
Age of Female	N/A	N/A	35-44	N/A
Age of Male	45-54, 65+	25-34, 65+	35-44	65+
Children Group	Child in [6-11), child in [12-17)	N/A	N/A	Family size >0, yet no children
Combined Household Income (per year)	$25,000 to $34,999; $100,000 and greater; $15,000 to $19,999; $12,000 to $14,999[5]	$35,000 to $44,999	$12,000 to $14,999	$20,000 to $24,999; $25,000 to $34,999[6]
Education Level Reached by Female	Graduated from college, postgraduate work	Some college, graduated from college	Graduated high school, postgraduate work[7]	N/A
Education Level Reached by Male	N/A	Some college	N/A	N/A
Family Size	Five people	N/A	One person	N/A
Female Working Hours	N/A	N/A	N/A	Unemployed
Male Working Hours	N/A	Full time >35hrs./week	N/A	Unemployed, homemaker
Marital Status	Married	N/A	Widowed, single	N/A
Occupation of Female	Retired, professional or technical	Operative (machine operator), clerical	Manager or administrator, sales, private household worker	Unemployed
Occupation of Male	Retired, unemployed, manager or administrator, professional or technical	Professional or technical, operative (machine operator), private household worker	Sales, cleaning, food, health service worker, operative (machine operator)	Unemployed, labourer

[5] The greyed characteristic of combined household income is not as important as the other characteristics of combined household income in profiling Opportunistic Explorers.
[6] The greyed characteristic of combined household incomel is not as important as the other characteristics of combined household income in profiling Opportunistic Exploiters.
[7] The greyed characteristic of education level reached by female is not as important as the other characteristics of education level reached by female in profiling Promotion-averse Explorers.

Each behavioural segment was profiled by at least seven demographic variables in 2004. Opportunistic Explorers came from households with a large family size, which included married couples and children in 6–11 years old and/or 12–17 years old. These households had relatively higher combined household incomes than Promotion-averse Explorers and Opportunistic Exploiters. The males of the households were either middle aged (i.e. between 45 and 54 years old) or more than 65 years old. They were engaged in work with high autonomy, in retirement, or unemployed. The females of the households were well educated and either retired or working as professional or technical staff.

Opportunistic Exploiters came from households without children. Their combined household incomes were between \$20,000 and \$34,999 per year. The males of the households were old consumers who were either unemployed or engaged in routinized work. The females of the households were unemployed. Compared to the Opportunistic Explorers, the Opportunistic Exploiters had relatively lower combined household incomes, smaller family sizes, and more-routinized occupations. These demographic differences between Opportunistic Exploiters and Opportunistic Explorers explain why Opportunistic Exploiters were less likely to extend their market knowledge via trying alternatives than Opportunistic Explorers were (see Section 2.5.2). The demographic variables that can be used to differentiate between the two behavioural segments are listed in Table 6.13.

Table 6.13: Summary of the demographic variables used for differentiating behavioural segments in the toilet tissue market

	Opportunistic Exploiters	**Promotion-averse Explorers**	**Promotion-averse Exploiters**
Opportunistic Explorers	Combined household income, occupation of female, occupation of male, children group	Education level reached by female, family size, occupation of female, age of male, marital status, occupation of male	Combined household income, education level reached by female, occupation of female, occupation of male, age of male
Opportunistic Exploiters		Combined household income, occupation of female, occupation of male, age of male	Combined household income, male working hour, occupation of female, occupation of male
Promotion-averse Explorers			Combined household income, occupation of female, occupation of male, age of male,

			education reached by female

Promotion-averse Explorers came from low-income households with only one person in the family, who was engaged in routinized work. Consumers in these households were either widowed or single and were aged between 35 and 44 years old. The female households were normally poorly educated. Compared to the Opportunistic Explorers, the Promotion-averse Explorers had lower combined household incomes, much smaller family sizes, and more-routinized work. The male Promotion-averse Explorers were younger than the male Opportunistic Explorers were. The female Promotion-averse Explorers had lower education levels than the female Opportunistic Explorers did. The two types of explorers also differed in their marital status in 2004. Promotion-averse Explorers had entirely different brand selection behaviours in reaction to promotions in the toilet tissue market from Opportunistic Exploiters did (see Section 5.4.). Compared to the Opportunistic Exploiters, the Promotion-averse Explorers had lower combined household incomes and younger ages. Differing from the Promotion-averse Explorers, the Opportunistic Exploiters were unemployed, which might be because the Opportunistic Exploiters were beyond the age of retirement. These differences in demographics may explain why the Promotion-averse Explorers behaved entirely differently from the Opportunistic Exploiters in purchases.

Promotion-averse Exploiters came from college-level households with combined household incomes between $35,000 and $44,999 per year. The males were either young consumers or old consumers beyond the age of retirement. They were engaged in full-time work as professional or technical staff, machine operators, or private household workers. The females were engaged in routinized work. The Promotion-averse Exploiters had contrary purchase behaviour to the Opportunistic Explorers, which could be explained by the differences in their demographic characteristics. Compared to the male Opportunistic Explorers, the male Promotion-averse Exploiters were younger. The female Promotion-averse Exploiters had lower education levels and were engaged in more-routinized work than the female Opportunistic Explorers were. Besides, the combined household income and the occupations of males also differentiated the Promotion-averse Exploiters from the Opportunistic Explorers. Compared to the Opportunistic Exploiters, the Promotion-averse Exploiters had higher combined household incomes and allocated more time to working. The Promotion-averse Exploiters also had higher combined household incomes than the Promotion-averse Explorers did. Compared to the Promotion-averse Explorers, the Promotion-averse Exploiters came from households with better-educated female members.

In addition, the Promotion-averse Exploiters and the Promotion-averse Explorers differed in the ages and occupations of males and the occupations of females.

In general, the results for the demographic profiling in the year 2004 indicate that the generated behavioural segments in the toilet tissue market differ across demographic variables. The assessment results of criterion-related validity thus support that the behavioural segmentation in the Pittsfield toilet tissue market was valid.

6.4.2 Behaviour-related demographic profile for targeting

To target consumers based on behaviour-related demographics, Table 6.14 is presented to show the demographic profiles of behavioural segments across the four consecutive years from 2004 to 2007.

Table 6.14: Demographic profiles of behavioural segments over the years in the toilet tissue market

Behavioural Segment	Demographic Variable	Year 2004	Year 2005	Year 2006	Year 2007
Opportunistic Explorers	**Age of female**	N/A	N/A	N/A	N/A
	Age of male	45–54, 65+	N/A	N/A	N/A
	Children group	Child in [6-11), child in [12-17)	N/A	N/A	N/A
	Combined household income	$25,000 to $34,999; $100,000 and greater; $15,000 to $19,999; $12,000 to $14,999[8]	$100,000 and greater; $10,000 to $11,999; $25,000 to $34,999	$25,000 to $34,999; $100,000 and greater; $15,000 to $19,999	$20,000 to $24,999; $35,000 to $44,999; $12,000 to $14,999[9]
	Education level reached by female	Graduated from college, postgraduate work	N/A	Technical school, graduated from college, postgraduate work	Graduated high school
	Education level reached by male	N/A	Completed grade school, some high school	Some college	Technical school
	Family size	**Five people**	**Five people**	**Five people**	**Five people**
	Female working hours	N/A	Unemployed, part time <35hrs/wk, retired, homemaker	Unemployed, homemaker	Retired, part time <35hrs/wk, homemaker
	Male working hours	N/A	Retired	Retired	unemployed
	Marital status	Married	Married	N/A	N/A
	Occupation of female	Retired, professional, technical	Unemployed, retired, labourer	Unemployed, labourer	Retired, sales
	Occupation of male	Retired, unemployed, manager, administrator,	Manager, administrator, retired, craftsman	Unemployed, retired, manager, administrator,	N/A

8 The greyed characteristic of combined household income is not as important as the other characteristics of combined household income in profiling Opportunistic Explorers in year 2004

9 The greyed characteristics of combined household income are not as important as the other characteristics of combined household income in profiling Opportunistic Explorers in year 2007

		professional, technical		craftsman	
Promotion-Averse Exploiters	**Age of female**	N/A	45–54	N/A	45–54
	Age of male	25–34, 65+	N/A	N/A	N/A
	Children group	N/A	N/A	Family size >0, yet no children	N/A
	Combined household income	**$35,000 to $44,999**	**$35,000 to $44,999**; $0 to $9,999; $45,000 to $54,999	**$35,000 to $44,999**; $12,000 to $14,999; $45,000 to $54,999; $75,000 to $99,999	**$35,000 to $44,999**, $75,000 to $99,999
	Education level reached by female	Some college, graduated from college	Graduated high school, some high school	N/A	Some high school, graduated high school
	Education level reached by male	Some college	Graduated from college	N/A	N/A
	Family size	N/A	Three people	One person or three people	Three people
	Female working hours	N/A	N/A	Full time >35hrs/wk	Full time >35hrs/wk
	Male working hours	Full time >35hrs/wk	Full time >35hrs/wk	N/A	Unemployed
	Marital status	N/A	Divorced	N/A	N/A
	Occupation of female	Operative (machine operator), clerical	Clerical, private household worker	Clerical, private household worker	Private household worker
	Occupation of male	Professional, technical, operative (machine operator), private household worker	Labourer, operative (machine operator)	Labourer, professional, technical	Sales, private household worker
Promotion-	**Age of female**	35–44	N/A	N/A	35–44

Averse Explorers	**Age of male**	35–44	N/A	25–44	25–44
	Children group	N/A	N/A	N/A	Children in [6-11)&[12-17)
	Combined household income	Low income (i.e. $12,000 to $14,999)	$45,000 to $54,999; $10,000 to $11,999[10]	$55,000 to $64,999; $20,000 to $24,999; $45,000 to $54,999; $10,000 to $11,999[11]	$55,000 to $64,999, $100,000 and greater
	Education level reached by female	Graduated high school, postgraduate work	Graduated high school, postgraduate work	Graduated high school, completed grade school	N/A
	Education level reached by male	N/A	Graduated high school	Graduated high school	N/A
	Family size	One person	N/A	One person	N/A
	Female working hours	N/A	Full time >35hrs/wk	N/A	Unemployed
	Male working hours	N/A	N/A	Full time >35hrs/wk	N/A
	Marital status	Widowed, single	Single, separated	N/A	N/A
	Occupation of female	Manager, administrator, sales, private household worker	Private household worker	Retired, private household worker, labourer	N/A
	Occupation of male	Sales, cleaning, food, health service worker, operative (machine operator)	Operative (machine operator), private household worker, professional, technical, clerical	Operative (machine operator), clerical, sales, private household worker	Manager, administrator, labourer, clerical

[10] The greyed characteristic of combined household income is not as important as the other characteristics of combined household income in profiling Promotion-averse Explorers in year 2005

[11] The greyed characteristic of combined household income is not as important as the other characteristics of combined household income in profiling Promotion-averse Explorers in year 2006

Opportunistic Exploiters	**Age of female**	N/A	N/A	N/A	65+
	Age of male	65+	N/A	N/A	65+
	Children group	Family size >0, yet no children	N/A	N/A	N/A
	Combined household income	$20,000 to $24,999; $25,000 to $34,999[12]	$15,000 to $19,999; $100,000 and greater; $12,000 to $14,999	$65,000 to $74,999; $15,000 to $19,999; $10,000 to $11,999; $25,000 to $34,999[13]	$25,000 to $34,999; $12,000 to $14,999; $15,000 to $19,999[14]
	Education level reached by female	N/A	Some high school	Some high school, technical school, graduated from college	Some college, graduated from college
	Education level reached by male	N/A	N/A	N/A	Graduated from college
	Family size	N/A	N/A	N/A	N/A
	Female working hours	Unemployed	Homemaker, unemployed	N/A	Full time >35hrs/wk
	Male working hours	Unemployed, homemaker	Unemployed, homemaker	Unemployed	N/A
	Marital status	N/A	N/A	N/A	N/A
	Occupation of female	Unemployed	Unemployed, manager, administrator	Cleaning, food, health service worker, clerical	Clerical, sales, professional, technical, cleaning, food, health service worker
	Occupation of male	Unemployed, labourer	Unemployed, labourer	Cleaning, food, health service worker, unemployed	Cleaning, food, health service worker

[12] The greyed characteristic of combined household income is not as important as the other characteristics of combined household income in profiling Opportunistic Exploiters in year 2004

[13] The greyed characteristic of combined household income is not as important as the other characteristics of combined household income in profiling Opportunistic Exploiters in year 2006

[14] The greyed characteristic of combined household income is not as important as the other characteristics of combined household income in profiling Opportunistic Exploiters in year 2007

Table 6.14 shows that no stable demographic characteristics that remained unchanged over the four years were identified in profiling Promotion-averse Explorers and Opportunistic Exploiters. This indicates that none of the demographic variable had significant capability in influencing the purchase decision making of these Promotion-averse Explorers and Opportunistic Exploiters. Marketers would thus find it difficult to target these consumers by using demographic variables.

In the toilet tissue market, Opportunistic Explorers and Promotion-averse Exploiters could be targeted by using demographic variables. Opportunistic Explorers were profiled as coming from households with five family members. Targeting households with five family members would enable marketers to identify at least 11.57% more Opportunistic Explorers than targeting all households. Promotion-averse Exploiters came from households who had combined incomes between $35,000 and $44,999 per year. Compared to a consumer in a population, a consumer with a combined household income between $35,000 and $44,999 per year was at least 6.19% more likely to be a Promotion-averse Exploiter. A summary of the performance improvements from using demographics to target consumers with given purchase behaviours in both the learning datasets and validation datasets is presented in Table 6.15.

Table 6.15: Improved performances in targeting using demographic variables in the toilet tissue market

	Learning dataset		**Validation dataset**	
Stable demographics	Opportunistic Explorers	Promotion-averse Exploiters	Opportunistic Explorers	Promotion-averse Exploiters
Family size	Five people (11.57%)		Five people (13.67%)	
Combined household income		$35,000 to $44,999 (8.73%)		$35,000 to $44,999 (6.19%)

In general, there is an increase in the probability that a consumer from a household with five family members is an Opportunistic Explorer and a consumer with a combined household income between $35,000 and $44,999 per year is a Promotion-averse Exploiter. However, demographic variables could not be used to target all consumers with expected purchase behaviours in the toilet tissue market.

6.5 Market Comparison

In general, the behavioural segments in each of the salty snack, yogurt, and toilet tissue markets differ across demographic variables that are theoretically related to them. This suggests that the behavioural segmentation in each of these product markets was valid in terms of the criterion-related validity. For the purpose of targeting a group of consumers with expected brand selection behaviours in relation to promotions by using behaviour-related demographic variables, the capability of demographic variables in influencing the purchase decision making of consumers in each behavioural segment is examined across these product markets. A comparison of the behaviour-related demographic profiles in targeting across product markets is summarized and presented in Table 6.16.

Table 6.16: Comparison of the demographic profiling in targeting across the salty snack, yogurt and toilet tissue markets

	Salty Snack Market				Yogurt Market				Toilet Tissue Market			
	Promotion-averse Exploiters	Opportunistic Exploiters	Bargain hunters	Explorers	Promotion-averse Exploiters	Opportunistic Exploiters	Opportunistic Explorers	Promotion-averse Explorers	Promotion-averse Exploiters	Opportunistic Exploiters	Opportunistic Explorers	Promotion-averse Explorers
Combined household income (per year)	$0–$24,999 (4.62%)	$25,000–$44,999 (4.47%)	$45,000–$54,999 (4.53%)	$75,000–$99,999 (10.95%)				$45,000–$54,999 (4.75%); $75,000–$99,999 (5.32%); $45,000–$54,999 and $75,000–$99,999 (5.10%)	$35,000 to $44,999 (6.19%)			
Occupation of male		Retired (8.64%)		Manager or administrator (4.72%)								
Male working hours		Retired (8.64%)		Full time (3.14%)								
Education level reached by male			Graduated high school (3.17%)									
Age of male				35–44 (4.64%); 45–54 (4.51%);								

				35-54 (4.56%)								
Occupation of female			Unemployed (7.49%)	Professional or technical (4.97%)								
Female working hours			Unemployed (9.11%)	Full time (4.08%)	Homemaker (8.99%)			Part time (4.62%); full time (1.82%); Part TIME and full time (2.77%)				
Family size											Five people (11.57%)	

As shown in Table 6.16, the demographic characteristics of Promotion-averse Exploiters were different among the salty snack, yogurt, and toilet tissue markets. The behavioural segments that had similar behavioural features across these product markets also had different demographic profiles. For example, the demographic profile of Bargain Hunters in the salty snack market was entirely different from that of Opportunistic Explorers in the toilet tissue market. These findings indicate that the demographic profiles of the behavioural segments with similar purchase behaviours may differ across different product markets. This suggests that to target consumers with desired purchase behaviours, it may be necessary to use different demographic characteristics in different product markets. In other words, the demographic profile of a group of consumers with the desired purchase behaviours in a product market may not be generalizable to other product markets.

Among these three product markets, demographic variables could only be used to target consumers in all behavioural segments in the salty snack market. In the yogurt and toilet tissue markets, two out of the four behavioural segments could not be targeted by using demographic variables. These findings suggest that the capability of demographics in predicting consumers' brand selection behaviours in relation to promotions was higher in the salty snack market than that in the yogurt and toilet tissue markets.

The difference in the predictive capability of demographics was also reflected in the number of demographic variables that could be used to target consumers in a behavioural segment and the associated improved performances in this targeting. In the salty snack market, six demographic variables could be used to target Explorers, regardless of their purchase experiences. The purchase behaviours of Promotion-averse Explorers in the yogurt market were similar to those of Explorers in the salty snack market (see Section 5.5). However, only two demographic variables could be used to target Promotion-averse Explorers in the yogurt market. Besides, the improved performances in targeting Explorers in the salty snack market using combined household income or female working hours were much higher than those in targeting Promotion-averse Explorers in the yogurt market using the same demographic variables. In general, compared to the behavioural segments in the yogurt market, the behavioural segments in the salty snack market could be targeted by using more demographic variables with higher-improved performances in targeting. The evidence supports that the capability of demographics in predicting consumers' brand selection behaviours in relation to promotions was higher in the salty snack market than that in the yogurt market.

Compared to the yogurt market, the number of stable demographic variables that could be used to target a group of consumers was smaller in the toilet tissue market. In addition, the improved performance in targeting Promotion-averse Exploiters in the toilet tissue market was lower than that in the yogurt market. These comparative findings support that the capability of demographics in predicting consumer purchase behaviours in the toilet tissue market was lower than that in the yogurt market. In general, the capability of demographics in successfully targeting a group of consumers with expected purchase behaviours was highest in the salty snack market and lowest in the toilet tissue market.

As discussed in Section 4.3, the salty snack, yogurt, and toilet tissue markets differed in the number of brands available for selection. The comparative findings suggest that the capability of demographics in predicting and influencing consumers' brand selection behaviours in relation to promotions was higher in a market with a large number of brands available for selection than in a market with a small number of brands. In other words, the degree of influence of demographic characteristics on brand selection behaviours in relation to promotions is suggested to be positively related to the number of brands available for selection in a product market.

Consumers in a product market with a large number of brands only explore a small proportion of available brands over the years. Their accumulated market knowledge thus only slightly changes over the years in the highly competitive product market. Consumers in such a product market only slightly differ from one another in their market knowledge. In purchases, the behaviours of consumers are co-determined by their purchase experiences and their associated demographic characteristics. As consumers' market knowledge only slightly changes over the years in a highly competitive product market with a large number of brands, the associated demographic characteristics are proposed to have significant influences on their purchase behaviours.

Based on the above, marketers in a highly competitive market are thus suggested to use demographics to target consumers with expected purchase behaviours for tailoring and providing promotions in order to improve the performances of marketing. As for markets with a small number of brands, marketers are suggested to use demographics in combination with consumer purchase experiences to predict the future purchase behaviours of consumers for the purpose of tailoring promotions. In the next chapter, the dynamic behavioural evolvements are discussed.

CHAPTER 7: ANALYSIS OF DYNAMIC BEHAVIOURAL EVOLVEMENTS

7.1 Introduction

The purchase decisions of consumers are co-determined by the market experiences and demographic characteristics of consumers (Heilman *et al.*, 2000; Teunter, 2002). According to Heilman *et al.* (2000), consumers' purchase behaviours dynamically evolve with an increase in market knowledge. The evolvements of the brand selection behaviours in relation to promotions in the consumer purchase lifecycle are explored in the salty snack, yogurt, and toilet tissue markets in the following three sections in this chapter.

In each product market, the size of each behavioural segment across the four consecutive years from 2004 to 2007 is compared and demonstrated in a figure (i.e. Figure 7.1, 7.6, and 7.13). The change in segment size over the years indicates the general direction of behavioural evolvements over those four years, with the final status of consumer purchase behaviours at the end of the fourth year. In order to clarify how the purchase behaviours of consumers evolve in their purchase lifecycles, their associated behavioural segments across two consecutive years from 2004 to 2007 are compared. In this research, three stages of dynamic behavioural evolvements are generated over those four consecutive years in learning and validation datasets. Each behavioural evolvement stage consists of the behavioural evolvements of consumers in two consecutive years and is visualized by using a figure. In order to identify the typical patterns of the dynamic behavioural evolvements in each behavioural evolvement stage, the transitional probabilities of behavioural evolvement types were calculated and compared. A transitional probability of a behavioural evolvement type, for example, evolving from behavioural segment A to behavioural segment B over two years, equals the percentage of consumers in behavioural segment A in a year evolving to behavioural segment B in the year after. The transitional probability of the behavioural evolvement type reflects the likelihood of a consumer evolving from behavioural segment A to behavioural segment B over those two years. The typical patterns of the dynamic behavioural evolvements consist of the behavioural evolvement types that have high transitional probabilities.

In order to find out how the typical dynamic behavioural evolvement patterns differ across behavioural evolvement stages in terms of the behavioural evolvement types, the transitional probabilities of behavioural evolvement types are compared. The comparison of the transitional probabilities of behavioural evolvement types across behavioural evolvement stages is visualized in figures (i.e. Figure 7.2, 7.7, and 7.14). In these figures, a group of bars represents a behavioural evolvement type. For example, each of the six bars coded by ‘11’ represents the behavioural evolvement type where consumers evolved from Segment 1 to Segment 1 in a product market. The height of a bar represents the transitional probability of a behavioural evolvement type. The transitional probabilities of a behavioural evolvement type identified in different datasets are differentiated by using different colours in the figures.

In each stage, the implied patterns of dynamic behavioural evolvements are uncovered and visualized by using solid lines in the figure of the behavioural evolvement stage. The descriptions and explanations of the dynamic behavioural evolvement patterns are presented in the appendices (i.e. Appendix K, L, and M). Understanding the behavioural evolvement patterns may allow marketers to understand the behavioural trends of consumers in brand selection in relation to promotions. To clarify how and why the purchase behaviours of consumers evolve from one segment to another over time, the typical behavioural evolvement approach of each typical behavioural evolvement type is visualized in figures (Figure 7.4, 7.9, 7.16, 7.17, and 7.18). The lines in those figures demonstrate how the Prevalence of Promotion and the Value of Information from Purchases changed when a consumer evolved from one behavioural segment to another. The changes of the Prevalence of Promotion and the Value of Information from Purchases explained why the purchase behaviours of consumers evolved in that particular evolvement type.

Due to their lack of market knowledge, the initial status of consumers is likely to be exploiters. New consumers in a product market are thus likely to be either Promotion-averse Exploiters or Opportunistic Exploiters. Inferred from the typical behavioural evolvement patterns in each behavioural evolvement stage, two behavioural evolvement routes are generated and presented in this research. These behavioural evolvement routes show how consumers evolve from their initial status with an increase in market knowledge. They demonstrate consumers’ learning processes in purchases. To understand these behavioural evolvement routes, the behavioural evolvement approaches are used in this research to clarify them. The trade-offs between the extension of market knowledge and the maximization of immediate purchase value in consumer purchase decision making are visualized and discussed to explain the evolvements of consumer purchase behaviours in their purchase lifecycles.

In the final section of this chapter, a comparative analysis of the dynamic behavioural evolvements across the salty snack, yogurt, and toilet tissue markets is presented. The empirical findings of the dynamic behavioural evolvements in these three product markets are compared.

7.2 Salty Snack Market

The sizes of the identified behavioural segments in the salty snack market are shown in Figure 7.1.

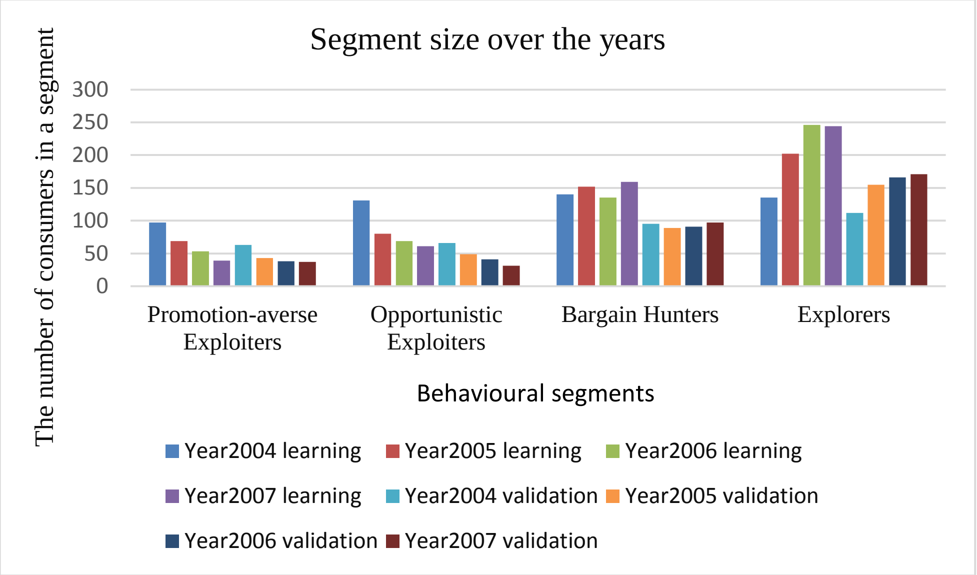

Figure 7.1: Sizes of the behavioural segments over the years in the salty snack market

In the learning datasets, the number of Promotion-averse Exploiters and Opportunistic Exploiters gradually decreased over the four years. On the contrary, the number of Explorers significantly increased over those four years. The number of Bargain Hunters, however, remained relatively stable from 2004 to 2007. These trends identified in the learning datasets were confirmed and validated in the validation datasets. According to the statistics on segment size over the years, Promotion-averse Exploiters and Opportunistic Exploiters gradually evolved into Explorers and/or Bargain Hunters in their purchase lifecycles in the US salty snack market. The final purchase status of consumers in the Pittsfield salty snack market was thus proposed to be Explorers or Bargain Hunters. Brand loyalty is therefore suggested to not exist in the salty snack market. This might be because the large number of brands motivated consumers who had increased brand-differentiating capability to increase their market knowledge via exploration.

As can be seen in Figure 7.2, the transitional probabilities of ‘11’, ‘22’, ‘33’, and ‘44’ were higher than those of the rest of the behavioural evolvement types. This suggests that consumers were most likely to have similar purchase behaviours in two consecutive years. The differences in the transitional probabilities of behavioural evolvement types in a behavioural evolvement stage indicate that the purchase behaviour of a consumer was likely to evolve in a predictable pattern that consisted of the behavioural evolvement types with high transitional probabilities in the evolvement stage. In salty snack market, the transitional probabilities of behavioural evolvement types remained stable across behavioural evolvement stages in both the learning and validation datasets. This suggests that the typical dynamic behavioural evolvement patterns were similar in each stage of dynamic behavioural evolvements. Descriptions and explanations of the dynamic behavioural evolvement patterns of consumers in the salty snack market are presented in Appendix K.

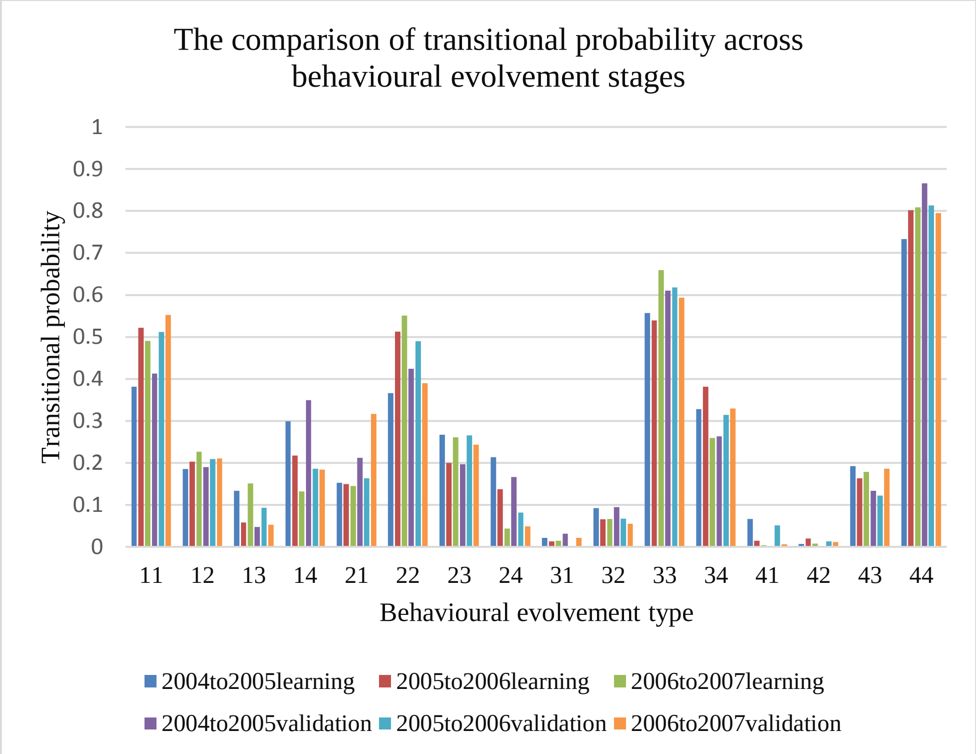

Figure 7.2: Comparison of the transitional probabilities of behavioural evolvement types over the years in the salty snack market[15]

Inferred from the dynamic behavioural evolvement pattern in each behavioural evolvement stage, the two behavioural evolvement routes from exploiters to Bargain Hunters or to

[15] Segment 1: Promotion-averse Exploiters; Segment 2: Opportunistic Exploiters; Segment3: Bargain Hunters; and Segment 4: Explorers

Explorers were identified and are discussed in the following two sub-sections.

7.2.1 Promotion-averse Exploiters to Explorers and Bargain Hunters

Promotion-averse Exploiters were not motivated and inclined to take risks to extend their market knowledge via trying alternatives due to their lack of brand-differentiation capability in purchases. They thus would not directly evolve to become Explorers before obtaining sufficient market knowledge enabling them to differentiate among brands. The behavioural evolvement route of Promotion-averse Exploiters is presented in Figure 7.3.

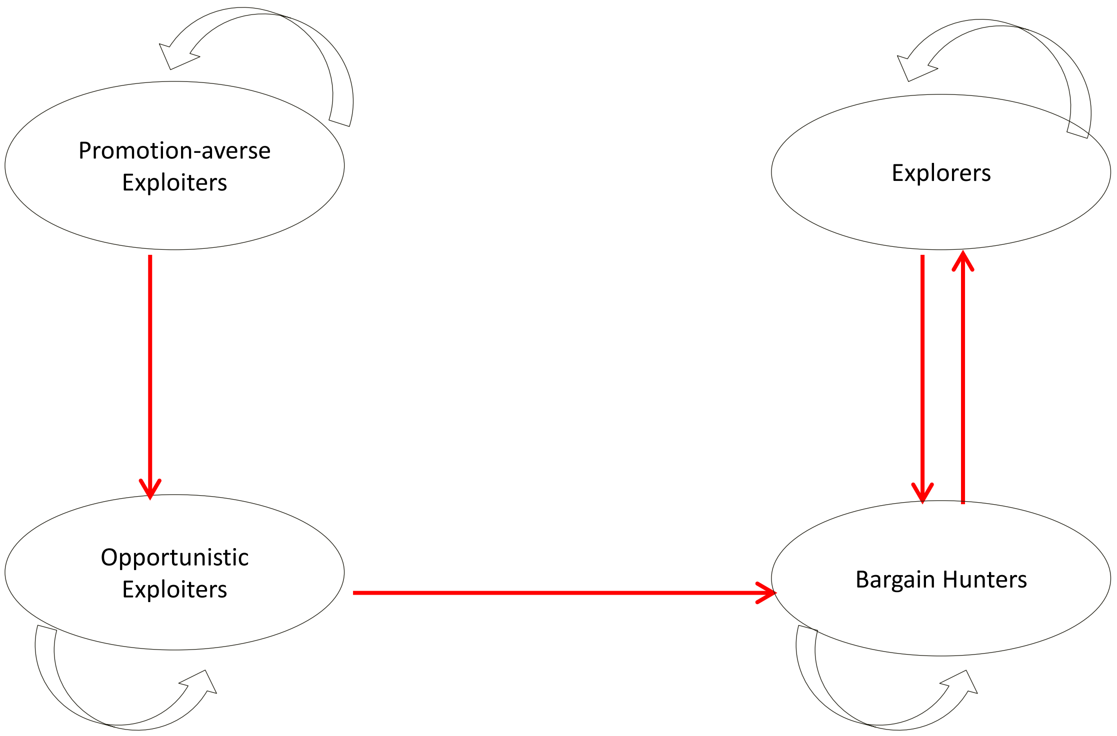

Figure 7.3: Dynamic behavioural evolvement route of Promotion-averse Exploiters in the salty snack market

With the accumulation of purchase experiences over time, the Promotion-averse Exploiters gradually evolved to be Opportunistic Exploiters. To clarify the typical behavioural evolvement types in the behavioural evolvement routes, the typical behavioural evolvement approaches of each behavioural evolvement type are presented in Figure 7.4.

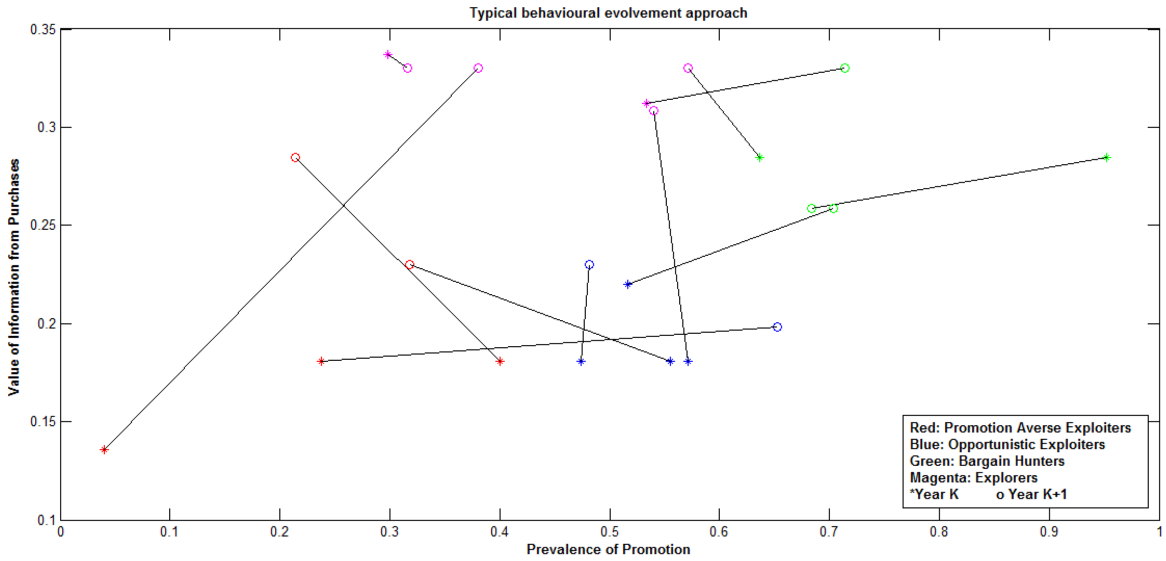

Figure 7.4: Typical dynamic behavioural evolvement approaches in the salty snack market

Figure 7.4 shows that the evolvement from Promotion-averse Exploiters to Opportunistic Exploiters was mainly due to the significantly increased value in the Prevalence of Promotion. As consumers modify their purchase behaviours based on their past experiences with promotions (Wakefield and Barnes, 1996), we would expect that those consumers would become inclined to take advantage of promotions to buy their preferred products when they realize that the provision of promotions would not sacrifice product quality from purchases.

With a further increase in purchase experiences, Opportunistic Exploiters gradually evolved to be Bargain Hunters. In the evolvement process, the value of the Prevalence of Promotion significantly increased and the value of the Value of Information from Purchases slightly increased. This indicates that Opportunistic Exploiters became likely to take advantage of promotions to extend their market knowledge with their increased market knowledge (see Section 3.4) and with their experiences in purchasing promotions in the evolvement process. The differences in the increased value in these two behavioural variables in the evolvement process suggest that the maximization of immediate purchase value dominated the extension of market knowledge in influencing the behavioural evolvement from Opportunistic Exploiters to Bargain Hunters.

In the behavioural evolvement process, the market knowledge of consumers was accumulated from occasionally trying alternative brands. The Value of Information from Purchases presented an increasing trend over time, as consumers entered the salty snack market as exploiters. A relatively high Value of Information from Purchases motivated Bargain Hunters in this stage to extend their market knowledge via exploration. This meant that the Value of Information from Purchases kept increasing with the further exploration of Bargain Hunters. As can be seen in Figure 7.4, the Value of Information from Purchases significantly increased in the evolvement process from Bargain Hunters to Explorers. The significantly increased Value of Information from Purchases might be the reason why the extension of market knowledge gradually overtook the maximization of immediate purchase value in influencing the purchase decisions of consumers in the evolvement process.

In the behavioural evolvement routes in the salty snack market, Explorers and Bargain Hunters were found to evolve between each other in the later stage of the consumer purchase lifecycle. The evolvement from Explorers to Bargain Hunters was associated with a significantly increased value in the Prevalence of Promotion and a slightly increased value in the Value of Information from Purchases. This indicates that Explorers were inclined to extend their market knowledge when promotions were available. The higher increased value in the Prevalence of Promotion than that in the Value of Information from Purchases suggests that Explorers might also be inclined to take advantage of promotions to buy a subset of preferred brands. This occurred when their expected costs from exploration exceeded their expected benefits obtained from information searches (Heilman *et al.*, 2000). In the evolvement process from Explorers to Bargain Hunters, the maximization of immediate purchase value gradually overtook the extension of market knowledge in influencing the purchase decision making of Explorers. Motivated by the high Value of Information from Purchases, these Bargain Hunters were inclined to re-take advantage of promotions to try alternatives and evolved to be Explorers. This occurred when the expected benefits from exploration of these Bargain Hunters exceeded their expected costs. The exploration activities were thus expected to be resumed over some period of repeat purchases.

7.2.2 Opportunistic Exploiters to Explorers and Bargain Hunters

The initial status of new entrants was also likely to be Opportunistic Exploiters. These Opportunistic Exploiters evolved to be Explorers and Bargain Hunters directly or indirectly in their purchase lifecycles with the increase in market knowledge and experiences. Figure 7.5 demonstrates the dynamic behavioural evolvement route of Opportunistic Exploiters in the salty snack market.

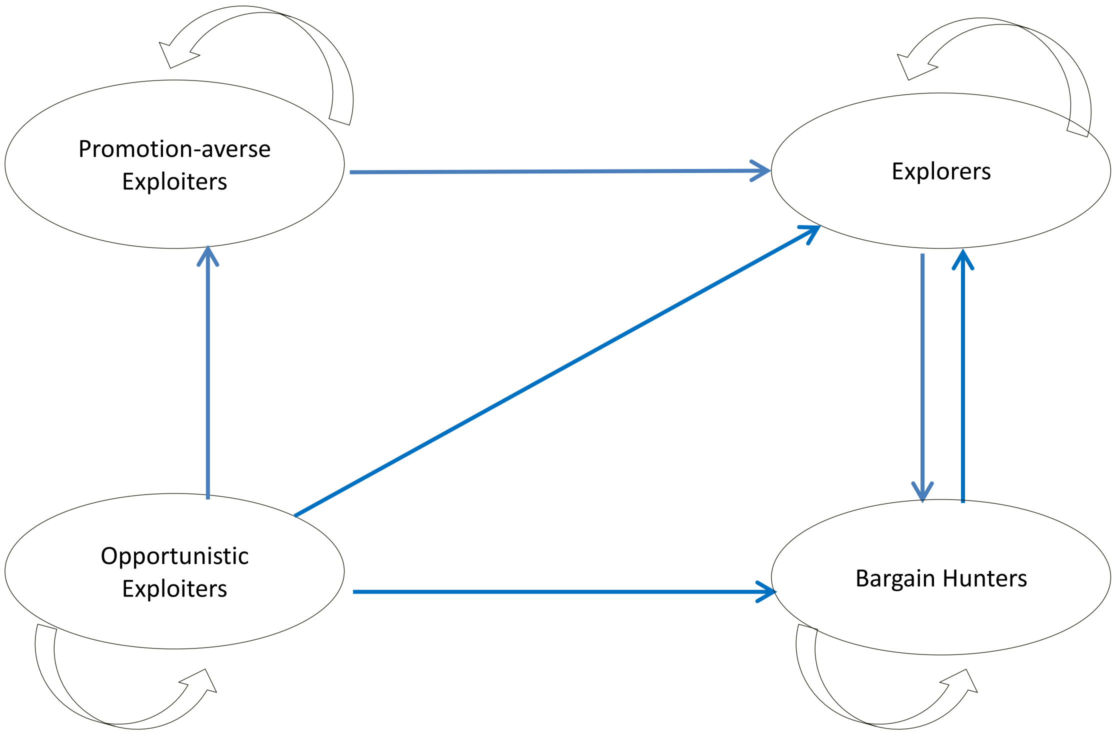

Figure 7.5: Dynamic behavioural evolvement route of Opportunistic Exploiters in the salty snack market

Opportunistic Exploiters were expected to be inclined to repeatedly purchase a subset of their familiar big brands or preferred brands (see Section 5.2). Their market knowledge from exploring big brands thus accumulated, which enhanced their capabilities in differentiating among brands. As can be seen in Figure 7.4, the evolvement from Opportunistic Exploiters to Explorers was associated with a significantly increased Value of Information from Purchases. This suggests that these Opportunistic Exploiters were motivated by the increased information value to extend their market knowledge via trying alternatives. In the evolvement process, the extension of market knowledge gradually dominated the maximization of immediate purchase value in influencing the purchase decision making of consumers.

Opportunistic Exploiters also evolved to be Explorers either via Promotion-averse Exploiters or via Bargain Hunters. The evolvement from Opportunistic Exploiters to Promotion-averse Exploiters was associated with a decreased value in the Prevalence of Promotion and an increased value in the Value of Information from Purchases. This indicates that these Opportunistic Exploiters became less likely to pay for promotions and more likely to extend their market knowledge via exploration in the evolvement process. The extension of market knowledge is thus suggested to play a more important role than the maximization of immediate purchase value does in the decision making of Promotion-averse Exploiters who evolved from Opportunistic Exploiters.

In general, the Promotion-averse Exploiters who evolved from Opportunistic Exploiters had a higher Value of Information from Purchases than new entrants did. With a further increase in the Value of Information from Purchases, these Promotion-averse Exploiters gradually evolved to be Explorers. The increased values in the Value of Information from Purchases and the Prevalence of Promotion in the evolvement process indicate that these Promotion-averse Exploiters became inclined to take advantage of promotions to extend their market knowledge. The significantly increased high Value of Information from Purchases in the evolvement process is suggested to be the main motivator of this behavioural evolvement type.

Opportunistic Exploiters also evolved to be Explorers via Bargain Hunters. In the evolvement from Opportunistic Exploiters to Bargain Hunters, the Value of Information from Purchases and the Prevalence of Promotion were increased. This indicates that these Opportunistic Exploiters became inclined to take advantage of promotions to extend their market knowledge via exploration in the evolvement process. The increased Value of Information from Purchases suggests that the importance of the extension of market knowledge gradually increased in the evolvement process.

Motivated by a high Value of Information from Purchases, these Bargain Hunters evolved to be Explorers. In this evolvement process, the Value of Information from Purchases increased and the Prevalence of Promotion slightly decreased. This indicates that these Bargain Hunters became inclined to extend their market knowledge (regardless of the availability of promotions) with an increase in market knowledge. The maximization of immediate purchase value was thus overtaken by the extension of market knowledge in determining these Bargain Hunters' purchase decisions in the evolvement process.

In this behavioural evolvement route, Explorers and Bargain Hunters also evolved between each other, as in the behavioural evolvement route of Promotion-averse Exploiters (see Section 7.2.1). The behavioural evolvement approaches between Explorers and Bargain Hunters in this evolvement route were the same as that in the first evolvement route.

In general, with an increase in market experiences and knowledge from purchases, consumers adapted their brand selection behaviours in relation to promotions to satisfy their purchase requirements. They optimized their exploration activities via making trade-offs between immediate purchase value maximization and market knowledge extension to obtain the optimized value from purchases.

7.3 Yogurt Market

Figure 7.6 presents the sizes of the identified behavioural segments in the yogurt market in the four consecutive years from 2004 to 2007.

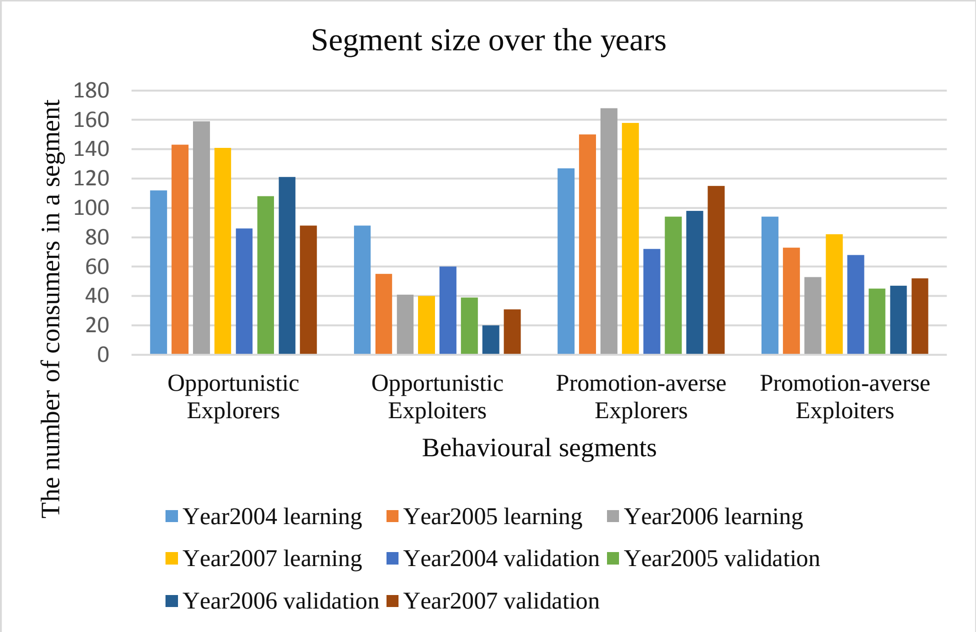

Figure 7.6: Sizes of the behavioural segments over the years in the yogurt market

In the learning datasets, the number of Opportunistic Explorers and Promotion-averse Explorers presented an inverted U-shape over the years from 2004 to 2007. On the contrary, the number of Opportunistic Exploiters and Promotion-averse Exploiters presented a U-shape over the years. These identified trends in segment sizes over the years in the learning datasets were also identified in the validation datasets. This suggests that these identified trends were reliable and could be generalized in the Pittsfield yogurt market.

With the increase in market experiences and knowledge from purchases, the number of explorers gradually increased to a maximum over a period of time. On the contrary, the number of exploiters gradually decreased to a minimum. These findings suggest that these exploiters gradually evolved to be explorers with the increase in market experiences and knowledge. The number of explorers then decreased from a maximum after a period of making purchases to extend market knowledge. The number of exploiters then increased from a minimum after a period of purchases. These findings indicate that these explorers evolved to be exploiters after a certain period of exploration. The final purchase status of consumers in the Pittsfield yogurt market was exploiters. Brand loyalty thus existed in the yogurt market, which had a small number of brands. Consumers at the end of their purchase lifecycles are suggested to be loyal to a subset of preferred brands in the yogurt market.

As can be seen in Figure 7.7, the transitional probabilities of ‘11’, ‘22’, ‘33’, and ‘44’ were higher than those of the rest of the behavioural evolvement types. This suggests that most of the consumers were not likely to significantly change their purchase behaviours within the two consecutive years. The differences in the transitional probabilities of behavioural evolvement types in a behavioural evolvement stage indicate that the purchase behaviour of a consumer was likely to evolve in a predictable pattern that consisted of the behavioural evolvement types with high transitional probabilities in the evolvement stage. In the yogurt market, the transitional probabilities of behavioural evolvement types significantly changed across the behavioural evolvement stages in the learning datasets, which were confirmed in the validation datasets. The change in the transitional probabilities of behavioural evolvement types across the dynamic behavioural evolvement stages was explainable and predictable. It suggests that the identified behavioural evolvement patterns in the three behavioural evolvement stages might be different from each other. The purchase behaviours of consumers were suggested to evolve in predictable patterns in different behavioural evolvement stages. A description and explanation of the dynamic behavioural evolvement patterns of consumers in the yogurt market are presented in Appendix L.

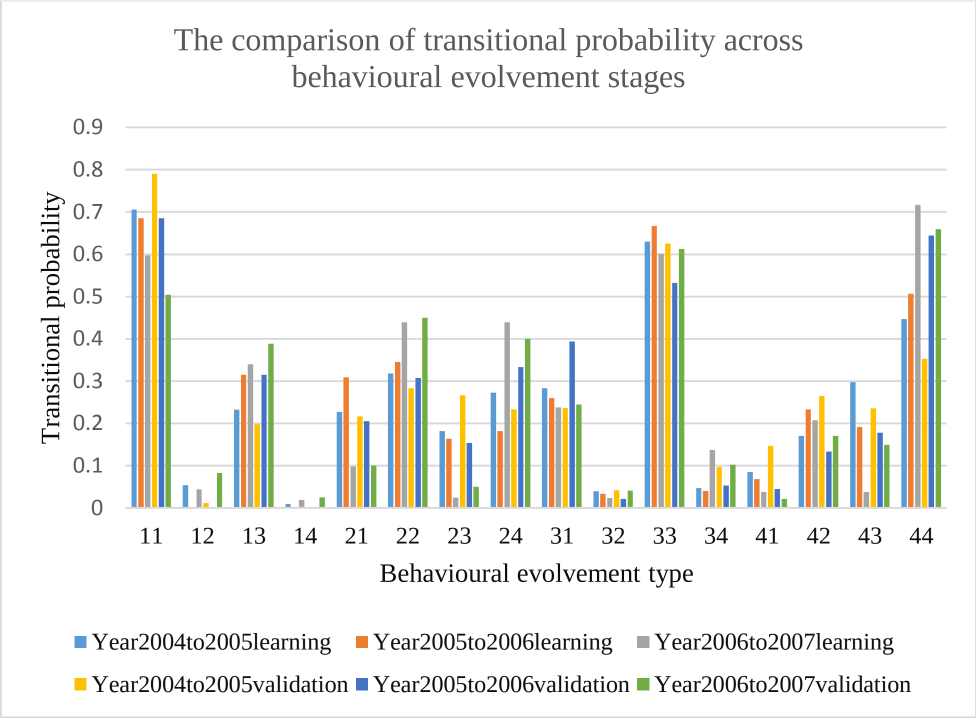

Figure 7.7: Comparison of the transitional probabilities of behavioural evolvement types over the years in the yogurt market[16]

Inferred from the dynamic behavioural evolvement patterns in dynamic behavioural evolvement stages, the two dynamic behavioural evolvement routes from exploiters to brand-loyal consumers were identified and are discussed in the following two sub-sections.

7.3.1 Opportunistic Exploiters to brand-loyal consumers via explorers

As can be seen in Figure 7.7, the transitional probabilities of the evolvements from Opportunistic Exploiters to Opportunistic Explorers and Promotion-averse Explorers presented a decreased trend over the behavioural evolvement stages. This indicates that the likelihood of the evolvement from Opportunistic Exploiters to explorers decreased over the behavioural evolvement stages. These Opportunistic Exploiters were thus likely to directly enter an exploration stage after they had been in the yogurt market for a period of time. On the contrary, the transitional probabilities of the behavioural evolvements from Opportunistic Exploiters to Opportunistic Exploiters and Promotion-averse Exploiters presented an increased trend across the behavioural evolvement stages. This indicates that the likelihood of the evolvement from Opportunistic Exploiters to exploiters increased over the behavioural

[16] Segment 1: Opportunistic Explorers; Segment 2: Opportunistic Exploiters; Segment 3: Promotion-averse Explorers; and Segment 4: Promotion-averse Exploiters

evolvement stages. Consumers were thus likely to enter an exploitation stage at the end of their purchase lifecycles. In general, these findings suggest that Opportunistic Exploiters were likely to evolve to be exploiters via explorers in their purchase lifecycles. Figure 7.8 demonstrates the behavioural evolvement route of Opportunistic Exploiters in their purchase lifecycles.

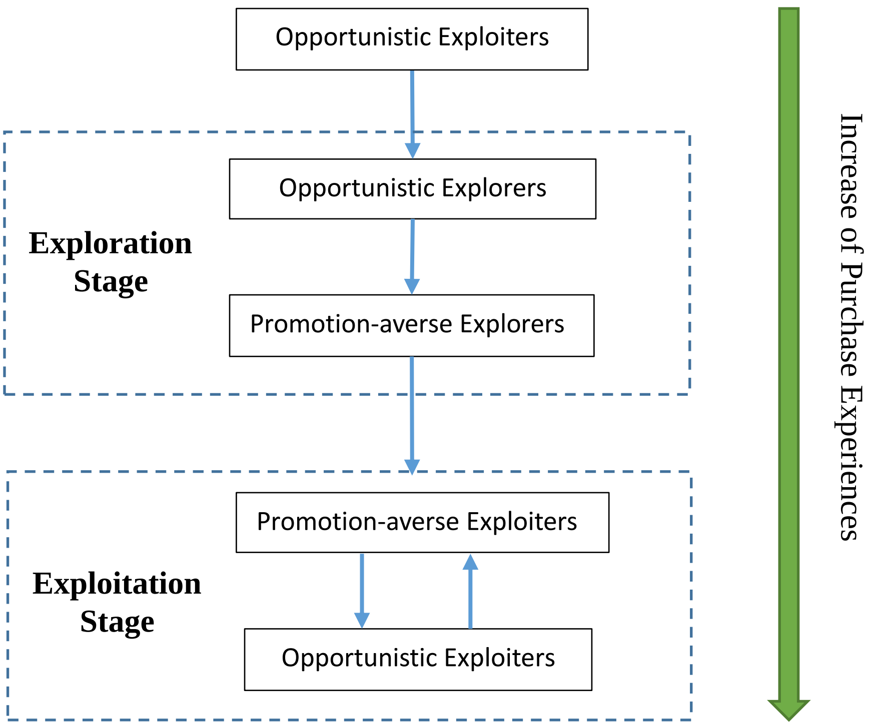

Figure 7.8: Dynamic behavioural evolvement route of Opportunistic Exploiters in their purchase lifecycles in the yogurt market

Opportunistic Exploiters in the yogurt market were inclined to take advantage of promotions to purchase familiar big brands (see Section 5.3). With the accumulation of market knowledge from occasionally sampling familiar big brands, which improved their capability in differentiating among brands, these Opportunistic Exploiters entered the exploration stage. Figure 7.7 shows that the transitional probability of the evolvement from Opportunistic Exploiters to Opportunistic Explorers was higher than that of the evolvement from Opportunistic Exploiters to Promotion-averse Explorers. This indicates that Opportunistic Exploiters were more likely to evolve to be Opportunistic Explorers than to be Promotion-averse Explorers in their exploration stage. This finding suggests and confirms that the maximization of immediate purchase value via taking advantage of promotions played a critical role in the brand selection decision making of these Opportunistic Exploiters. To clarify the behavioural evolvement routes, Figure 7.9 is presented to show the typical behavioural evolvement approaches of behavioural evolvement types.

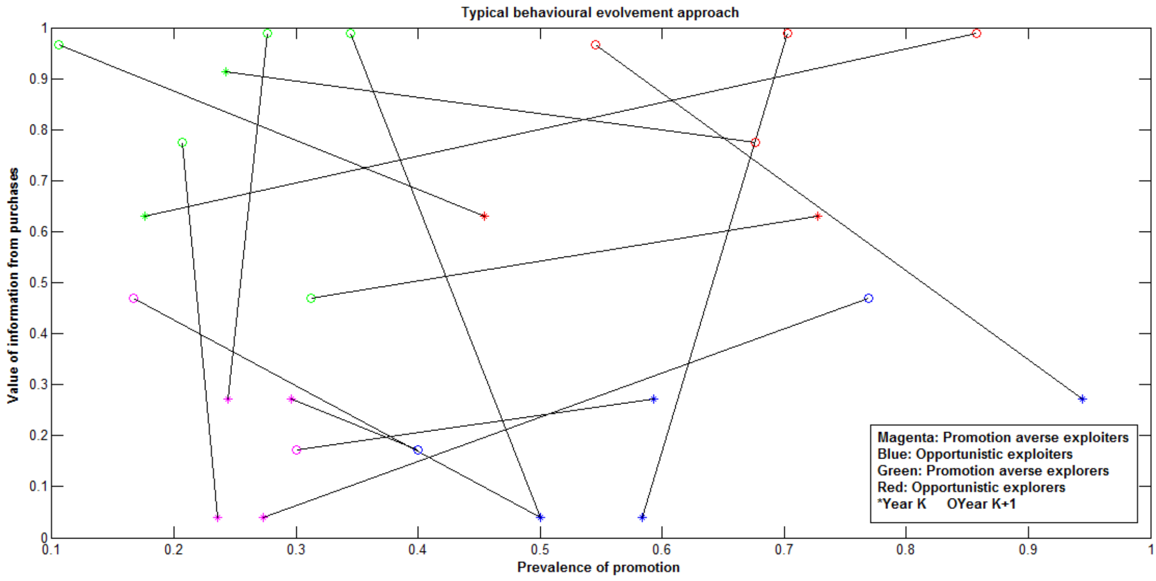

Figure 7.9: Typical dynamic behavioural evolvement approaches in the yogurt market

The behavioural evolvement from Opportunistic Exploiters to Opportunistic Explorers was associated with a significantly increased Value of Information from Purchases. This indicates that these Opportunistic Exploiters were motivated by the significantly increased information value to extend their market knowledge in the evolvement process. The importance of the extension of market knowledge in decision making is therefore suggested to increase in the evolvement process to Opportunistic Explorers. In this evolvement process, these Opportunistic Exploiters gradually became inclined to take advantage of promotions to extend their market knowledge.

The transitional probability of the evolvement from Opportunistic Explorers to Promotion-averse Explorers was high and increased across behavioural evolvement stages over the years. This indicates that Opportunistic Explorers gradually evolved to be Promotion-averse Explorers with a further increase in market knowledge in the exploration stage. In the evolvement process, the value of the Prevalence of Promotion significantly decreased. This suggests that the importance of the maximization of immediate purchase value decreased in the decision making of these Opportunistic Explorers in the evolvement process. The increased and decreased values in the Value of Information from Purchases in this evolvement indicate that these Opportunistic Explorers further extended their market knowledge via trying alternative brands (see Section 3.4.2). The behavioural evolvement approaches of this behavioural evolvement type suggest that these Opportunistic Explorers gradually became inclined to extend their market knowledge over time, regardless of the availability of promotions. In the behavioural evolvement process, the extension of market knowledge thus gradually dominated the maximization of immediate purchase value in influencing the brand selection decisions in relation to promotions for these Opportunistic Explorers.

With a further increase in market experiences and knowledge over time, the transitional probability of the evolvement from Promotion-averse Explorers to explorers decreased but that of the evolvement from Promotion-averse Explorers to exploiters increased. This indicates that these Promotion-averse Explorers gradually evolved to be exploiters. In the evolvement, the Value of Information from Purchases decreased, while the market knowledge of these Promotion-averse Explorers remained stable. This suggests that the decreased Value of Information from Purchases was due to consistent purchases of a subset of preferred brands in the dynamic yogurt market, rather than the further extension of market knowledge via exploration. These Promotion-averse Explorers became inclined to be loyal to their preferred brands and less likely to take risks to further extend their market knowledge (see Sections 2.3.2 and 3.4.2). The importance of the extension of market knowledge gradually decreased in the decision making of these Promotion-averse Explorers in this evolvement. These Promotion-averse Explorers therefore proceeded to the exploitation stage at the end of their purchase lifecycles.

In the exploitation stage, Promotion-averse Exploiters and Opportunistic Exploiters evolved between each other. The evolvement from Promotion-averse Exploiters to Opportunistic Exploiters was associated with the increased value in the Prevalence of Promotion. This indicates that these Promotion-averse Exploiters took advantage of promotions to purchase preferred brands. This suggests that Promotion-averse Exploiters were likely to evolve to be Opportunistic Exploiters when promotions of preferred brands were available. The decreased Prevalence of Promotion in the evolvement from Opportunistic Exploiters to Promotion-averse Exploiters indicates that these Opportunistic Exploiters consistently purchased preferred brands, regardless of promotions. This suggests that the evolvement from Opportunistic Exploiters to Promotion-averse Exploiters was because promotions of their preferred brands were not available. In the exploitation stage, whether the preferred brands were on promotion thus determined the responsiveness of these exploiters to promotions. In general, the avoidance of risks from exploration played a dominant role in the decision making of these exploiters. The maximization of immediate purchase value thus overtook the extension of market knowledge in influencing the decision making of consumers in the exploitation stage. Figure 7.10 demonstrates the trade-offs between the extension of market knowledge and the maximization of immediate purchase value in the evolvement process of Opportunistic Exploiters.

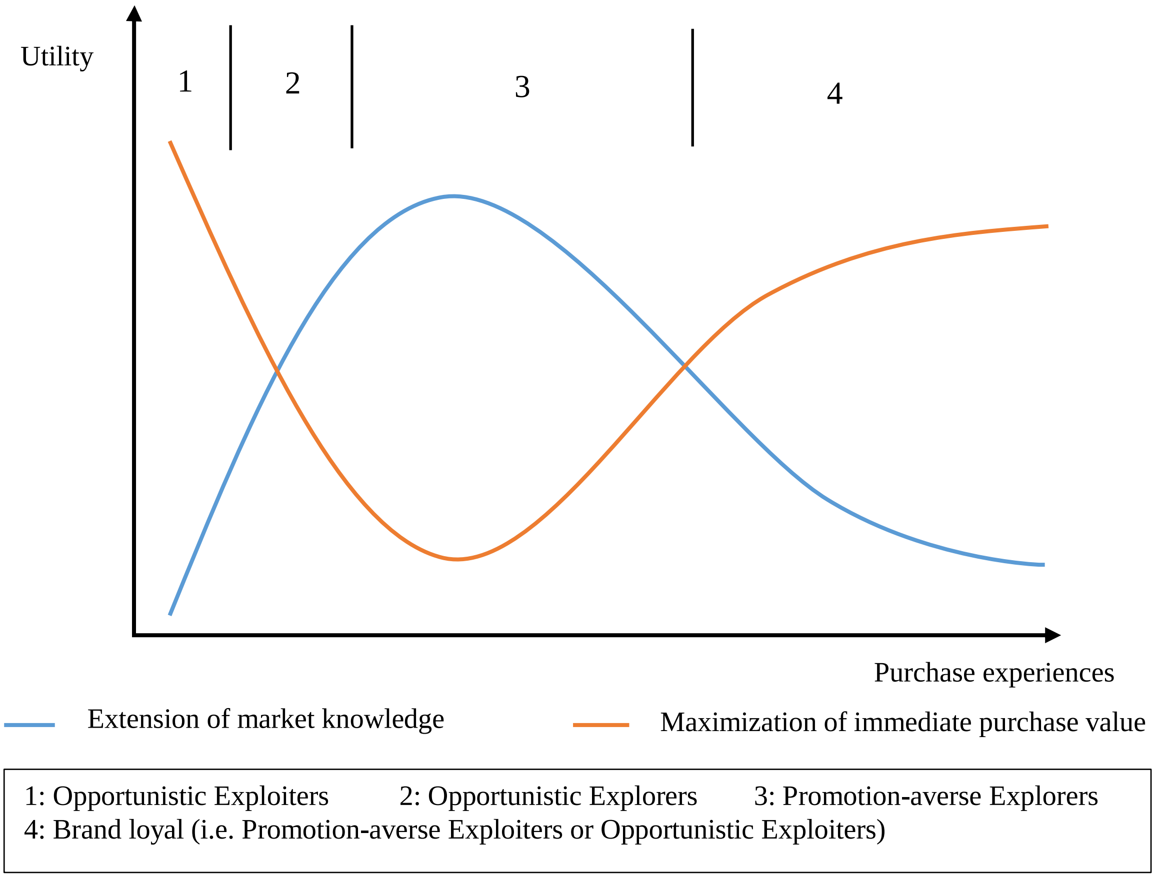

Figure 7.10: Trade-offs between the extension of market knowledge and the maximization of immediate purchase value in the dynamic behavioural evolvement process from Opportunistic Exploiters in the yogurt market

7.3.2 Promotion-averse Exploiters to brand-loyal consumers via explorers

Figure 7.7 shows that the transitional probability of the evolvement from Promotion-averse Exploiters to Promotion-averse Explorers and Opportunistic Explorers decreased over the behavioural evolvement stages. This indicates that the likelihood of the evolvement from Promotion-averse Exploiters to explorers presented a decreased trend with an increase in purchase experiences over the evolvement stages. This suggests that these Promotion-averse Exploiters were likely to directly proceed to an exploration stage after a certain period of purchasing familiar big brands. On the contrary, the transitional probability from Promotion-averse Exploiters to exploiters presented an increased trend over the behavioural evolvement stages. The increased likelihood of the evolvement from Promotion-averse Exploiters to exploiters with an increase in purchase experiences suggests that these Promotion-averse Exploiters were likely to enter the exploitation stage at the end of their purchase lifecycles. These findings thus suggest that Promotion-averse Exploiters were likely to evolve to be exploiters via explorers in their purchase lifecycles. Figure 7.11 demonstrates the identified dynamic behavioural evolvement route of Promotion-averse Exploiters in their purchase lifecycles.

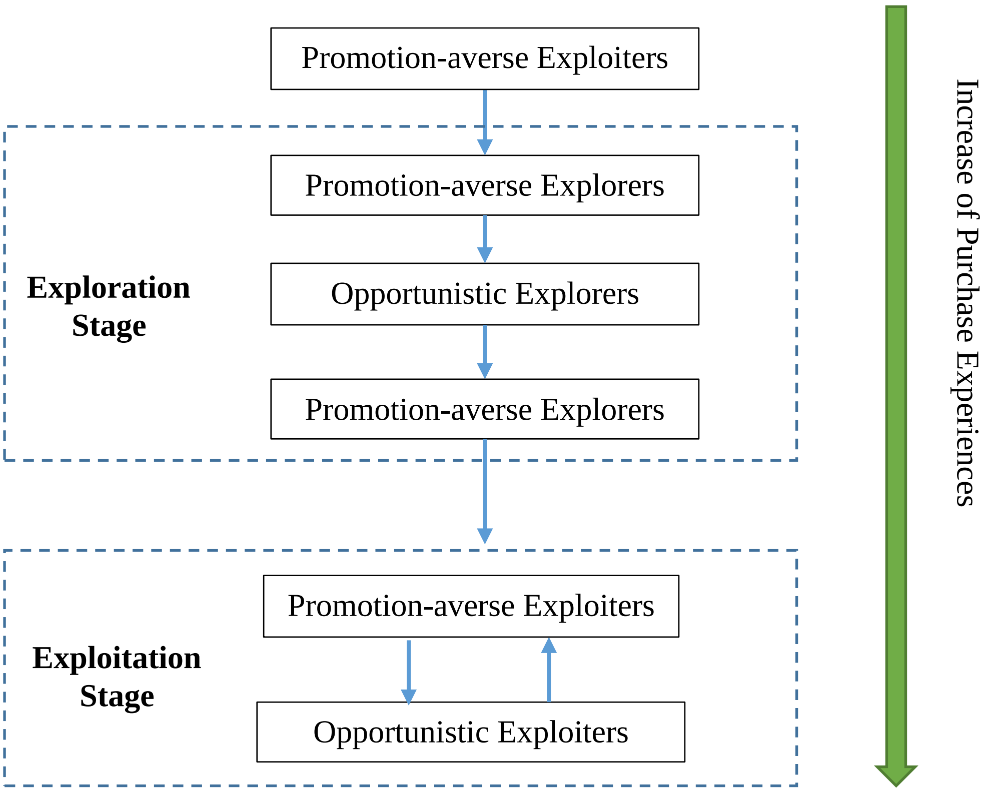

Figure 7.11: Dynamic behavioural evolvement route of Promotion-averse Exploiters in their purchase lifecycles in the yogurt market

Promotion-averse Exploiters were more likely to maximize immediate purchase value than to extend their market knowledge (see Section 5.3). This suggests that the importance of the maximization of immediate purchase value was higher than that of the extension of market knowledge in their purchase decision making. These Promotion-averse Exploiters were inclined to consistently purchase a subset of preferred big brands, regardless of promotions. Their accumulated market experiences from occasionally sampling big brands motivated them to enter the exploration stage.

Figure 7.7 shows that the transitional probability of the evolvement from Promotion-averse Exploiters to Promotion-averse Explorers was higher than that of the evolvement from Promotion-averse Exploiters to Opportunistic Explorers. This indicates that these Promotion-averse Exploiters were more likely to evolve to be Promotion-averse Explorers than to be Opportunistic Explorers when they initially entered the exploration stage. As can be seen in Figure 7.9, the behavioural evolvement from Promotion-averse Exploiters to Promotion-averse Explorers was associated with a significantly increased Value of Information from Purchases and a slightly changed Prevalence of Promotion. This indicates that these Promotion-averse Exploiters were motivated by the increased information value to extend their market knowledge in the evolvement process, regardless of promotions. This finding suggests that the extension of market knowledge gradually overtook and dominated the maximization of immediate purchase value in influencing the decision making of the Promotion-averse Explorers who had evolved from Promotion-averse Exploiters.

The high transitional probability of the evolvement from Promotion-averse Explorers to Opportunistic Explorers indicates that these Promotion-averse Explorers gradually evolved to be Opportunistic Explorers with the increase in market experiences over time. In the evolvement process, the value of the Prevalence of Promotion significantly increased. This indicates that these Promotion-averse Explorers became more responsive to promotions in the evolvement process. The importance of maximizing immediate purchase value increased in influencing the purchase decision making of these Promotion-averse Explorers. In this behavioural evolvement process, the high values in the Value of Information from Purchases either increased or decreased with the increase in market knowledge. The findings indicate that these Promotion-averse Explorers further extended their market knowledge via trying alternative brands in the evolvement process and became more inclined to take advantage of promotions (see Section 3.4.2). The extension of market knowledge and the maximization of immediate purchase value are thus suggested to co-determine the purchase decision making of the newly evolved Opportunistic Explorers.

As for those Opportunistic Explorers who had evolved from Promotion-averse Explorers, the value in the Value of Information from Purchases decreased with the further extension of market knowledge via trying alternative brands. The importance of the extension of market knowledge in their purchase decision making thus decreased with a further increase in market knowledge. The maximization of immediate purchase value gradually overtook and dominated the extension of market knowledge in influencing the brand selection decisions of these Opportunistic Explorers with the increase in market knowledge over time.

The transitional probability of the evolvement from Opportunistic Explorers to exploiters was very low (i.e. Opportunistic Exploiters and Promotion-averse Exploiters). This indicates that these Opportunistic Explorers were not likely to directly evolve to be exploiters. The transitional probability of the evolvement from Opportunistic Explorers to Promotion-averse Explorers increased across behavioural evolvement stages over the years. This indicates that these Opportunistic Explorers were likely to evolve to be Promotion-averse Explorers at the end of the exploration stage. In this evolvement, the value of the Prevalence of Promotion was significantly decreased. This suggests that the importance of the maximization of immediate purchase value in influencing the purchase decision making of these Opportunistic Explorers decreased in the behavioural evolvement process. The Value of Information from Purchases was slightly decreased in the behavioural evolvement process. However, for most of these Opportunistic Explorers, the decreased Value of Information from Purchases was associated with the same number of brands being explored by these consumers across the two years from 2006 to 2007. For some of these consumers, the decreased Value of Information from Purchases was associated with the increased number of brands explored by them from 2006 to 2007. These findings suggest that the slightly decreased Value of Information from Purchases in the behavioural evolvement process was mainly because these Opportunistic Explorers consistently purchased a subset of preferred brands across these two years in the dynamic yogurt market. The importance of the extension of market knowledge thus further decreased in the purchase decision making of these Opportunistic Explorers in the evolvement process. Differing from the Promotion-averse Explorers in the evolvement route of Opportunistic Exploiters, these Promotion-averse Explorers at the end of the exploration stage in this evolvement route were inclined to be loyal to their preferred brands, regardless of the availability of promotions.

The transitional probability of the evolvement from Promotion-averse Explorers to exploiters significantly increased at the end of the consumer purchase lifecycle. In the meantime, the transitional probability of the evolvement from Promotion-averse Explorers to Opportunistic Explorers decreased. These findings suggest that these Promotion-averse Explorers evolved to be exploiters and proceeded to the exploitation stage. The exploitation stage in this route was the same as the exploitation stage in the evolvement route of Opportunistic Exploiters, which was discussed in Section 7.3.1. The maximization of immediate purchase value played a more important role than the extension of market knowledge did in influencing the brand selection of those consumers who were loyal to their preferred brands in purchases. Figure 7.12 visualizes the evolvement of the trade-offs between the extension of market knowledge and the maximization of immediate purchase value in the decision making of consumers in the purchase lifecycle.

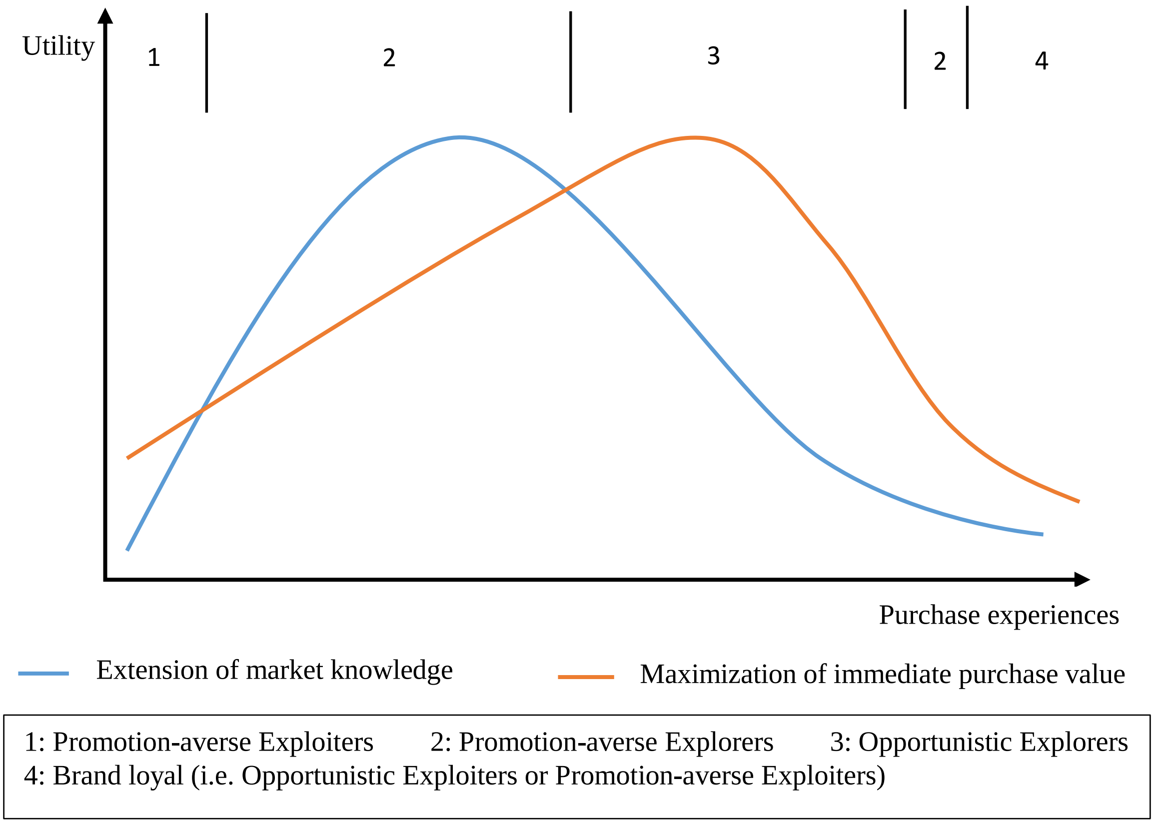

Figure 7.12: Trade-offs between the extension of market knowledge and the maximization of immediate purchase value in the dynamic behavioural evolvement process from Promotion-averse Exploiters in the yogurt market

7.4 Toilet Tissue Market

The sizes of the identified behavioural segments in the toilet tissue market are demonstrated in Figure 7.13.

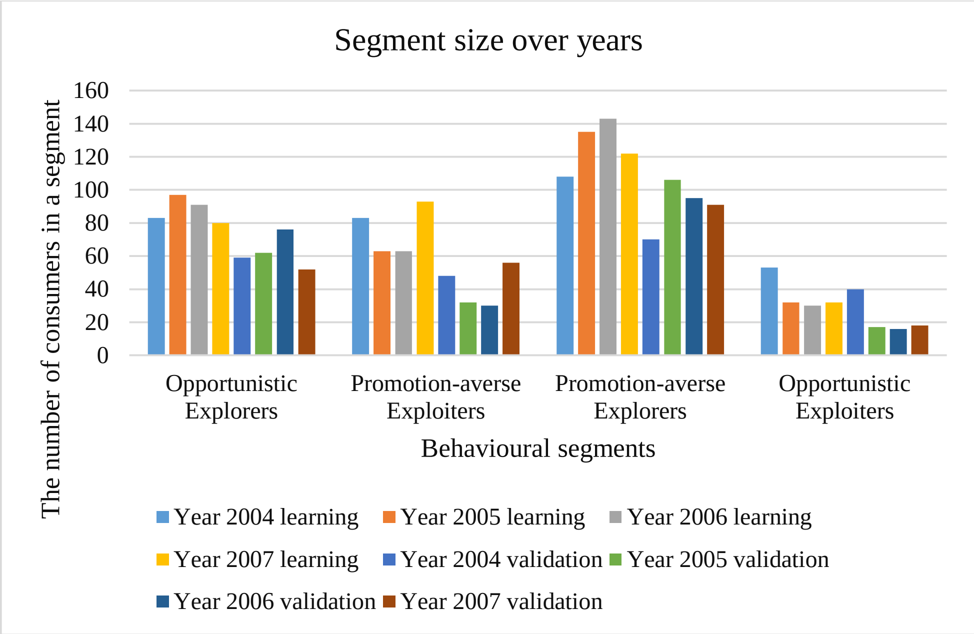

Figure 7.13: Sizes of behavioural segments over the years in the toilet tissue market

In the toilet tissue market, the number of Promotion-averse Exploiters and Opportunistic Exploiters presented a U-shape over the years from 2004 to 2007. On the contrary, the number of Promotion-averse Explorers and Opportunistic Explorers presented an inverted U-shape across the four years. These trends in the segment size over the years were identified in both the learning and validation datasets. This suggests that these identified trends were reliable and could be generalized in the Pittsfield toilet tissue market.

With the increase in market experiences and knowledge from purchases, the number of explorers increased to a maximum while the number of exploiters decreased to a minimum over a period of time. This suggests that these exploiters evolved to be explorers with the increase in market experiences and knowledge over that period of time. The number of explorers then decreased from the maximum while the number of exploiters then increased from the minimum with the further increase in market experiences and knowledge after that period. This suggests that these explorers gradually evolved to be exploiters with the further increase in market experiences and knowledge after that period. The final purchase status of consumers in the Pittsfield toilet tissue market was exploiters. In the toilet tissue market, brand loyalty thus existed. Consumers were expected to develop a subset of preferred brands and to be loyal to their preferred brands at the end of their purchase lifecycles (Heilman *et al.*, 2000).

As can be seen in Figure 7.14, the transitional probabilities of ‘11’, ‘22’, ‘33’, and ‘44’ were higher than those of the rest of the behavioural evolvement types. This suggests that most of the consumers would not likely significantly change their purchase behaviour within two consecutive years. In a behavioural evolvement stage, the transitional probabilities of behavioural evolvement types significantly differed from each other. This suggests that the purchase behaviours of consumers were likely to evolve in a pattern that consisted of the behavioural evolvement types with high transitional probabilities in the evolvement stage. In the toilet tissue market, the transitional probabilities of behavioural evolvement types changed in some predictable and explainable trends across behavioural evolvement stages. This suggests that the behavioural evolvement patterns identified in each behavioural evolvement stage might differ from each other. The description and explanation of the dynamic behavioural evolvement patterns of consumers in the yogurt market are presented in Appendix M.

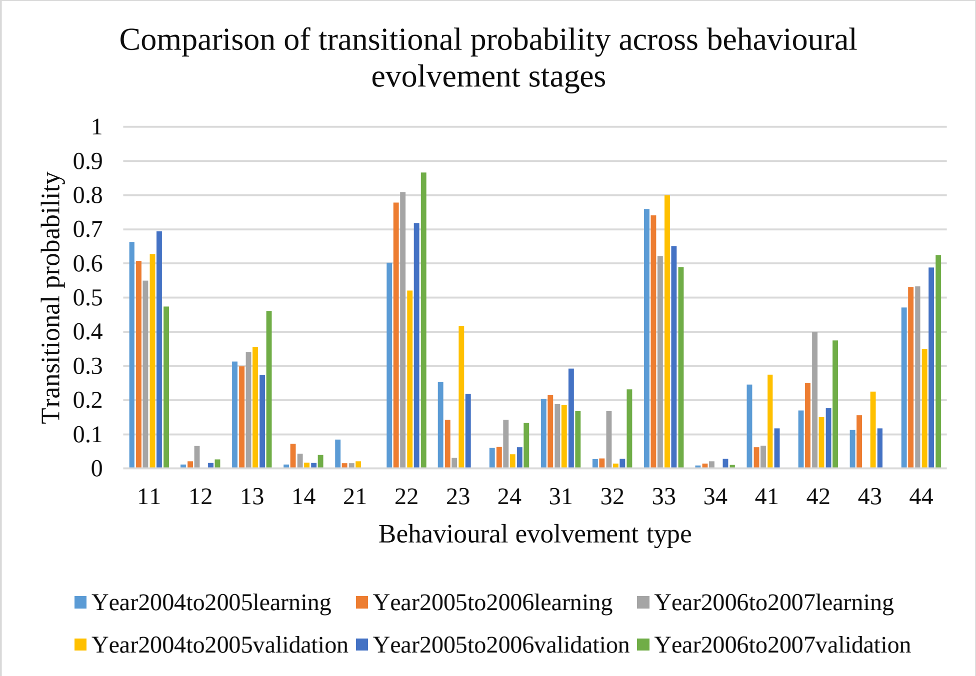

Figure 7.14: Comparison of the transitional probabilities of behavioural evolvement types over the years in the Pittsfield toilet tissue market [17]

Inferred from the dynamic behavioural evolvement patterns in dynamic behavioural evolvement stages, the two behavioural evolvement routes from exploiters to brand-loyal consumers were identified and are discussed in the following two sub-sections.

[17] "1" denotes "Opportunistic Explorers"; "2" denotes "Promotion-averse Exploiters"; "3" denotes "Promotion-averse Explorers"; and "4" denotes "Opportunistic Exploiters"

7.4.1 Opportunistic Exploiters to brand-loyal consumers via explorers

Figure 7.14 shows that the transitional probability of the evolvement from Opportunistic Exploiters to explorers presented a decreased trend over the behavioural evolvement stages. On the contrary, the transitional probability of the evolvement from Opportunistic Exploiters to exploiters presented an increased trend over the years across the behavioural evolvement stages. These findings suggest that these Opportunistic Exploiters were likely to evolve to be exploiters via explorers in their purchase lifecycles. Figure 7.15 visualizes the behavioural evolvement route of Opportunistic Exploiters in their purchase lifecycles.

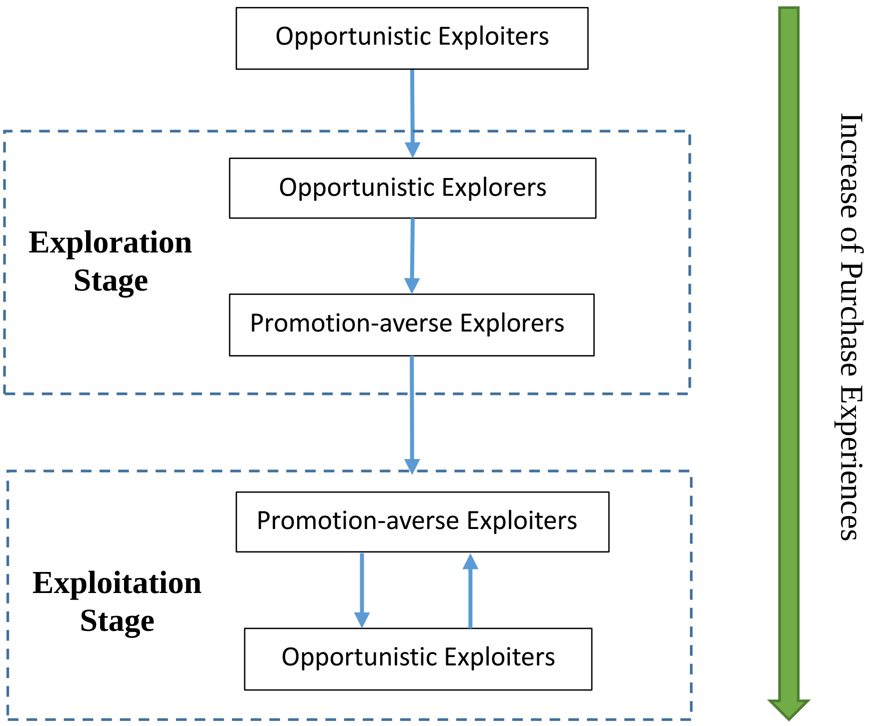

Figure 7.15: Dynamic behavioural evolvement route of Opportunistic Exploiters in their purchase lifecycles in the toilet tissue market

Opportunistic Exploiters in the toilet tissue market were inclined to take advantage of promotions to purchase familiar big brands (see Section 5.4). In their purchase decision making, the maximization of immediate purchase value played a more important role than the extension of market knowledge. The higher transitional probability of the evolvement from Opportunistic Exploiters to explorers than that of the evolvement from Opportunistic Exploiters to Promotion-averse Exploiters in the first behavioural evolvement stage indicates that these Opportunistic Exploiters entered the exploration stage in their purchase lifecycles with the increase in market experiences and knowledge. This might be motivated by the increased information value due to the accumulation of market knowledge from occasionally sampling big brands (see Section 3.4.2). The higher transitional probability of the evolvement from Opportunistic Exploiters to Opportunistic Explorers than that of the evolvement from Opportunistic Exploiters to Promotion-averse Explorers in the first behavioural evolvement stage indicates that these Opportunistic Exploiters were more likely to evolve to be Opportunistic Explorers than to be Promotion-averse Explorers when entering the exploration stage. To clarify the behavioural evolvement routes, Figures 7.16, 7.17, and 7.18 are presented to show the typical behavioural evolvement approaches of behavioural evolvement types in the three behavioural evolvement stages.

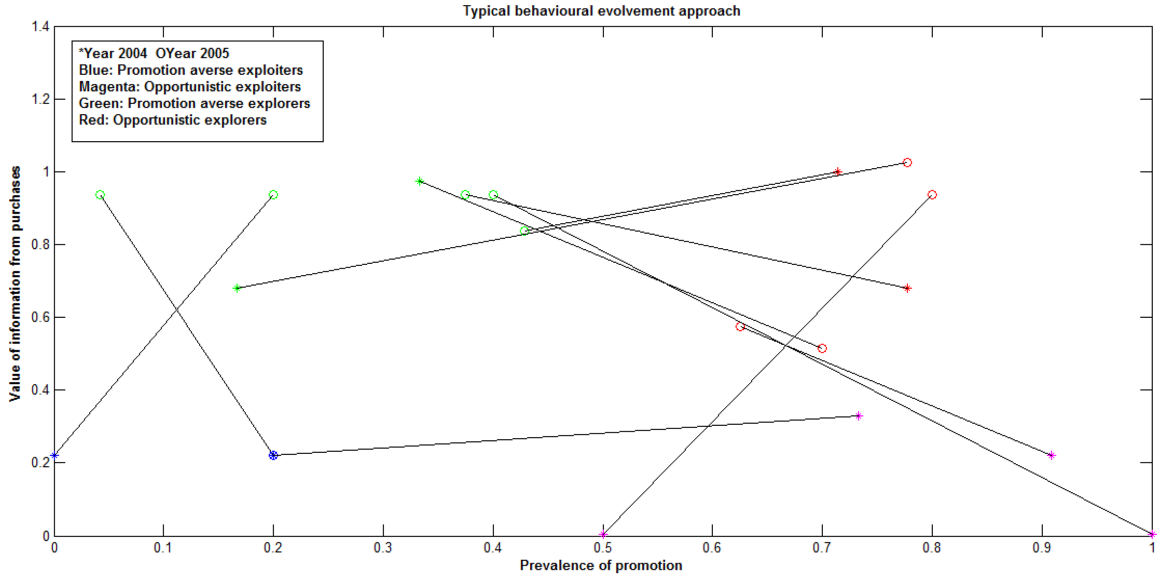

Figure 7.16: Typical dynamic behavioural evolvement approaches in the first behavioural evolvement stage in the toilet tissue market

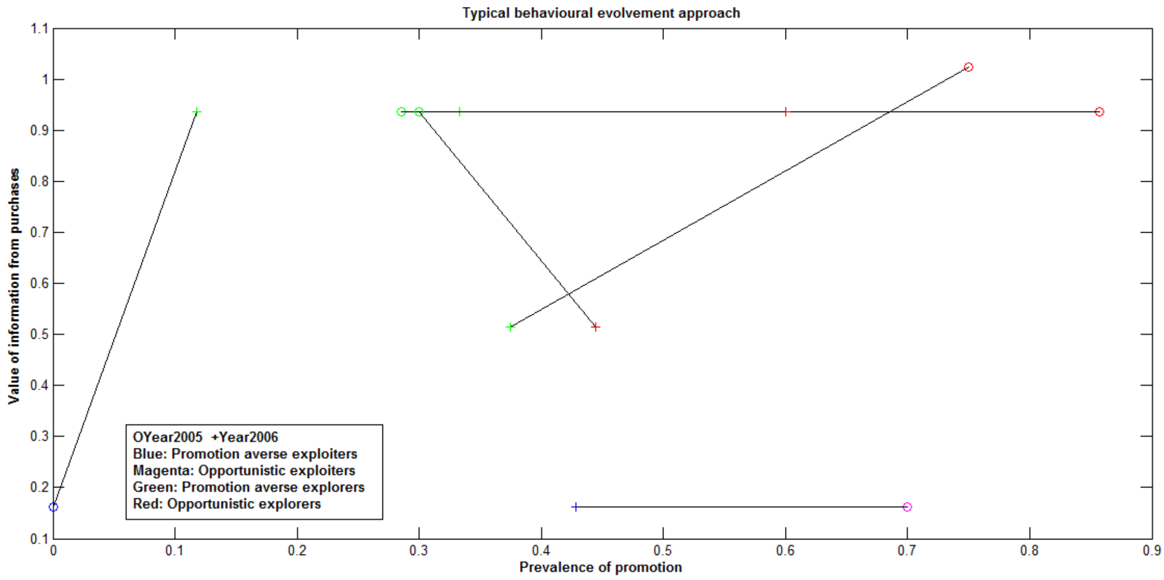

Figure 7.17: Typical dynamic behavioural evolvement approaches in the second behavioural evolvement stage in the toilet tissue market

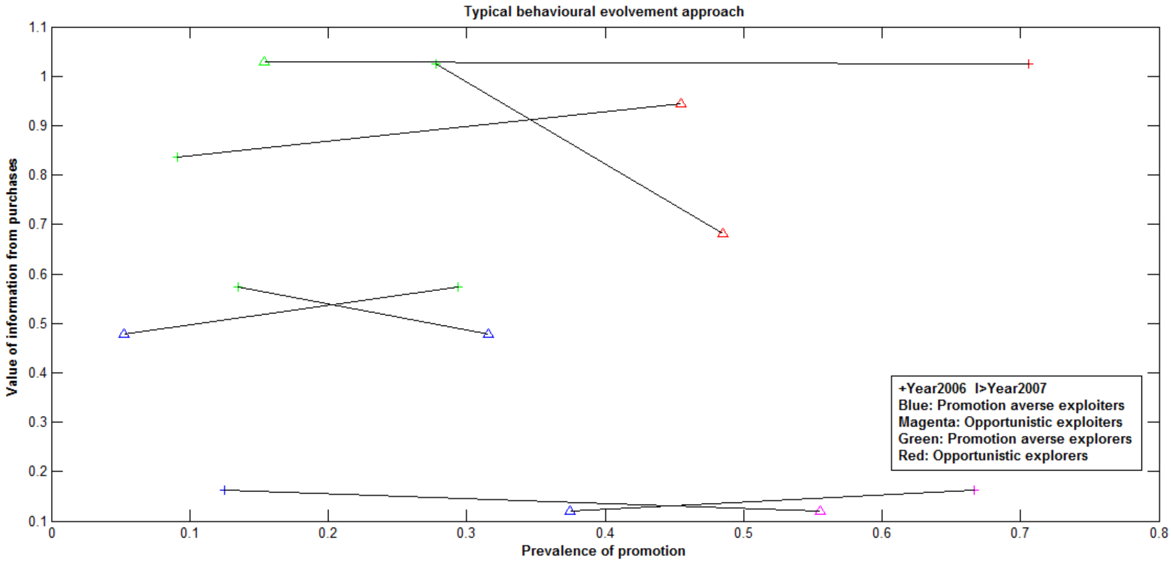

Figure 7.18: Typical dynamic behavioural evolvement approaches in the third behavioural evolvement stage in the toilet tissue market

As can be seen in Figure 7.16, the behavioural evolvement from Opportunistic Exploiters to Opportunistic Explorers was associated with the significantly increased Value of Information from Purchases. This indicates that these Opportunistic Exploiters were motivated by the increased information value to extend their market knowledge in the behavioural evolvement process. The importance of the extension of market knowledge in the decision making of these Opportunistic Exploiters therefore increased in this evolvement process. Compared to the change in the Value of Information from Purchases, the change in the value of the Prevalence of Promotion was less significant in this behavioural evolvement. The either increased or decreased value in the Prevalence of Promotion suggested that these Opportunistic Exploiters either took advantage of promotions to extend their market knowledge or extended their market knowledge regardless of promotions. These findings suggest that the importance of the maximization of immediate purchase value was gradually weakened in the decision making of these Opportunistic Exploiters in the evolvement process. These Opportunistic Exploiters became inclined to take advantage of promotions to extend their market knowledge over time. Their brand selection decisions thus gradually became co-determined by the maximization of immediate purchase value and the extension of market knowledge when they evolved to be Opportunistic Explorers.

The higher transitional probability of the evolvement from Opportunistic Explorers to Promotion-averse Explorers than that of the evolvement from Opportunistic Explorers to exploiters indicates that these Opportunistic Explorers gradually evolved to be Promotion-averse Explorers with the increase in purchase experiences. In this behavioural evolvement process, the significantly decreased value in the Prevalence of Promotion suggests that the importance of the maximization of immediate purchase value decreased in the decision making of these Opportunistic Explorers. Figures 7.16 and 7.17 show that the Value of Information from Purchases in this behavioural evolvement process either increased or decreased. The changes in the Value of Information from Purchases in this behavioural evolvement process were associated with an increased value in Market Knowledge. This suggests that these Opportunistic Explorers further extended their market knowledge via trying alternative brands in the evolvement process to Promotion-averse Explorers. In general, in the evolvement from Opportunistic Explorers to Promotion-averse Explorers, these Opportunistic Explorers became more inclined to extend their market knowledge, regardless of promotions. The extension of market knowledge thus dominated the maximization of immediate purchase value in influencing the brand selection decisions of these Promotion-averse Explorers.

The decreased transitional probability of the evolvement from Promotion-averse Explorers to explorers and the increased transitional probability of the evolvement from Promotion-averse Explorers to exploiters indicate that these Promotion-averse Explorers gradually proceeded to the exploitation stage with the increase in purchase experiences. The significantly increased transitional probability of the evolvement from Promotion-averse Explorers to Promotion-averse Exploiters in the third behavioural evolvement stage suggests that these Promotion-averse Explorers evolved to be the Promotion-averse Exploiters when they entered the exploitation stage. In the evolvement process to Promotion-averse Exploiters from Promotion-averse Explorers, the Value of Information from Purchases decreased. However, this decreased Value of Information from Purchases was associated with an unchanged value in market knowledge from 2006 to 2007. This suggests that these Promotion-averse Explorers developed a subset of preferred brands and consistently purchased their preferred brands from 2006 to 2007, regardless of the promotions. The importance of the extension of market knowledge in the decision making of these Promotion-averse Explorers thus gradually decreased with the increase in market knowledge over the years. In the evolvement from Promotion-averse Explorers to Promotion-averse Exploiters, the value of the Prevalence of Promotion either decreased or increased. This suggests that the avoidance of trying new brands dominated the maximization of immediate purchase value in influencing the brand selection of the Promotion-averse Explorers who evolved to be Promotion-averse Exploiters.

The significantly increased transitional probability of the evolvement from Promotion-averse Exploiters to Opportunistic Exploiters in the third behavioural evolvement stage suggests that these Promotion-averse Exploiters evolved to be Opportunistic Exploiters in the exploitation stage. By the same token, the significantly increased transitional probability of the evolvement from Opportunistic Exploiters to Promotion-averse Exploiters over the behavioural evolvement stages suggests that these Opportunistic Exploiters evolved to be Promotion-averse Exploiters in the exploitation stage. Therefore, Promotion-averse Exploiters and Opportunistic Exploiters evolved between each other in the exploitation stage.

In the evolvement from Promotion-averse Exploiters to Opportunistic Exploiters, the value of the Prevalence of Promotion significantly increased, while the Value of Information from Purchases slightly decreased. This indicates that these Promotion-averse Exploiters took advantage of promotions to consistently purchase their preferred brands in the evolvement process. On the contrary, in the evolvement from Opportunistic Exploiters to Promotion-averse Exploiters, the value of the Prevalence of Promotion significantly decreased and the Value of Information from Purchases slightly decreased. This indicates that these Opportunistic Exploiters consistently purchased a subset of preferred brands without taking advantage of promotions in the evolvement process. In general, these findings suggest that consumers in the exploitation stage were loyal to a subset of preferred brands, regardless of promotions. The brand selection of these brand-loyal consumers in relation to promotions was determined by whether their preferred brands were on promotion. The avoidance of risks from trying alternative brands was thus confirmed to play a dominant role in the decision making of these brand-loyal consumers. The maximization of immediate purchase value overtook the extension of market knowledge in influencing the decision making of these brand-loyal consumers in the exploitation stage. Figure 7.19 visualizes the trade-offs between the extension of market knowledge and the maximization of immediate purchase value in the evolvement process of Opportunistic Exploiters.

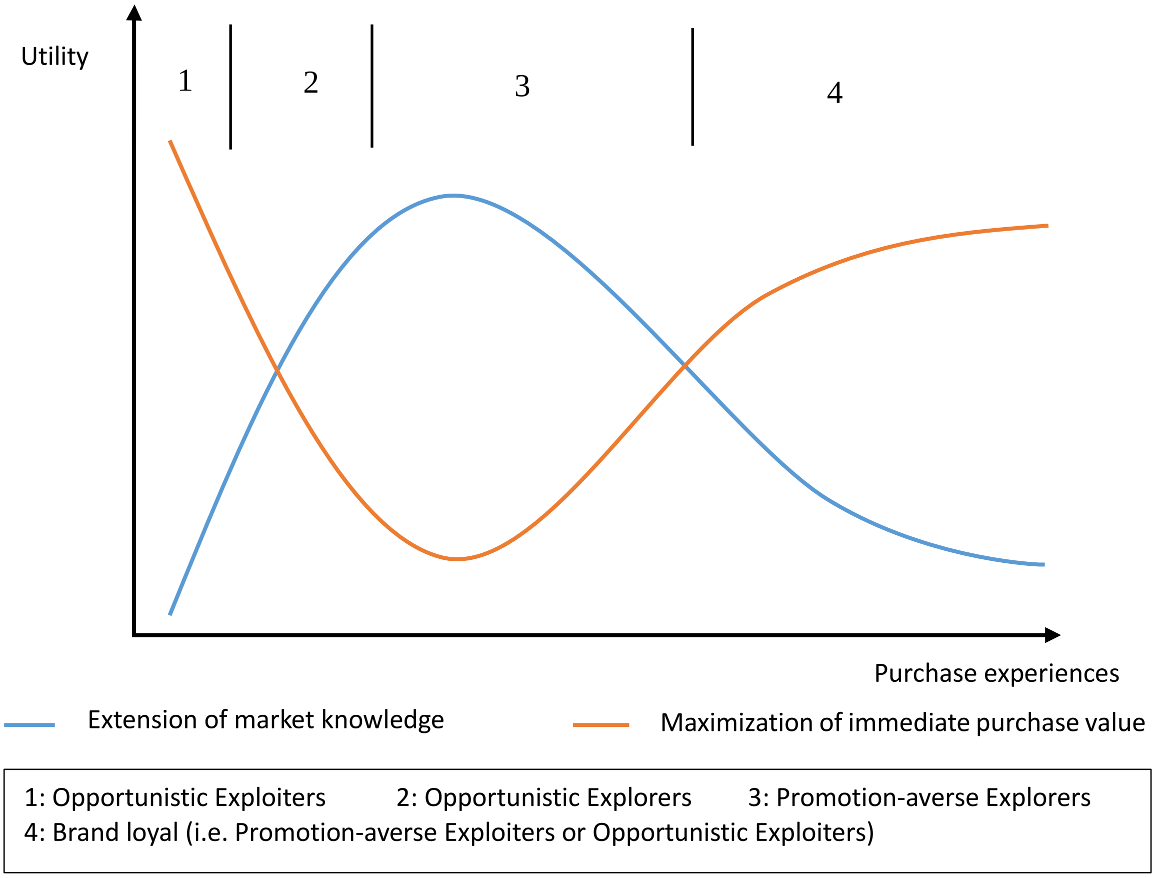

Figure 7.19: Trade-offs between the extension of market knowledge and the maximization of immediate purchase value in the dynamic behavioural evolvement process from Opportunistic Exploiters in the toilet tissue market

7.4.2 Promotion-averse Exploiters to brand-loyal consumers via explorers

As can be seen in Figure 7.14, over the behavioural evolvement stages, the transitional probability of the evolvement from Promotion-averse Exploiters to explorers decreased, while that of the evolvement from Promotion-averse Exploiters to exploiters increased. This suggests that these Promotion-averse Exploiters were likely to evolve to be exploiters via explorers in their purchase lifecycles. Figure 7.20 demonstrates the identified behavioural evolvement route of Promotion-averse Exploiters in their purchase lifecycles.

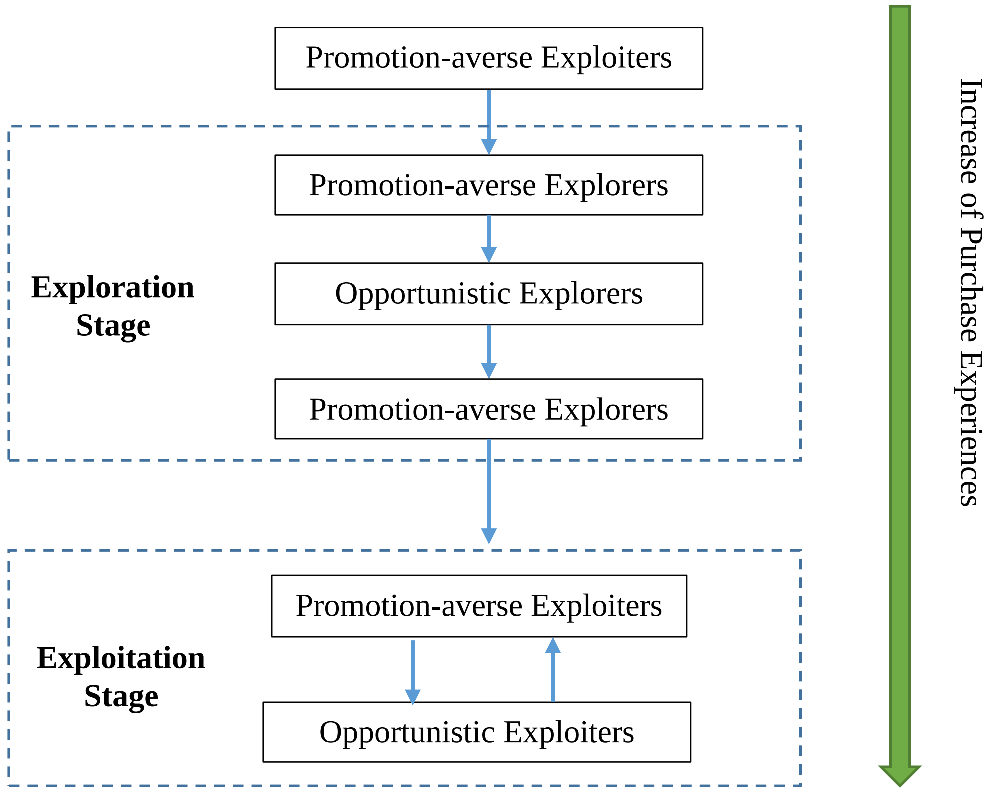

Figure 7.20: Dynamic behavioural evolvement route of Promotion-averse Exploiters in their purchase lifecycles in the toilet tissue market

Promotion-averse Exploiters in the toilet tissue market were inclined to avoid the risks from trying unfamiliar small brands, regardless of promotions (see Section 5.4). The extension of market knowledge thus had less importance than the maximization of immediate purchase value in influencing the purchase decision making of these Promotion-averse Exploiters. As can be seen in Figure 7.14, in the first evolvement stage, the transitional probability of the evolvement from Promotion-averse Exploiters to Promotion-averse Explorers was higher than that of the evolvement from Promotion-averse Exploiters to Opportunistic Explorers and Opportunistic Exploiters. This suggests that these Promotion-averse Exploiters were more likely to evolve to be Promotion-averse Explorers than to be Opportunistic Explorers and Opportunistic Exploiters when they initially entered the exploration stage.

In the evolvement from Promotion-averse Exploiters to Promotion-averse Explorers, the Value of Information from Purchases was significantly increased, while the value of the Prevalence of Promotion was either slightly increased or slightly decreased. This indicates that these Promotion-averse Exploiters extended their market knowledge via trying alternative brands in the evolvement process, regardless of promotions (see Section 3.4.2).

This suggests that the extension of market knowledge gradually overtook and dominated the maximization of immediate purchase value in influencing the purchase decision making of the Promotion-averse Explorers who evolved from Promotion-averse Exploiters.

The high transitional probability of the evolvement from Promotion-averse Explorers to Opportunistic Explorers in the second behavioural evolvement stage indicates that those Promotion-averse Explorers evolved to be Opportunistic Explorers with the increase in market experiences and knowledge over time. In the evolvement process, the significantly increased value in the Prevalence of Promotion indicates that these Promotion-averse Explorers became more responsive to promotions in the evolvement process. This suggests that the importance of the maximization of immediate purchase value increased in influencing the purchase decision making of these Promotion-averse Explorers in this evolvement process. On the contrary, the Value of Information from Purchases either decreased or remained stable in this behavioural evolvement process. The decreased Value of Information from Purchases in this behavioural evolvement stage was associated with the increased value in the Market Knowledge. This indicates that these Promotion-averse Explorers further extended their market knowledge in the evolvement process. In general, these Promotion-averse Explorers became more inclined to take advantage of promotions to extend their market knowledge in the process of evolving to be Opportunistic Explorers. The stable Value of Information from Purchases and the significantly increased value in the Prevalence of Promotion suggest that these Promotion-averse Explorers took advantage of promotions to consistently purchase a subset of preferred brands in the behavioural evolvement process. The maximization of immediate purchase value therefore overtook and dominated the extension of market knowledge in influencing the brand selection decisions of these Opportunistic Explorers.

The transitional probability of the evolvement from Opportunistic Explorers to exploiters was very low. This indicates that these Opportunistic Explorers were not likely to directly evolve to be exploiters. The transitional probability of the evolvement from Opportunistic Explorers to Promotion-averse Explorers in the third behavioural evolvement stage was high and increased from that in the second behavioural evolvement stage. This indicates that these Opportunistic Explorers evolved to be Promotion-averse Explorers at the end of the exploration stage. In this behavioural evolvement process, the significantly decreased value in the Prevalence of Promotion suggests that the importance of the maximization of immediate purchase value in influencing the purchase decision making of these

Opportunistic Explorers decreased with the increase in purchase experiences over time. The values in the Value of Information from Purchases and in the Market Knowledge remained unchanged in this behavioural evolvement process. This suggests that the evolvement from Opportunistic Explorers to Promotion-averse Explorers at the end of the exploration stage was due to the consistent purchase of a subset of preferred brands. The importance of the extension of market knowledge thus was further decreased in the purchase decision making of these Opportunistic Explorers in this evolvement process. The Promotion-averse Explorers at the end of the exploration stage were inclined to be loyal to their preferred brands, regardless of the availability of promotions.

The transitional probability of the evolvement from Promotion-averse Explorers to Promotion-averse Exploiters was significantly increased in the third behavioural evolvement stage. On the contrary, the transitional probability of the evolvement from Promotion-averse Explorers to explorers was significantly decreased at the end of the consumer purchase lifecycle. These findings suggest that these Promotion-averse Explorers proceeded to the exploitation stage. The exploitation stage in this route was the same as the exploitation stage in the evolvement route of Opportunistic Exploiters, which was discussed in Section 7.4.1. The maximization of immediate purchase value played a more important role than the extension of market knowledge in influencing the brand selection of those consumers who were loyal to their preferred brands in purchases. Figure 7.21 visualizes the evolvement of the trade-offs between the extension of market knowledge and the maximization of immediate purchase value in the decision making of consumers in the purchase lifecycle in the toilet tissue market.

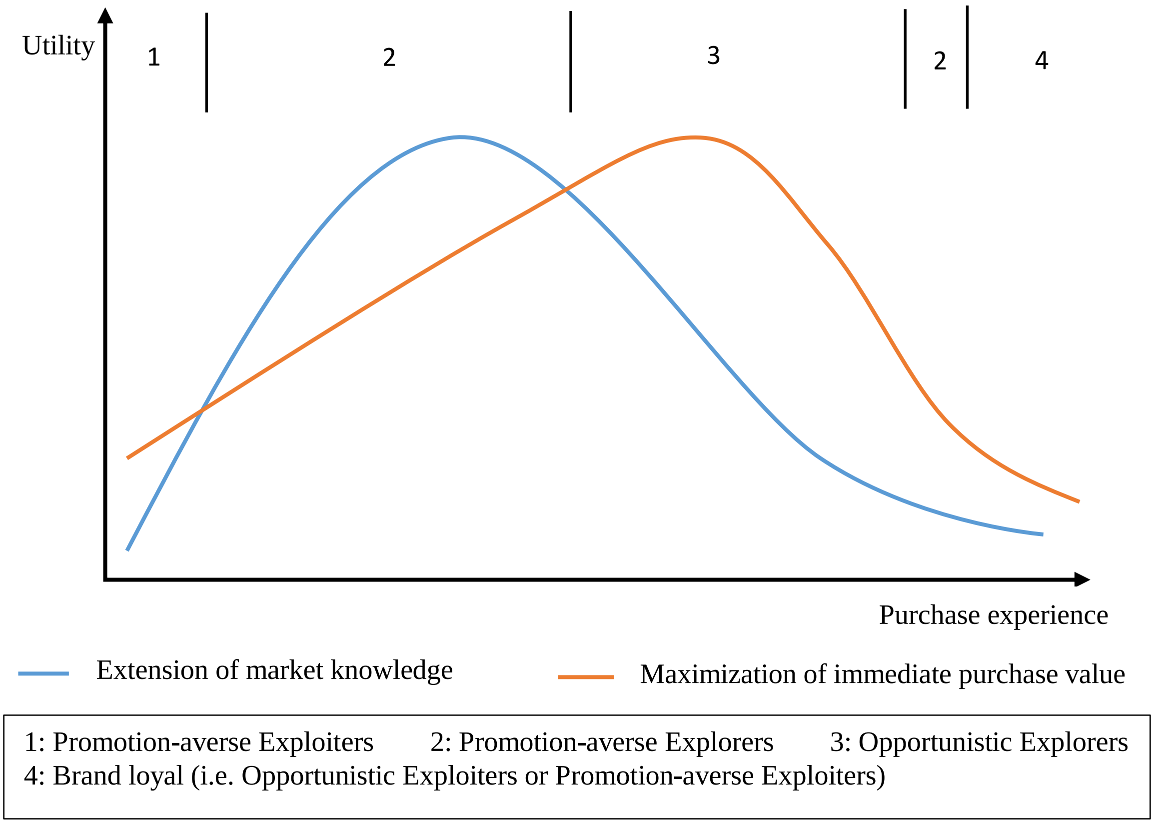

Figure 7.21: Trade-offs between the extension of market knowledge and the maximization of immediate purchase value in the dynamic behavioural evolvement process from Promotion-averse Exploiters in the toilet tissue market

7.5 Market Comparison

In general, with the increase in purchase experiences, the purchase behaviours of consumers evolved in a predictable route, which could be explained by using the trade-offs between the maximization of immediate purchase value and the extension of market knowledge in purchase decision making. A comparison of the dynamic behavioural evolvements in the salty snack, yogurt, and toilet tissue markets is presented in Table 7.1.

Table 7.1: A comparison of the dynamic behavioural evolvements across the salty snack, yogurt, and toilet tissue markets from 2004 to 2007

	Salty snack market	**Yogurt market**	**Toilet tissue market**
Initial status	Promotion-averse Exploiters or Opportunistic	Promotion-averse Exploiters or Opportunistic	Promotion-averse Exploiters or Opportunistic

	Exploiters	Exploiters	Exploiters
Final status	Bargain Hunters and Explorers	Brand loyal (i.e. Opportunistic Exploiters and Promotion-averse Exploiters)	Brand loyal (i.e. Opportunistic Exploiters and Promotion-averse Exploiters)
Behavioural evolvement routes	Exploiters to Explorers	Exploiters to exploiters via Explorers	Exploiters to exploiters via Explorers
Differences of the transitional probability of a behavioural evolvement type across years	Minor	Significant	Significant

Even though the initial status of consumers in the three product markets was the same, the final status of consumers in the salty snack market was different from that in the yogurt and toilet tissue markets. Consumers in the salty snack market evolved from their initial status to either Bargain Hunters or Explorers over the four years. In the meantime, consumers in the yogurt and toilet tissue markets evolved to be brand-loyal consumers via explorers.

Compared to the behavioural evolvement routes of consumers in the yogurt and toilet tissue markets, those in the salty snack market lacked an exploitation stage at the end of the consumer purchase lifecycle. As the salty snack market differed from the yogurt and toilet tissue markets in the number of brands available in the market (see Section 4.3), brand loyalty is thus suggested to not exist in the product markets with a large number of brands available for selection. On the contrary, brand loyalty is suggested to exist in the product markets with a small number of brands for selection. In general, consumers in a product market with a small number of brands were more likely to proceed to the exploitation stage than those in a product market with a large number of brands, after a period of time in the product market.

Compared to the consumers who had rich purchase experiences in the yogurt and toilet tissue markets, similarly experienced consumers in the salty snack market were more likely to take advantage of promotions to extend their market knowledge. The extension of market knowledge played a more important role in the decision making of these experienced consumers in the salty snack market than that in the yogurt and toilet tissue markets. The importance of the extension of market knowledge in influencing the decision making of experienced consumers therefore was positively related to the number of brands available in the product market. Compared to the experienced consumers in the yogurt and toilet tissue markets, the experienced consumers in the salty snack market were more likely to be attracted and motivated by new brands to make purchases. Experienced consumers in a product market with a large number of brands for selection were thus more likely to be attracted by new brands to extend their market knowledge than those in a product market with a small number of brands for selection.

Table 7.1 shows that the dynamic behavioural evolvements of consumers across these three product markets also differed in the change in the transitional probability of a behavioural evolvement type across the years. The change in the transitional probability of a behavioural evolvement type across the years was largest in the toilet tissue market and smallest in the salty snack market (see Figures 7.2, 7.7, and 7.14). This suggests that the behavioural evolvements of consumers were most likely to be influenced by increased purchase experiences in the toilet tissue market and least likely to be influenced by increased purchase experiences in the salty snack market. The influence of past purchase experiences on current consumer purchase behaviour thus was highest in the toilet tissue market and lowest in the salty snack market. Inferring from these findings, the influence of the past purchase experiences of the consumers on their current purchase behaviours was negatively related to the number of brands available in the product market. Marketers in a product market with a small number of brands are thus suggested to tailor promotions based on the past purchase experiences of consumers.

CHAPTER 8: CONCLUSION

8.1 Summary and Discussions of Findings

The **first research question** was about **how we could measure a consumer's brand selection behaviour in relation to promotions**. In order to answer this research question, this research developed a set of algorithms to deal with the transactional data. The Prevalence of Promotion was used in this research to quantify the proneness of a consumer to the promotional mix. The value of the Prevalence of Promotion indicates and reflects how likely a consumer would be to buy a promoted brand in a purchase to maximize the immediate purchase value (see Section 3.2). The higher the value of the Prevalence of Promotion is, the more likely a consumer would be to buy a promoted brand in a purchase. The larger proportion of purchases made by a consumer is on promotion, the higher the value of the Prevalence of Promotion is. Therefore, the Prevalence of Promotion provides a valid representation of consumer reactions to promotion.

The Value of Information from Purchases, which was developed by adapting the generalized entropy measurement in understanding financial market behaviour, was used to measure the brand selection behaviour of an individual consumer. The Value of Information from Purchases indicates and reflects how likely a consumer would be to be motivated to search information and extend their market knowledge via trying alternative brands (see Section 3.4). It provides a valid representation of information search in purchases with an increase in market knowledge in the consumer purchase life cycle. The use of the Prevalence of Promotion in combination with the Value of Information from Purchases thus could reflect the consumer's reactions to promotions in brand selection and provide a valid representation of consumer choice.

In practice, marketers normally have no idea about the first purchase made by a consumer in a product market. The lack of information about the past purchase experiences of consumers may result in bias in predicting the current brand selection behaviours of consumers based on their past purchase experiences. However, this bias in prediction might be reduced to some extent by using the developed Value of Information from Purchases to measure the brand selection behaviour of a consumer. As presented in Section 3.4.2, the Value of Information from Purchases presented an inverted U-shape with the increase in market knowledge. For consumers with limited market knowledge and those with full market knowledge, the Value of Information from Purchases is low. If a consumer explored a small proportion of brands for a few years, he/she would be regarded as an exploiter, no matter how knowledgeable the consumer was in purchases in previous years. If the consumer had rich experiences in purchases in previous years, the consistent purchase of a small proportion of brands in the latest few years could indicate that the consumer may be a brand-loyal consumer. The consumer would be expected to be inclined to consistently purchase a subset of preferred brands. On the contrary, if the consumer had limited purchase experiences in previous years, the consistent purchase of a small proportion of brands in the latest few years could indicate that the consumer lacks market knowledge in decision making regarding brand selection. The consumer would be expected to be inclined to consistently purchase familiar big brands to avoid the risks from trying alternatives. In both of the conditions, the consumer would be less likely to try alternatives to extend his/her market knowledge.

By the same token, if a consumer actively explored the brands available in a product market over several years, he/she would be regarded as an explorer. Explorers usually have some market knowledge and are inclined to further extend their market knowledge. If the consumer had some purchase experiences in previous years, the active brand exploration during the last several years would indicate that his/her past purchase experiences were insufficient to make him/her a brand-loyal consumer. In that case, the consumer would be inclined to extend their market knowledge via trying alternatives. In general, although the full purchase experiences of consumers cannot be obtained in practice, the use of the developed measurement of brand selection behaviours in dealing with transactional data could reduce the bias in predicting the current purchase behaviours of consumers based on their past purchase experiences in a certain period of time.

The **second research question** was about **whether a consumer's purchase behaviour in relation to promotions depends on the type of promotion**. In order to answer this research question, this research developed and used the Prevalence of Advertising, the Prevalence of Point-of-Display, and the Prevalence of Price-Reduction to quantify the proneness of a consumer to advertising, point of display, and price reduction, respectively. A correlation analysis was conducted using these three behavioural variables. The high and significant correlation among the three behavioural variables indicates that consumers are likely to have similar purchase behaviours in response to such in-store promotions as in-store advertisements, point of display, and in-store price reductions. This suggests that the purchase behaviours of consumers in relation to promotions are not dependent on nor differ across types of promotions.

The **third research question** was about **how consumers differ in their brand selection behaviours in relation to promotions**. To answer this research question, the purchase behaviours of consumers in the salty snack, yogurt, and toilet tissue markets in Pittsfield, US, were analysed. In each of these product markets, consumers were segmented into four groups based on their characteristics in the Prevalence of Promotion and the Value of Information from Purchases. In this research, we typified a type of brand selection behaviour in relation to promotions with a particular type of consumers. Four typical brand selection behaviours in relation to promotions were thus identified in each product market. In the salty snack market, Promotion-averse Exploiters, Opportunistic Exploiters, Explorers, and Bargain Hunters were identified as the types of consumers based on their purchase behaviours. In the yogurt and toilet tissue markets, promotion-averse exploiters, Opportunistic Exploiters, Promotion-averse Explorers, and Opportunistic Explorers were identified as the four types of consumers based on their purchase behaviours. In a product market, consumers differed across these four typical behavioural segments not only in the Prevalence of Promotion and the Value of Information from Purchases but also in the relative weights of these two behavioural variables in influencing their purchase decision making.

In each of the three product markets, the four behavioural segments were generated by using clustering analysis, rather than by setting critical values of the behavioural variables to cut the consumers into four groups (see Sections 3.6.2 and 4.5). Using critical values of behavioural variables in segmentation would produce the same behavioural segments across product markets. In this research, similar behavioural segments were produced across the product markets with a similar number of brands available for selection (i.e. the yogurt and toilet tissue markets). The behavioural segments identified in the yogurt and toilet tissue markets, however, were different from the behavioural segments identified in the salty snack market, which had a much larger number of brands for selection than the yogurt and toilet tissue markets.

In the salty snack market, the Prevalence of Promotion and the Value of Information from Purchases significantly differed in their weights in determining a behavioural segment (see Section 5.2). This indicates that the maximization of immediate purchase value and the extension of market knowledge significantly differed in their importance in the decision making of those consumers in the behavioural segment. In a product market with a large number of brands for selection, trying a new brand further improved the capability of a consumer to increase the Value of Information from Purchases at the end of the fourth year (see Sections 4.3 and 7.5). Motivated by the high Value of Information from Purchases, experienced consumers in the salty snack market were normally in the exploration stage (see Section 7.2). In this research, Bargain Hunters and Explorers were found to be the final status of consumers in their purchase lifecycles. The evolvement found between Bargain Hunters and explorers at the end of the consumer purchase lifecycle in the salty snack market (see Section 7.2) agrees with the findings of prior research (see Section 2.3.3). The analysis of this behavioural evolvement might allow us to capture the trade-offs between the maximization of immediate purchase value and the extension of market knowledge in consumer purchase decision making (see Section 7.2).

If we segmented consumers using critical values, Promotion-averse Explorers and Opportunistic Explorers would be identified in the salty snack market. The Prevalence of Promotion and the Value of Information from Purchases would be equally important in determining the membership of consumers in these two behavioural segments. The evolvement between these two behavioural segments would normally be due to a change in the Prevalence of Promotion. However, it might not make sense that experienced Opportunistic Explorers become inclined to extend their market knowledge without taking advantage of promotions at the end of their purchase lifecycles in the salty snack market. In addition, the analysis of this behavioural evolvement would not be able to capture the trade-offs between the maximization of immediate purchase value and the extension of market knowledge.

In general, these stated findings suggest that the generation of different behavioural segments across different product markets via using clustering analysis might not purely occur by chance. These findings seem to indicate that using clustering analysis in behavioural segmentation might produce more-explainable results than using critical values. By using clustering analysis to segment consumers to identify typical brand selection behaviours in relation to promotions, marketers might capture the trade-offs between immediate purchase value maximization and market knowledge extension in consumer decision making. In this research, the behavioural segments generated from the clustering analysis could be differentiated by using behaviour-related demographics in each product market. This indicates that the behavioural segmentation in this research was valid in terms of the criterion-related validation analysis.

In order to segment consumers based on their Prevalence of Promotion and the Value of Information from Purchases, the full replacement was selected and used to generate initial seeds for clustering analysis in this research. The other seed initialization methods, such as first, MacQueen's k-means algorithm, principle components, and partial replacement were also used to generate the initial seeds for segmenting the same consumers in this research. The comparison of the segmentation results generated by using different seed initialization methods shows that the generated behavioural segments differ only slightly when using different seed initialization methods in clustering analysis. This indicates that our findings are not sensitive to the specific method used for cluster analysis.

The **fourth research question** was about **whether demographics can be used to target a group of consumers with expected brand selection behaviours in relation to promotions**. To answer this research question, we profiled the generated behavioural segments in four consecutive years by using the demographic characteristics of consumers. This research found that some types of consumers are associated with certain demographic characteristics. This indicates that demographics could be used to target a group of consumers with expected brand selection behaviours in relation to promotions to some extent. The use of demographics in targeting might allow marketers to improve their marketing mix performances by targeting groups of consumers with an increased likelihood of exhibiting certain purchase behaviours (see Sections 6.2.2, 6.3.2, and 6.4.2). Table 8.1 summarizes the demographic profiles of behavioural segments in the three product markets. In general, the brand selection behaviours of consumers in relation to promotions are influenced by their demographic characteristics.

Table 8.1: Demographic profiles of behavioural segments and the associated business implications

Product Market	**Behavioural Segments**	**Demographic Profiles**	**Marketing Strategies**
Salty snack market	Promotion-averse Exploiters	Low-income households	Money-based sales promotions and/or extra products free inside or on packs of consumers' preferred brands; customer loyalty schemes
	Opportunistic Exploiters	Lower-medium-income households with retired male household members	Money-based sales promotions, free mail-in, free with product, and/or extra products of consumers' preferred brands; customer

			loyalty schemes
	Bargain Hunters	Higher-medium-income households with poorly educated male household members and/or unemployed female household members	Any promotions
	Explorers	Dual-career households with high-income, high-autonomy occupations; households with male members aged between 35 and 54 years old	Samples of new brands, point-of-sale displays, demonstrations
Yogurt market	Promotion-averse Explorers	Households with incomes either between $45,000 and $54,999 or between $75,000 and $99,999 per year, and/or working female households	Samples of new brands, point-of-sale displays, demonstrations
	Promotion-averse Exploiters	Female homemakers	Money-based sales promotions, free mail-in, free with product, and/or extra products free inside or on packs of consumers' preferred brands; customer loyalty schemes
	Opportunistic Explorers	N/A	N/A
	Opportunistic Exploiters	N/A	N/A
Toilet tissue market	Promotion-averse Explorers	N/A	N/A
	Promotion-averse Exploiters	Household income between $35,000 and $44,999	Money-based sales promotions and/or extra product free inside or on packs of consumers' preferred brands; customer loyalty schemes
	Opportunistic Explorers	Large family size	Any promotions
	Opportunistic Exploiters	N/A	N/A

The **fifth research question** was about **how brand selection behaviours in relation to promotions evolve in the consumer purchase lifecycle**. In order to answer this research question, this research compared the behavioural segments of consumers across the years to identify the behavioural evolvement patterns, routes and approaches of consumers. The research found that with the increase in market experiences and knowledge from purchases, the values in the Prevalence of Promotion and the Value of Information from Purchases might change accordingly. This indicates that the relative importance levels of the maximization of immediate purchase value and the extension of market knowledge in influencing the purchase decision making of consumers are likely to change with the increase in purchase experiences in the consumer purchase lifecycle. In order to optimize their purchase value and better satisfy their purchase needs, consumers normally adapt their purchase behaviour via making trade-offs between the maximization of immediate purchase value and the extension of market knowledge in their purchase lifecycle. Due to the lack of market knowledge in differentiating among brands, new entrants are likely to be either Promotion-averse Exploiters or Opportunistic Exploiters. In the salty snack market, these exploiters evolved to be Bargain Hunters or Explorers at the end of the year 2007. They adapted their purchase behaviours based on their updated information sets from purchases to satisfy their purchase needs via optimizing the value from purchases. In the yogurt and toilet tissue markets, exploiters evolved to be brand-loyal consumers via explorers in the purchase lifecycle.

The **sixth research question** was about **how the purchase behaviours of consumers differ across product markets**. To answer the sixth research question, this research compared the brand selection conditions, the typical brand selection behaviours in relation to promotions, the demographic profiles of behavioural segments, and the dynamic behavioural evolvements of consumers across the salty snack, yogurt, and toilet tissue markets. In general, the purchase behaviours of consumers differed across the product markets. The results of the comparative analysis show that:

1. The **average proportion** of brands explored by consumers in a product market was **negatively** related to the number of brands available for selection in the product market.

2. The **average number** of brands explored by consumers in a product market was **positively** related to the number of brands available for selection in the product market.

3. The typical purchase behaviours of consumers were likely to be **similar** across product markets with **a similar number of brands** available for selection.

4. The demographic profile of a group of consumers with a desired purchase behaviour in a product market might **not** be generalizable to other product markets.

5. The degree of influence of demographic characteristics on brand selection behaviour in relation to promotions was **positively** related to the number of brands available for selection in the product market.

6. Consumers in a product market with a small number of brands were more likely to proceed to the exploitation stage than those in a product market with a large number of brands, after a period of time in the product market.

7. The experienced consumers in a product market with a large number of brands for selection were more likely to be attracted by new brands to extend their market knowledge than those in a product market with a small number of brands for selection.

8. The influence of the past purchase experiences of consumers on their current purchase behaviour was **negatively** related to the number of brands available in the product market.

The differences between the three markets are linked to consumer behaviour in markets of different types/size. The calculation of the Prevalence of Promotion in quantifying consumers' reactions to promotions is only related to the percentage of purchases on promotion that a consumer bought in a certain period of time. The market size was not considered in the calculation of the Prevalence of Promotion and therefore does not have an impact on the calculation. In terms of the calculation of the Value of Information from Purchases, the market size was considered in the calculation and therefore might potentially have impact on the differences identified between the three product markets. However, in the calculation of the Value of Information from Purchases, the market size was used for quantifying the market knowledge a consumer obtained from prior purchases. The market knowledge of a consumer is linked to and determined by the consumer's purchase behaviour. Therefore, the differences between the three product markets are mainly linked to consumer behaviours but might potentially be affected by artefacts from the modelling methodology.

8.2 Contributions

Overall, this research developed a data-mining model for transactional data to measure consumer brand selection behaviours in response to the promotional mix. The results represent both academic and practical contributions. The following two sub-sections discuss the theoretical contributions and business implications of this research.

8.2.1 Theoretical contributions

8.2.1.1 Contribution of behavioural measurement

In general, there has been no easy processing algorithm specifically proposed for measuring consumers' dynamic choice process from the perspective of the multi-armed bandit problem. This research filled the literature gap by developing a new and unique measurement of brand selection behaviour in a reactive environment. The Value of Information from Purchases was developed specifically for measuring the exploration and exploitation behaviours of consumers in brand selection in a reactive environment. Compared to the measurements of dynamic choice behaviour of consumers in prior research, the adapted measurement of information value in this research did not involve complicated calculations in quantifying behaviours. It was thus easier to implement in dealing with a large amount of data. In summary, this research re-contextualized an existing behavioural measurement from the financial market to the retail market via adapting the generalized entropy measurement to specifically measure the exploration and exploitation behaviours in consumer purchases. The developed behavioural measurement also provides a new and easy solution to the problem of quantifying dynamic choice behaviour.

8.2.1.2 Confirmation of an existing concept

In addition to the contribution in behavioural measurement, this research also contributed to the literature on marketing theory. In prior research, there were no conclusive results about the variation of promotion proneness across types of promotions. This research used actual transactional data to find out the proneness of consumers to three types of in-store promotions. The findings in this research contribute to the marketing literature by supporting that the promotion proneness of a consumer does not vary across each type of promotion.

8.2.1.3 Contribution of the behavioural segmentation model

The use of predictive models in understanding the dynamic choice process does not allow marketers to understand how consumers make trade-offs between extending market knowledge and maximizing immediate purchase value. This research extended prior research on the dynamic choice process to uniquely clarify how consumers make the trade-offs in their decision making to optimize purchase utility. Compared to the predictive models used in prior research, the clustering analysis used in this research may allow researchers to model the implied trade-offs in purchase decision making. In general, this research provided a new solution to understand the dynamic choice process of consumers in their purchase lifecycles. Therefore, it could be used by marketers to predict how consumers evolve with the increase in purchase experiences in their purchase lifecycles.

8.2.2 Business implications

In addition to the theoretical contributions discussed above, this research also contributes to businesses in practice. Understanding the typical purchase behaviours of groups of consumers should allow marketers to tailor promotions to better satisfy the requirements of consumers. Table 8.1 provides the suggested promotions for each type of consumers in product markets based on their purchase behaviours and demographic characteristics. Explorers should be offered promotions on brands they have not previously purchased. On the contrary, exploiters should be offered promotions on their preferred brands. Marketers can thus tailor the promotions for each individual exploiter based on the past purchase experiences of the exploiters. The high value in the Prevalence of Promotions dominated the purchase decision making of Bargain Hunters. This indicates that Bargain Hunters are inclined to take advantage of promotions to make purchases. Any promotions could thus be provided to Bargain Hunters to accelerate their purchases. On the contrary, consumers who are not sensitive to promotions are less likely to adapt their purchase decision making due to the availability of promotions. It is suggested that these consumers are likely to buy promoted brands that can satisfy their requirements for the extension of market knowledge. Understanding the importance and the requirements of the extension of market knowledge in the decision making of these consumers would therefore allow marketers to create attractive promotions for these consumers.

The understanding of the dynamic behavioural evolvements in the consumer purchase lifecycle could allow marketers to understand and predict the trade-offs between the maximization of immediate purchase value and the extension of market knowledge in consumer decision making. To motivate Promotion-averse Explorers to make purchases, marketers are suggested to inform these consumers about new brands using advertisements or points of display. To accelerate the purchases of Promotion-averse Exploiters, marketers are suggested to provide these consumers with promotions on their preferred brands. As for Promotion-averse Exploiters with limited market knowledge, marketers are also suggested to motivate these consumers by providing promotions of big brands.

Complementing the dynamic behavioural evolvements of consumers, the demographic profiles of behavioural segments not only allow marketers to target consumers with predicted purchase behaviours but also allow marketers to better understand the purchase behaviours of each behavioural segment. Marketers could then determine the promotional types for motivating consumers to make purchases. For example, Opportunistic Exploiters in the salty snack market are likely to be households with retired male members who had limited shopping budgets but more time for searching for bargains. Marketers are therefore suggested to provide these consumers with money-based sales promotions on their preferred brands, such as reduced price offers, coupons, and rebates, in order to motivate them to make purchases.

The findings in this research not only could support marketers in tailoring their marketing strategies but also could support businesses in creating their investment strategies. According to the comparative analysis across the product markets, consumers in a product market with a large number of brands available for selection are more likely to make purchases of newly released brands than those in a product market with a small number of brands. Enterprises are thus suggested to invest in releasing new brands in a product market with a large number of brands. In a product market with a large number of brands, the capability of demographics in predicting the purchase behaviours of consumers is high. Marketers are thus suggested to use demographics to target consumers and to create tailored promotions to attract them.

In summary, the findings of this research provide insights into consumer purchase behaviours for businesses, which could allow them to better understand consumers. The analytical categories derived from the examination of the data might allow businesses, especially marketing managers, to tailor their marketing and investment strategies and decision making to improve their performances and achieve a competitive edge, e.g. by focusing / tailoring marketing to segments that are sensitive to promotions. In the next section, the limitations and avenues for future research are discussed.

8.3 Limitations and Future Research

8.3.1 Limitations

Like most studies, this research had limitations that need to be taken into account. Of the four main limitations, the first limitation concerned the lack of information about the first purchases made by consumers. In other words, the consumer purchase behaviour prior to the period considered is not known. Consumers' purchase behaviours in the prior period might have an impact on their purchase behaviours in the selected periods. Therefore, it is impossible to cleanly separate a consumer's purchase behaviour from the selected periods to the prior period. In this research, we selected transactional data from 2004 to 2007 in three product markets for analysis. The lack of transactional data prior to 2004 did not mean that the selected consumers made their first purchases in 2004. The lack of information on the past purchase experiences of the consumers may have resulted in bias in predicting the current brand selection behaviours of the consumers based on their past purchase experiences.

This research analysed and simulated consumer purchase behaviours based on the real transactional data of consumers in Pittsfield, US. However, it would be impossible to contact the consumers in the panel dataset to verify the results generated in the research. The lack of direct contact with consumers was the second limitation of this research.

Thirdly, in answering the second research question, only three types of in-store promotions were considered. The lack of information about out-of-store promotions made it impossible to find out whether purchase behaviours in relation to promotions were dependent on the classification of the type of promotion.

Finally, the number of consumers who met the selection requirements in this research was not large. It was difficult to use the limited data to find out how purchase behaviour changes are associated with changes in demographics over the years. The demographic profiles of the behavioural evolvement types thus could not be generated in this research. Marketers thus cannot use the findings to predict how a consumer would change their purchase behaviour due to changes in their demographic characteristics over the years. In general, the lack of data for analysis was the fourth limitation of this research.

Following the discussion of the limitations in this research, suggestions for future research directions are provided in the next sub-section.

8.3.2 Future research

In this section, seven areas for future research are provided and discussed. Firstly, future research could extend this research to find out the demographic profiles of the behavioural evolvement types. Conducting such research would require researchers to collect a large amount of transactional data from a large number of consumers. The generated demographic profiles would provide marketers with insights into the purchase behavioural evolvement of consumers. This might allow marketers to better understand consumers to achieve a competitive edge.

Secondly, an in-depth qualitative study of brand selection behaviours in response to promotions over the years in the US market could be conducted. The identification of the trade-offs between extending market knowledge and maximizing immediate purchase value in the consumer purchase lifecycle from the qualitative study might allow marketers to better understand how consumers make their purchase decisions via making the trade-offs and why consumers make such trade-offs in purchases. The understanding of the trade-offs in consumer decision making might allow marketers to recognize the needs of consumers in different stages of the consumer purchase lifecycle.

Thirdly, to identify the factors influencing the trade-offs in consumer purchase decision making, future research could also use eye-tracking data. Eye tracking is a way to directly measure the attention and involvement of people via tracking their eye movements (Yang *et al.*, 2015). It has been conducted in numerous marketing areas, such as branding, advertising, search effectiveness, and brand displays on supermarket shelves. The importance of the factors influencing the trade-offs could be found out by examining the time periods in which consumers fix their eyesight on a specific location when selecting a brand and the eye movements between two fixations.

In this research, the purchase behaviours of consumers in Pittsfield, US, were analysed. As culture has been found to be a factor influencing consumer purchase behaviours in prior research (e.g. Arnould and Thompson, 2005; Kacen and Lee, 2002; Mooij, 2011), it would be beneficial to conduct a cross-cultural study using the data-mining model proposed in this research to deal with store scanner data in other countries. The cross-cultural study might allow researchers and marketers to find out how the brand selection behaviours in relation to promotions, the demographic profiles of purchase behaviours, and the dynamic behavioural evolvement process differ according to cultural factors. The results of the cross-cultural study could be beneficial to marketers in tailoring global marketing strategies.

In the network era, online shopping is playing an increasingly important role in the daily lives of consumers. It could also be beneficial to expand this research via analysing the brand selection behaviours of consumers in response to promotions in online shopping. A comparison of the results between physical-store shopping and online shopping might allow researchers and marketers to understand the influence of shopping approaches on consumer purchase behaviours. This could support marketers in tailoring their marketing strategies to satisfy the needs of consumers.

In this research, the IRI Marketing data was used to analyse consumer brand selection behaviour in relation to promotions. In order to find out whether the developed data mining model can be generalized to deal with other types of data, future research could use the panel data directly collected from a retailer. The results generated from analysing the data collected from a particular retailer could support and help the retailer to tailor its marketing and investment strategies for improving performances.

Besides the use of different dataset in future analysis, future research also could use alternative techniques to process data. Using demographics and consumer past purchase experiences in predicting consumer current brand selection decisions could be another area for future research. The predictive models could and suggested to be established between the current brand selection decisions and the demographics and past purchase experiences in future research.

Demographic-Related Purchase Behaviours of Consumers: The Evolving Tension between Exploration and Exploitation in Frequently Purchased Consumer Goods Markets

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REFERENCES

Agrawal, M. (1995). Warning Labels: The Role of Expertise and Perceived Risk in PharmaceuticalPurchase Behavior. *Health Marketing Quarterl, 13*(2), 99-115.

Ailawadi, K. L., Neslin, S. A., & Gedenk, K. (2001). Pursuing the Value-Conscious Consumer: Store Brands Versus National Brand Promotions. *Journal of Marketing, 65*(1), 71-89.

Ainslie, A., & Rossi, P. E. (1998). Similarities in Choice Behavior Across Product Categories. *Marketing Science, 17*(2), 91-106.

Alba, J. W., Mela, C. F., Shimp, T. A., & Urbany, J. E. (1999). The Effect of Discount Frequency and Depth on Consumer Price Judgments. *Journal of Consumer Research, 26*(2), 99-114.

Alvarez, B. A., & Casielles, R. V. (2005). Consumer Evaluations of Sales Promotion: The Effect on Brand Choice. *European Journal of Marketing, 39*(1/2), 54 - 70.

Amine, A. (1998). Consumers' True Brand Loyalty: The Central Role of Commitment. *Journal of Strategic Marketing, 6*, 305-319.

Andrews, M. L., Benedicktus, R. L., & Brady, M. K. (2010). The Effect of Incentives on Customer Evaluations of Service Bundles. *Journal of Business Research, 63*(1), 71-76.

Anic, I.-D., & Radas, S. (2006). The Consumer In-Store Purchasing Behavior Associated With Deal-Proneness for a Hypermarket Retailer in Croatia. *Economic Trends and Economic Policy, 16*(109), 63-81.

Annesley, C. (2012). *Tesco Plans Targeted Approach With Clubcard Data*. Retrieved 6 5, 2013, from Internet Retailing: http://internetretailing.net/2012/06/tesco-plans-targeted-approach-with-clubcard-data/

Aribarg, A., & Foutz, N. Z. (2009). Category-Based Screening in Choice of Complementary Products. *Journal of Marketing Research, 46*(4), 518-530.

Arnould, E. J., & Thompson, C. J. (2005). Consumer Culture Theory (CCT): Twenty Years of Research. *Journal of Consumer Research, 31*(4), 868-882.

Audibert, J. Y., Munos, R., & Szepesv´ari, C. (2008, October 1). Exploration-Exploitation Trade-off Using Variance Estimates in Multi-armed Bandits. *Theoretical Computer Science*, 1-42.

Babej, M. E., & Pollak, T. (2007). *In-store Advertising: Coming of Age?* Retrieved from Forbes: http://www.forbes.com/2007/10/29/unsolicited-advice-supermarkets-oped_meb_1030advice.html

Bae, S. H., Nam, S., & Kim, S.-H. (2011, February). *Empirical Investigation of Consumers' Impulse Purchases from Television Home Shopping Channels: A Case of Order Cancellation Behavior.* Retrieved from Rutgers University: http://andromeda.rutgers.edu/~sjnam/files/BNK2011.pdf

Bakos, Y., & Brynjolfsson, E. (1999). Bundling Information Goods: Pricing, Profits, and

Efficiency. *Management Science, 45*(12), 1613-1630.

Bashar, A., Ahmad, I., & Wasiq, M. (2013). A Study of Influence of Demographic Factors on Consumer Impulse Buying Behavior. *Journal of Management Research, 13*(3), 145-154.

Bassi, F. (2011). The Dirichlet Model: Analysis of A Market and Comparison of Estimation Procedures. *Marketing Bulletin, 22*, 1-11.

Baum, J. A., Li, S. X., & Usher, J. M. (2000). Making the Next Move: How Experiential and Vicarious Learning Shape the Locations of Chains' Acquisitions. *Administrative Science Quarterly, 45*, 766-801.

Bauner, C., & Wang, E. (2014). *Strategic Retailer Reactions to Wholesale Club Market Presence.* Retrieved 3 7, 2016, from University of Massachusetts Amherst: http://people.umass.edu/eywang/EYWang%20Costco.pdf

Bawa, K. (1990). Modeling Inertia and Variety Seeking Tendencies in Brand Choice Behavior. *Marketing Science, 9*(3), 263-278.

Bawa, K., & Ghosh, A. (1999). A Model of Household Grocery Shopping Behavior. *Marketing Letters, 10*(2), 149–160.

Bawa, K., & Shoemaker, R. W. (1987). The Coupon-Prone Consumer: Some Findings Based on Purchase Behavior across Product Classes. *Journal of Marketing, 51*(4), 99-110.

Bawa, K., Srinivasan, S. S., & Srivastava, R. K. (1997). Coupon Attractiveness and Coupon Proneness: A Framework for Modeling Coupon Redemption. *Journal of Marketing Research, 34*(4), 517-525.

Beane, T. P., & Ennis, D. M. (1987). Market Segmentation: A Review. *European Journal of Marketing, 21*(5), 20-42.

Beatty, S. E., & Ferrell, M. E. (1998). Impulse Buying: Modeling Its Precursors. *Journal of Retailing, 74*(2), 169-191.

Bell, D. R., Chiang, J., & Padmanabhan, V. (1999). The Decomposition of Promotional Response: An Empirical Generalization. *Marketing Science, 18*(4), 504-526.

Bellenger, D. N., Robertson, D. H., & Hirschman, E. C. (1978). Impulse Buying Varies by Product. *Journal of Advertising Research, 18*(6), 15-18.

Benner, M. J., & Tushman, M. (2002). Process Management and Technological Innovation: A Longitudinal Study of the Photography and Paint Industries. *Administrative Science Quarterly, 47*(4), 676-706.

Bettman, J. R., & Park, W. C. (1980). Effects of Prior Knowledge on Experience and Phase of the Choice Process on Consumers' Decision Process: A Protocol Analysis. *Journal of Consumer Research, 7*(3), 234–248.

Blackwell, R. D., Miniard, P. W., & Engel, J. F. (2006). *Consumer Behavior* (10th ed.). Mason: Thomson Higher Education.

Blattberg, R. C., & Neslin, S. A. (1990). *Sales Promotion, Concepts, Methods, and Strategies.*

Englewood Cliffs: Prentice Hall.

Blattberg, R. C., & Sen, S. K. (1974). Market Segmentation Using Models of Multidimensional Purchasing Behavior. *Journal of Marketing, 38*(4), 17-28.

Blattberg, R., Buesing, T., Peacock, P., & Sen, S. (1978). Identifying the Deal Prone Segment. *Journal of Marketing Research*, 369-377.

Blythe, J. (2014). *Principles & Practice of Marketing* (3rd ed.). London: SAGE Publications Ltd.

Bose, R. (2009). Advanced Analytics: Opportunities and Challenges. *Industrial Management & Data Systems*, *109*(2), 155-172.

Bottomley, P., & Nairn, A. (2004). Blinded by Science: The Managerial Consequences of Inadequately Validated Cluster Analysis Solutions. *International Journal of Market Research, 46*(2), 171-187.

Brassington, F., & Pettitt, S. (2006). *Principles of Marketing* (3rd ed.). Essex: Pearson Education Limited.

Bridges, E., Briesch, R. A., & Yim, C. K. (2006). Effects of Prior Brand Usage and Promotion on Consumer Promotional Response. *Journal of Retailing, 82*(4), 295–307.

Bronnenberg, B. J., & Mela, C. F. (2004). Market Roll-Out and Retailer Adoption for New Brands. *Marketing Science*, *23*(4), 500-518.

Bronnenberg, B. J., Kruger, M. W., & Mela, C. F. (2008). Database Paper: The IRI Marketing Data Set. *Marketing Sciencce, 27*(4), 745-748.

Brown, J. S., & Duguid, P. (2001). Knowledge and Organization: A Social-Practice Perspective. *Organization Science, 12*(2), 198-213.

Brown, S. L., & Eisenhardt, K. M. (1997). The Art of Continuous Change: Linking Complexity Theory and Time-Paced Evolution in Relentlessly Shifting Organizations. *Administrative Science Quarterly, 42*(1), 1-34.

Bucklin, R. E., & Gupta, S. (1992). Brand Choice, Purchase Incidence, and Segmentation: An Integrated Modeling Approach. *Journal of Marketing Research*, *29*(3), 201-215.

Bucklin, R. E., & Lattin, J. M. (1991). A Two-State Model of Purchase Incidence and Brand Choice. *Marketing Science*, 24-39.

Bucklin, R. E., Gupta, S., & Han, S. (1995). A Brand's Eye View of Response Segmentation in Consumer Brand Choice Behavior. *Journal of Marketing Research*, 66-74.

Bucklin, R. E., Gupta, S., & Siddarth, S. (1998). Determining Segmentation in Sales Response Across Consumer Purchase Behaviors. *Journal of Marketing Research*, 189-197.

Burton, S., Lichtenstein, D. R., Netemeyer, R. G., & Garretson, J. A. (1998). A Scale for Measuring Attitude Towards Private Label Products and an Examination of Its Psychological and Behavioral Correlates. *Journal of the Academy of Marketing*

Science, 26(4), 293-306.

Buzzell, R. D., Quelch, J. A., & Salmon, W. J. (1990). The Costly Bargain of Trade Promotion. *Harvard Business Review, 62*(8), 141-149.

Caplovitz, D. (1963). *The Poor Pay More.* New York: Free Press.

Carpenter, J. M., & Moore, M. (2008). US Consumers' Perceptions of Non-Price Retail Promotions. *Journal of Retail & Distribution Management, 36*(2), 111-123.

Cerrito, P. B. (2005). *Comparison of Enterprise Miner and SAS/Stat for Data Mining.* Louisville: SAS Institute Inc.

Chakrabortty, R. K., Hossain, M., Azad, F. H., & Islam, J. (2013). Analyzing the Effects of Sales Promotion and Advertising on Consumer's Purchase Behavior. Melbourne: World Business Institute Australia.

Chan, T., Narasimhan, C., & Zhang, Q. (2008). Decomposing Promotional Effects with a Dynamic Structural Model of Flexible Consumption. *Journal of Marketing Research, 45*(4), 487-498.

Chandon, P., Wansink, B., & Laurent, G. (2000). A Benefit Congruency Framework of Sales Promotion Effectiveness. *Journal of Marketing, 64*(4), 65-81.

Che, H., Erdem, T., & Öncü, T. (2015). Consumer Learning and Evolution of Consumer Brand Preferences. *Quantitative Marketing and Economics*. doi:10.1007/s11129-015-9158-x

Chen, J. (2002). An Entropy Theory of Value. *working paper*.

Chen, J. (2004). Generalized Entropy Theory of Information and Market Patterns. *Corporate Finance Review*, 23-32.

Chen, J. (2005). Information Theory and Market Behavior. *Journal of Behavioral Finance*, 25-45.

Chen, S.-F. S., Monroe, K. B., & Lou, Y.-C. (1998). The Effectsof Framing Price Promotion Messages on Consumers' Perceptions and Purchase Intentions. *Journal of Retailing, 74*(3), 353-372.

Chevalier, J. A., & Kashyap, A. K. (2011). *Best Prices.* Chicago: National Bureau of Economic Research.

Ching, A. T., Imai, S., Ishihara, M., & Jain, N. (2012). A Practitioner's Guide to Bayesian Estimation of Discrete Choice Dynamic Programming Models. *Quantitative Marketing and Economics*, 151-196.

Chintagunta, P., Goettler, R., & Kim, M. (2012). New Drug Diffusion when Forward-Looking Physicians Learn from Patient Feedback and Detailing. *Journal of Marketing Research, 49*, 807-821.

CMO Council. (2013, February). *Marketing Spend*. Retrieved November 10, 2015, from Chief Marketing Officer Council World Wide: The Peer Powered Network: https://www.cmocouncil.org/facts-statscategories.php?view=all&category=marketing-spend

Collica, R. S. (2011). *Customer Segmentation and Clustering Using SAS Enterprise Miner* (2nd ed.). Cary: SAS Institute Inc.

Cooper, R., & Ross, T. W. (1985). Product Warranties and Double Moral Hazard. *The Rand Journal of Economics, 16*(1), 103-113.

Coriolis Research. (2004). *Tesco: A Case Study in Supermarket Excellence*. Retrieved 6 5, 2013, from Coriolis Research.Consulting.Strategy: http://www.coriolisresearch.com/pdfs/coriolis_tesco_study_in_excellence.pdf

Cotton, B. C., & Babb, E. M. (1978). Consumer Response to Promotional Deals. *Journal of Marketing, 42*(3), 109-113.

Danovitch, J. H., & Mills, C. M. (2009). *Children's Vulnerability to Advertising Messages from Familiar Characters.* Retrieved 1 28, 2016, from Michigan State University's Children's Central: http://www.childrenscentral.msu.edu/awards/Previous%20Award%20Winners/Danovitch%20Paper.pdf

Danziger, S., Hadar, L., & Morwitz, V. G. (2014). Retailer Pricing Strategy and Consumer Choice under Price Uncertainty. *Journal of Consumer Research, 41*, 000.

Davis, G. (2007, May 9). *How Tesco Became Britain's Top Supermarket*. Retrieved October 12, 2013, from Money Week: http://moneyweek.com/how-tesco-became-britains-top-supermarket/

Deighton, J., Henderson, C. M., & Neslin, S. A. (1994). The Effects of Advertising on Brand Switching and Repeat Purchasing. *Journal of Marketing Research, 31*(1), 28-43.

DelVecchio, D. (2005). Deal-Prone Consumers' Response to Promotion: The Effects of Relative and Absolute Promotion Value. *Psychology & Marketing, 22*(5), 373–391.

DeNavas-Walt, C., Bernadette , P. D., & Cheryl, L. H. (2005). *Income, Poverty, and Health Insurance Coverage in the United States: 2004.* Washington, DC: U.S. Census Bureau.

DeNavas-Walt, C., Bernadette, P. D., & Cheryl, L. H. (2006). *Income, Poverty, and Health Insurance Coverage in the United States: 2005.* Washington, DC: U.S. Census Bureau.

DeNavas-Walt, C., Bernadette, P. D., & Jessica, S. (2007). *Income, Poverty, and Health Insurance Coverage in the United States: 2006.* Washington, DC: U.S. Census Bureau.

DeNavas-Walt, C., Bernadette, P. D., & Jessica, S. C. (2008). *Income, Poverty, and Health Insurance Coverage in the United States: 2007.* Washington, DC: U.S. Census Bureau.

Dibb, S., & Stern, P. (1995). Questioning the Reliability of Market Segmentation Techniques. *International Journal of Management Science, 23*(6), 625-636.

Dickson, P. R., & Sawyer, A. G. (1990). The Price Knowledge and Search of Supermarket

Shoppers. *Journal of Marketing, 54*(3), 42-53.

Dodson, J. A., Tybout, A. M., & Sternthal, B. (1978). Impact of Deals and Deal Retraction on Brand Switching. *Journal of Marketing Research, 15*(1), 72-81.

Dube, J.-P., Hitsch, G. J., & Jindal, P. (2014). The Joint Identification of Utility and Discount Functions From Stated Choice Data: An Application to Durable Goods Adoption. *Quantitative Marketing Economics*, 331-377.

Dunn, R., & Wrigley, N. (1984). Store Loyalty for Grocery Products: An Empirical Study. *Area, 16*(4), 307-314.

Durankiev, G. (2015, 6 18). *11 Countries that Consume the Most Yogurt*. Retrieved 5 9, 2016, from Yogurt in Nutrition: http://www.yogurtinnutrition.com/11-countries-that-consume-the-most-yogurt/

East, R., Harris, P., Willson, G., & Hammond, K. (1995). Correlates of First-brand Loyalty. *Journal of Marketing Manageme, 11*, 487-497.

Ehrenberg, A. (1988). *Repeat-Buying: Facts, Theory and Applications.* London: Charles Griffin & Company.

Eppen, G. D., Hanson, W. A., & Martin , R. K. (1991). Bundling - New Products, New Markets, Low Risk. *Sloan Management Review, 32*(4), 7-14.

Erdem, T., & Keane, M. P. (1996). Decision-making under Uncertainty: Capturing Dynamic Brand Choice Processes in Turbulent Consumer Goods Markets. *Marketing Science, 15*(1), 1-20.

Evans, M., Jamal, A., & Foxall, G. (2009). *Consumer Behaviour* (2nd ed.). Chichester: John Wiley & Sons Ltd.

Experian. (2015). *U.S. Households: Do You Eat or Drink Yogurt and Smoothies?* Retrieved 5 9, 2016, from Statista: http://www.statista.com/statistics/279748/us-households-consumption-of-yogurt-and-smoothies/

Experian. (2016). *U.S. households: Do you eat or drink yogurt and smoothies?* Retrieved 3 28, 2016, from Statista: http://www.statista.com/statistics/279748/us-households-consumption-of-yogurt-and-smoothies/

Farias, D. P., & Megiddo, N. (2005). Exploration-Exploitation Trade-offs for Experts Algorithms in Reactive Environments. *Advances in Neural Information Processing Systems, 17*, 409-416.

Farley, J. U. (1964). "Brand Loyalty" and the Economics of Information. *The Journal of Business, 37*(4), 370-381.

Fazio, R. H., & Zanna, M. P. (1978). Attitudinal Qualities Relating to The Strength of The Attitude-Behavior Relationship. *Journal of Experimental Social Psychology, 14*, 398–408.

Fazio, R. H., Chen, J.-M., McDonel, E. C., & Sherman, S. J. (1982). Attitude Accessibility, Attitude Behavior Consistency, and The Strength of The Object Evaluation Association. *Journal of Experimental Social Psychology, 18*, 339–357.

Fazio, R. H., Powell, M. C., & Williams, C. J. (1989). The Role of Attitude Accessibility in The Attitude-to-Behavior Process. *Journal of Consumer Research*, *16*(3), 280–288.

Feinberg, F. M., Krishna, A., & Zhang, Z. J. (2002). Do We Care What Others Get? A Behaviorist Approach to Targeted Promotions. *Journal of Marketing Research, 39*(3), 277-291.

Financial Times. (n.d.). *Definition of data-driven marketing*. Retrieved November 10, 2015, from Financial Times: http://lexicon.ft.com/Term?term=data_driven-marketing

Flavian, C., MartmHnez, E., & Polo, Y. (2001). Loyalty to Grocery Stores in the Spanish Market of the 1990s. *Journal of Retailing and Consumer Services, 8*, 85-93.

Foxall, G. R. (1993). Consumer Behaviour as An Evolutionary Process. *European Journal of Marketing*, *27*(8), 46-57.

Fraiman, R., Justel, A., & Svarc, M. (2008). Selection of Variables for Cluster Analysis and Classification Rules. *Journal of the American Statistical Association*, 1294-1303.

Frank, R. E., Douglas, S. P., & Polli, R. E. (1968). Household Correlates of "Brand Loyalty" for Grocery Products. *The Journal of Business, 41*(2), 237-245.

Frank, R. E., Massey, W. F., & Wind, Y. (1972). *Market Segmentation*. Englewood Cliffs: Prentice Hall International Inc.

Frozen & Refrigerated Buyer. (2016). *Yogurt Sales in the United States from 2011 to 2015 (in Billion U.S. Dollars)**. Retrieved 3 28, 2016, from Statista: http://www.statista.com/statistics/279527/us-yogurt-sales/

Gázquez-Abad, J. C., & Sánchez-Pérez, M. (2009). Characterising the Deal-Proneness of Consumers by Analysis of Price Sensitivity and Brand Loyalty: An Analysis in the Retail Environment. *The International Review of Retail, Distribution and Consumer Research*, *19*(1), 1-28.

Gilbert, D. C., & Jackaria, N. (2002). The Efficacy of Sales Promotions in UK Supermarkets: A Consumer View. *International Journal of Retail & Distribution Management, 30*(6), 315-322.

Global DMA LLC and Winterberry Group LLC. (2014). *The Global Review of Data-Driven Marketing and Advertising.* Retrieved from GDMA: http://globaldma.s3.amazonaws.com/GDMA-and-Winterberry-Group--The-Global-Review-(Appendix)--November-2014.pdf

Gönül, F., & Srinivasan, K. (1996). Estimating the Impact of Consumer Expectations of Coupons on Purchase Behavior: A Dynamic Structure Model. *Marketing Science*, *15*(3), 262-279.

Goodhardt, G. J., Ehrenberg, A. S., & Chatfield, C. (1984). The Dirichlet: A Comprehensive Model of Buying Behaviour. *Journal of the Royal Statistical Society, 147*(5), 621-655.

Gross, B. L. (1987). Time and Scarcity: Interdisciplinary Perspectives and Implications for Consumer Behavior. *Research in Consumer Behavior, 2,* 1-54.

Guiltinan, J. P. (1987). The Price Bundling of Services. *Journal of Marketing, 51*(April), 74-85.

Gupta, A. K., Smith, K. G., & Shalley, C. E. (2006). The Interplay Between Exploration and Exploitation. *Academy of Management Journal, 49*(4), 693–706.

Gupta, S. (1988). Impact of Sales Promotions on When, What, and How Much to Buy. *Journal of Marketing Research*, *25*(4), 342-355.

Gupta, S., & Denbleyker, C. (2015). An Exploratory Investigation of Deal Proneness at the Bottom of the Pyramid. *Academy of Marketing Studies Journal*.

Hackleman, E. C., & Duker, J. M. (1980). Deal Proneness and Heavy Usage: Merging Two Market Segmentation Criteria. *Journal of the Academy of Marketing Science*, *8*(4), 332-344.

Hagerty, M. R., & Aaker, D. A. (1984). A Normative Model of Consumer Information Processing. *Marketing Science*, *3*(3), 227-246.

Halstead, D., Dröge, C., & Cooper, M. B. (1993). Product Warranties and Post-purchase Service: A Model of Consumer Satisfaction With Complaint Resolution. *Journal of Services Marketing, 7*(1), 33-40.

Harris, J., & Blair, E. A. (2006). Consumer Preferences for Product Bundles: The Role of Reduced Search Costs. *Journal of the Academy of Marketing Science, 34*(4), 506-513.

Hartmann, W. R., & Nair, H. S. (2010). Retail Competition and the Dynamics of Demand for Tied Goods. *Marketing Science*, *29*(2), 366-386.

Hauser, J. R., & Wisniewski, K. J. (1982). Dynamic Analysis of Consumer Response to Marketing Strategies. *Management Science, 28*(5), 455-486.

He, Z. (2006). *Farthest-Point Heuristic Based Initialization Methods for K-Modes Clustering.* Retrieved from Cornell University Library: http://arxiv.org/ftp/cs/papers/0610/0610043.pdf

He, Z.-L., & Wong, P.-K. (2004). Exploration vs. Exploitation: An Empirical Test of the Ambidexterity Hypothesis. *Organization Science*, *15*(4), 481-494.

Heilman, C. M., Bowman, D., & Wright, G. P. (2000). The Evolution of Brand Preferences and Choice Behaviors of Consumers New to a Market. *Journal of Marketing Research, 37*(2), 139-155.

Henderson, C. M. (1994). Promotion Heterogeneity and Consumer Learning: Refining the Deal-Proneness Construct. *Advances in Consumer Research, 21*(1), 86-94.

Hensher, D. A., Barnard, P. O., & Truong, T. P. (1988). The Role of Stated Preference Methods in Studies of Travel Choice. *Journal of Transport Economics and Policy, 22*(1), 45-58.

Hirsh, J. B., Mar, R. A., & Peterson, J. B. (2012). Psychological Entropy: A Framework for Understanding Uncertainty-Related Anxiety. *Psychological Review*, *119*(2), 304-320.

Hoyer, W. D. (1984). An examination of consumer decision making for a common repeat purchase product. *Journal of Consumer Research, 11*(3), 822-829.

Hoyer, W. D. (1984). An Examination of Consumer Decision Making for A Common Repeat Purchase Product. *Journal of Consumer Research, 11*(3), 822-829.

Hsieh, T. A., & Chang, T. W. (2004). The Effect of Consumer Participation on Price Sensitivity. *The Journal of Consumer Affairs, 38*(2), 282-296.

Huang, G., Khwaja, A., & Sudhir, K. (2015). Short-Run Needs and Long-Term Goals: A Dynamic Model of Thirst Management. *Marketing Science, 34*(5), 702-721.

Huang, R., Perloff, J. M., & Villas-Boas, S. B. (2006). Effect of Sales on Brand Loyalty. *Journal of Agricultural and Food Industrial Organization, 4*(1), 1-32.

Huchzermeier, A., Iyer, A., & Freiheit, J. (2002). The Supply Chain Impact of Smart Customers in a Promotional Environment. *Manufacturing & Service Operations Management, 4*(3), 228-240.

IBM. (2011). *From Stretched to Strengthened: Insights From the Global Chief Marketing Officer Study.* Portsmouth: IBM Corporation.

Inman, J. J., Ferraro, R., & Winer, R. S. (2004, April 30). *Where the Rubber Meets the Road: A Model of In-Store Consumer Decision-Making.* Retrieved from University of Houston: http://www.cba.uh.edu/mark/papers/inman.pdf

Ishikida, T., & Varaiya, P. (1994). Multi-Armed Bandit Problem Revisited. *Journal of Optimization Theory and Applications, 83*(1), 113-154.

Johnson, E. J., & Russo, E. J. (1984). Product Familiarity and Learning New Information. *Journal of Consumer Research, 11*(1), 542–550.

Kacen, J. J., & Lee, J. A. (2002). The Influence of Culture on Consumer Impulsive Buying Behavior. *Journal of Consumer Psychology, 12*(2), 163-176.

Kahl, J. A., & Davis, J. A. (1955). A Comparison of Indexes of Socio-Economic Status. *American Sociological Review, 20*(3), 317-325.

Kalil, B. (2008). *Tissue Market Continues to Grow*. Retrieved 4 1, 2016, from RISI: http://legacy.risiinfo.com/technologyarchives/PPMagOctober-Tissue-market-continues-to-grow.html

Kapur, J. N., Bector, C. R., & Kumar, U. (1984). A generalization of the entropy model for brand purchase behavior. *Naval Research Logistics Quarterly, 31*, 183-198.

Karunanithy, M., & Sivesan, S. (2013). An Empirical Study on the Promotional Mix and Brand Equity: Mobile Service Providers. *Industrial Engineering Letters, 3*(3), 1-9.

Katila, R., & Ahuja, G. (2002). Something Old, Something New: A Longitudinal Study of Search Behavior and New Product Introduction. *Academy of Management Journal, 45*(6), 1183-1194.

Keegan, W. J., & Green, M. C. (2008). *Global Marketing* (5th edition ed.). New Jersey: Pearson Prentice Hall.

Kelley, C. A. (1988). An Investigation of Consumer Product Warranties as Market Signals of Product Reliability. *Journal of the Academy of Marketing Science, 16*(2), 72-78.

Khan, F. (2012). An Initial Seed Selection Algorithm for K-Means Clustering of Georeferenced Data to Improve Replicability of Cluster Assignments for Mapping Application. *Applied Soft Computing*, 3698-3700.

Khan, S. S., & Ahmad, A. (2013). Cluster Center Initialization Algorithm for K-Modes Clustering. *Expert Systems with Applications*, 7444–7456.

Khan, U., & Dhar, R. (2010). Price Framing Effects on Purchase of Hedonic and Utilitarian Bundles. *Journal of Marketing Research, XLVII*(December 2010), 1090-1099.

Kim, B.-D., Srinivasan, K., & Wilcox, R. T. (1999). Identifying Price Sensitive Consumers: The Relative Merits of Demographic vs. Purchase Pattern Information. *Journal of Retailing, 75*(2), 173-193.

Knott, A. M. (2002). Exploration and Exploitation as Complements. In C. Choo, & N. Bontis, *The Strategic Management of Intellectual Capital and Organizational Knowledge* (pp. 339-358). New York: Oxford University Press.

Knox, S. (1998). Loyalty-Based Segmentation and the Customer Development Process. *European Management Journal, 16*(6), 729-737.

Knutsson, E. (2011). *Bundling for Consumers? Understanding Complementarity and Its Effect on Consumers' Preferences and Satisfaction.* Umeå: Umeå University.

Kohn, M. L., Naoi, A., Schoenbach, C., Schooler, C., & Slomczynski, K. M. (1990). Position in the Class Structure and Psychological Functioning in the United States, Japan, and Poland. *American Journal of Sociology, 95*(4), 964-1008.

Kopalle, P. K., & Lehmann, D. R. (2006). Setting Quality Expectations When Entering A Market: What Should the Promise Be? *Marketing Science, 25*(1), 8–24.

Kotler, P., & Keller, K. L. (2012). *Marketing Management* (14th ed.). Essex: Pearson Education Limited.

Kotler, P., Armstrong, G., Wong, V., & Saunders, J. (2008). *Principles of Marketing* (5th ed.). Essex: Pearson Education Limited.

Krishna, A. (1991). Effect of Dealing Patterns on Consumer Perceptions of Deal Frequency and Willingness to Pay. *Journal of Marketing Research, 28*(November), 441-451.

Krishna, A., Briesch, R., Lehmann, D. R., & Yuan, H. (2002). A Meta-analysis of the Impact of Price Presentation on Perceived Savings. *Journal of Retailing, 78*(2), 101-118.

Krishnamurthi, L., & Raj, S. P. (1991). An Empirical Analysis of the Relationship Between Brand Loyalty and Consumer Price Elasticity. *Marketing Science, 10*(2), 172-183.

Kroes, E. P., & Sheldon, R. J. (1988). Stated Preference Methods: An Introduction. *Journal of Transport Economics and Policy*, 11-25.

Kruger, M. W., & Pagni, D. (2013). *IRI Academic Data Set Description.* Chicago: Information Resources Incorporated.

Kuleshov, V., & Precup, D. (2010). Algorithms for the Multi-Armed Bandit Problem. *Journal of Machine Learning Research*, 1-48.

Kumar, S. R., & Advani, J. Y. (2005). Factors Affecting Brand Loyalty: A Study in An Emerging Market on Fast Moving Consumer Goods. *Journal of Customer Behaviour, 4*, 251-275.

Kwon, K.-N., & Kwon, Y. J. (2007). Demographics in Sales Promotion Proneness: A Socio-Cultural Approach. *Advances in Consumer Research, 34*, 288-294.

Lambert-Pandraud, R., Laurent, G., & Lapersonne, E. (2005). Repeat Purchasing of New Automobiles by Older Consumers: Empirical Evidence and Interpretations. *Journal of Marketing*, *69*(2), 97-113.

Laroche, M., Pons, F., Zgolli, N., & Kim, C. (2001). Consumers Use of Price Promotions: A Model and Its Potential Moderators. *Journal of Retailing and Consumer Services, 8*(5), 251-260.

Laroche, M., Pons, F., Zgolli, N., Cervellon, M.-C., & Kim, C. (2003). A Model of Consumer Response to Two Retail Sales Promotion Techniques. *Journal of Business Research, 56*, 513-522.

Lavie, D., Stettner, U., & Tushman, M. L. (2010). Exploration and Exploitation Within and Across Organizations. *The Academy of Management Annals, 4*(1), 109-155.

Lawless, M. W. (1991). Commodity Bundling for Competitive Advantage: Strategic Implications. *Journal of Management Studies, 28*(3), 267-280.

Lee, Y., & O’Connor, G. C. (2003). New Product Launch Strategy for Network Effects Products. *Journal of Academy of Marketing*, 241-255.

Lesser, J. A., & Lusch, R. F. (1988). Entropy and the Prediction of Consumer Behavior. *Behavioral Science*, 282-291.

Leszczyc, P. T., & Timmermans, H. J. (1997). Store-Switching Behavior. *Marketing Letters, 8*(2), 193–204.

Levedahl, J. W. (1988). Coupon Redeemers: Are They Better Shoppers? *The Journal of Consumer Affairs, 22*(3), 264-283.

Levinthal, D. A., & March, J. G. (1993). The Myopia of Learning. *Strategic Management Journal*, *14*, 95-112.

Lichtenstein, D. R., Burton, S., & Netemeyer, R. G. (1997). An Examination of Deal Proneness Across Sales Promotion Types: A Consumer Segmentation Perspective. *Journal of Retailing, 73*(2), 283-297.

Lichtenstein, D. R., Netemeyer, R. G., & Burton, S. (1990). Distinguishing Coupon Proneness From Value Consciousness: An Aquisition-Transaction Utility Theory Perspective. *Journal of Marketing, 54*(3), 54-67.

Lichtenstein, D. R., Netemeyer, R. G., & Burton, S. (1995). Assessing the Domain Specificity of Deal Proneness: A Field Study. *Journal of Consumer Research, 22*(3), 314-326.

Lichtenstein, D. R., Ridgway, N. M., & Netemeyer, R. G. (1993). Price Perceptions and Consumer Shopping Behavior: A Field Study. *Journal of Marketing Research, 30*(2), 234-245.

Lim, J., Currim, I. S., & Andrews, R. L. (2005). Consumer Heterogeneity in the Longer-Term Effects of Price Promotions. *International Journal of Research in Marketing, 22*(4), 441-457.

Lin, C.-F. (2002). Segmenting Customer Brand Preference: Demographic or Psychographic. *Journal of Product & Brand Management, 11*(4), 249-268.

Lindahl, M. (2008). Challenges and Developments in the US Tissue Market. *PERINI Journal, 26*.

Linn, S. (2004). *Consuming Kids: The Hostile Takeover of Childhood.* New York: The New Press.

Lodorfos, G. N., Mulvana, K. L., & Temperley, J. (2006). Consumer Behaviour: Experience, Price, Trust and Subjective Norms in the OTC Pharmaceutical Market. *Innovative Marketing, 2*(3), 41-66.

Luo, C., de.Bruijn, O., & Chen, Y.-w. (2015). Behavioural Segmentation Using Store Scanner Data in Retailing: Exploration and Exploitation in Frequently Purchased Consumer Goods Markets. *Journal of Business & Retail Management Research, 10*(1).

Maassen, H., & Uffink, J. B. (1988). Generalized Entropic Uncertainty Relations. *The American Physical Society, 60*(12), 1103-1106.

Macready, W. G., & Wolpert, D. H. (1998). Bandit Problems and the Exploration/Exploitation Trade-off. *IEEE Transactions on Evolutionary Computation, 2*(1), 2-22.

Mahajan, A., & Teneketzis, D. (2008). Multi-Armed Bandit Problems. In A. O. Hero III, D. A. Castañón, D. Cochran, & K. Kastella, *Foundations and Applications of Sensor Management* (pp. 121-151). Springer-Verlag.

Manchanda, P., Ansari, A., & Gupta, S. (1999). The "Shopping Basket": A Model for Multicategory Purchase Incidence Decisions. *Marketing Science, 18*(2), 95-114.

Mangold, W. G., & Faulds, D. J. (2009). Social Media: The New Hybrid Element of The Promotion Mix. *Business Horizons*, 357-365.

Mann, B. J., & Rashmi. (2010). Predicting Repeat Purchase Behaviour: An Indian Experience. *Asia-Pacific Business Review, VI*(4), 12-17.

March, J. G. (1991). Exploration and Exploitation in Organizational Learning. *Organization Science, 1*, 71-87.

MarketingCharts. (2012, August 23). *CMOs To Pull Back On Traditional Ad Spend; Still Bullish About Online*. Retrieved 11 10, 2015, from MarketingCharts: http://www.marketingcharts.com/uncategorized/cmos-to-pull-back-on-traditional-ad-spend-still-bullish-about-online-23037/?utm_campaign=rssfeed&utm_source=mc&utm_medium=textlink

Martínez, E., & Montaner, T. (2006). The Effect of Consumer's Psychographic Variables Upon Deal-Proneness. *Journal of Retailing and Consumer Services, 13*, 157-168.

Massy, W. F., & Frank, R. E. (1965). Short Term Price and Dealing Effects in Selected Market Segments. *Journal of Marketing Research, 2*(2), 171-185.

McDonald, H., Corkindale, D., & Sharp, B. (2003). Behavioral Versus Demographic Predictors of Early Adoption: A Critical Analysis and Comparative Test. *Journal of Marketing*, 84-97.

McElhatton, N. (2002). Case Study: Tesco. *Direct Response*, 33-34.

McGoldrick, J. P. (2002). *Retail Marketing* (2nd edition ed.). Maidenhead: McGraw-Hill Education.

McGoldrick, P. J., & Andre, E. (1997). Consumer Misbehaviour: Promiscuity or Loyalty in Grocery Shopping. *Journal of Retailing and Consumer Service, 4*(2), 73-81.

Meyer, R. J. (1982). A Descriptive Model of Consumer Information Search Behavior. *Marketing Science, 1*(1), 93-121.

Mislinski, J. (2016, 4 4). *Ratio of Part-Time Employed Remains Higher Than the Pre-Recession Levels*. Retrieved 5 8, 2016, from Advisor Perspectives: http://www.advisorperspectives.com/dshort/updates/Full-Time-vs-Part-Time-Employment

Misra, S., & Nair, H. S. (2011). A Structural Model of Sales-Force Compensation Dynamics: Estimation and Field Implementation. *Quantitative Marketing and Economics*, 211-257.

Mittal, B. (1994). An Integrated Framework for Relating Diverse Consumer Characteristics to Supermarket Coupon Redemption. *Journal of Marketing Research, 31*(4), 533-544.

Montgomery, D. B. (1971). Consumer Characteristics Associated with Dealing: An Empirical Example. *Journal of Marketing Research, 8*(1), 118-120.

Mooij, M. d. (2011). *Consumer Behavior and Culture: Consequences for Global Marketing and Advertising* (2 ed.). California: SAGE Publications, Inc.

Moorthy, S., Ratchford, B. T., & Talukdar, D. (1997). Consumer Information Search Revisited: Theory and Empirical Analysis. *Journal of Consumer Research, 23*(4), 263–277.

Moutinho, L., Davies, F., & Curry, B. (1996). The Impact of Gender on Car Buyer Satisfaction and Loyalty: A Neural Network Analysis. *Journal of Retailing and Consumer Services, 3*(3), 135-144.

Mulhern, F. J., & Leone, R. P. (1991). Implicit Price Bundling of Retail Products: A Multiproduct Approach to Maximizing Store. *Journal of Marketing, 55*(4), 63-76.

Nairn, A., & Bottomley, P. (2003). Something Approaching Science? Cluster Analysis Procedures in CRM Era. *International Journal of Market Research*, 241-261.

Narasimhan, C. (1984). A Price Discrimination Theory of Coupons. *Marketing Science, 3*(2), 128-147.

Narasimhan, C., Neslin, S. A., & Sen, S. K. (1996). Promotional Elasticities and Category Characteristics. *Journal of Marketing, 60*(2), 17-30.

Narayanan, S., Manchanda, P., & Chintagunta, P. K. (2005). Temporal Difference in the Role of Marketing Communication in New Product Categories. *Journal of Marketing Research*, *42*(3), 278-290.

Neelamegham, R., & Jain, D. (1999). Consumer Choice Process for Experience Goods: An Econometric Model and Analysis. *Journal of Marketing Research*, 373-386.

Neslin, S. A., Henderson, C., & Quelch, J. (1985). Consumer Promotions and the Acceleration of Product Purchases. *Marketing Science*, *2*, 147-165.

Niraj, R., Padmanabhan, V., & Seetharaman, P. B. (2008). Research Note—A Cross-Category Model of Households'. *Marketing Science, 27*(2), 225-235.

Odin, Y., Odin, N., & Valette-Florence, P. (2001). Conceptual and Operational Aspects of Brand Loyalty: An Empirical Investigation. *Journal of Business Research, 53*, 75-84.

Odunlami, I. B., & Ogunsiji, A. (2011). Effect of Sales Promotion as a Tool on Organizational Performance: A case Study of Sunshine Plastic Company. *Journal of Emerging Trends in Economics and Management Sciences, 2*(1), 9-13.

OECD. (2014). *Ageing and Employment Policies - Statistics on Average Effective Age of Retirement*. Retrieved 1 28, 2016, from OECD: http://www.oecd.org/els/emp/ageingandemploymentpolicies-statisticsonaverageeffectiveageofretirement.htm

O'Neill, R. M., & Lambert, D. R. (2001). The Emotional Side of Price. *Psychology & Marketing, 18*, 217-237.

Patterson, P. G. (2007). Demographic Correlates of Loyalty in a Service Context. *Journal of Service Marketing, 21*(2), 112-121.

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The Adaptive Decision Maker.* Cambridge: Cambridge University Press.

Pechtl, H. (2004). Profiling Intrinsic Deal Proneness for HILO and EDLP Price Promotion Strategies. *Journal of Retailing and Consumer Services, 11*, 223–233.

Perloff, J. M., & Denbaly, M. (2007). Data Needs for Consumer and Retail Firm Studies. *American Journal of Agricultural Economics, 89*(5), 1282-1287.

Pieters, R., Wedel, M., & Zhang, J. (2007). Optimal Feature Advertising Design under Competitive Clutter. *Management Science, 53*(11), 1815-1828.

Price, L. L., Feick, L. F., & Guskey-Federouch, A. (1988). Couponing Behaviors of the Market Maven: Profile of a Super Couponer. *Advances in Consumer Research, 15*, 354–359.

Radunovic, L. (2014, 7 24). *Kids And Advertising: (Ab)using The Most Vulnerable Target*

Group. Retrieved 1 28, 2016, from .me: http://domain.me/kids-and-advertising/

Raghubir, P., Inman, J. J., & Grande, H. (2004). The Three Faces of Consumer Promotions. *California Management Review, 46*(4), 23–42.

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

Raju, P. S. (1980). Optimum Stimulation Level: Its Relationship to Personality, Demographics, and Exploratory Behavior. *Journal of Consumer Research, 7*, 272-282.

Rakesh, S., & Khare, A. (2012). Impact of Promotions and Value Consciousness in Online Shopping Behaviour in India. *Database Marketing & Customer Strategy Management*, *19*(4), 311-320.

Rao, V. G. (2009). Effect of Sales Promotions on Consumer Preferences - The Moderating Role of Price Perceptions and Deal Proneness (A Study of FMCG Products). *Journal of Management*, 1-18.

Ratchford, B. T. (1980). The Value of Information for Selected Appliances. *Journal of Marketing Research*, *17*(1), 14-25.

Redbus. (2005). *In Store Advertising in the UK*. Retrieved from REDBUS: http://www.redbus.com/in_store_advertising_uk.htm

Richards, T. J. (2006). Sales by Multi-Product Retailers. *Managerial and Decision Economics, 27*(4), 261-277.

Rogers, E. M. (1995). *Diffusion of Innovations* (4th Edition ed.). New York: The Free Press.

Romaniuk, J., & Sharp, B. (2016). *How Brands Grow. Part 2*. Oxford; Oxford University Press.

Rosenkopf, L., & Nerkar, A. (2001). Beyond Local Search: Boundary-Spanning, Exploration, and Impact in the Optical Disk Idustry. *Strategic Management Journal*, *22*(4), 287–306.

Rothaermel, F. T., & Deeds, D. L. (2004). Exploration and Exploitation Alliances in Biotechnology: A System of New Product Development. *Strategic Management Journal, 25*(3), 201-221.

Rowley, J. (2005). Building Brand Webs: Customer Relationship Management Through the Tesco Clubcard Loyalty Scheme. *International Journal of Retail & Distribution Management, 33*(3), 194-206.

Rust, J. (1987). Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher. *Econometrica, 55*(5), 999-1033.

Rust, J. (1994). Structural Estimation of Markov Decision Processes. In R. Engle, & D. L. McFadden, *Handbook of Econometrics* (pp. 3081-3143). Amsterdam: North Holland.

Saad, R., Ishak, H., & Johari, N. R. (2013). The Impact of Demographic Factors Toward Customer Loyalty: A Study on Credit Card Users. *Elixir Marketing Management*, *55*, 13078-13084.

Sambandam, R. (2003). Cluster Analysis: Gets Complicated. *Marketing Research, 15*(1), 16-21.

Sarin, S., Sego, T., & Chanvarasuth, N. (2003). Strategic Use of Bundling for Reducing Consumers' Perceived Risk Associated with the Purchase of New High-Tech Products. *Journal of Marketing Theory and Practice, 11*(3), 71-83.

Sarin, S., Sego, T., & Chanvarasuth, N. (2003). Strategic Use of Bundling for Reducing Consumers' Perceived Risk Associated with the Purchase of New High-Tech Products. *Journal of Marketing Theory and Practice, 11*(3), 71-83.

Sarstedt, M., & Mooi, E. (2014). Cluster Analysis. In M. Sarstedt, & E. Mooi, *A Concise Guide to Market Research: The Process, Data, and Methods Using IBM SPSS Statistics* (2nd ed., pp. 273-324). Heidelberg: Springer.

SAS Institute Inc. (1999). The FASTCLUS Procedure. In S. I. Inc., *SAS/STAT User's Guide* (pp. 1194-1243). Cary: SAS Institute Inc.

SAS Institute Inc. (2009). *Getting Started with SAS Enterprise Miner 6.1.* Cary: SAS Institute Inc.

SAS Institute Inc. (2011). *SAS Enterprise Miner 12.3 Reference Help.* Cary: SAS Institute Inc.

Schaninger, C. M., & Allen, C. T. (1981). Wife's Occupational Status as a Consumer Behavior Construct. *Journal of Consumer Research, 8*(2), 189-196.

Schneider, L. G., & Currim, I. S. (1991). Consumer Purchase Behaviors Associated with Active and Passive Deal-Proneness. *International Journal of Research in Marketing, 8*(3), 205-222.

Schoenborn, C. A., & Heyman, K. M. (2009). Health Characteristics of Adults Aged 55 Years and Over: United States, 2004–2007. *National Health Statistics Reports*(16), 1-31.

Schor, J. B. (2004). *Born to Buy: The Commercialized Child and the New Consumer Culture: The Commercialised Child and the New Consumer Culture.* New York: Scribner.

Schultz, D. E., Robinson, W. A., & Petrison, L. A. (1998). *Sales Promotion Essentials: The 10 Basic Sales Promotion Techniques and How to Use Them* (3rd ed.). Chicago: McGraw-Hill Contemporary.

Sebastian, M. (2015, March 24). *Marketers to Boost Global Ad Spending This Year to $540 Billion*. Retrieved November 10, 2015, from AdvertisingAge: http://adage.com/article/media/marketers-boost-global-ad-spending-540-billion/297737/

Seetharaman, P. B., & Chintagunta, P. (1998). A Model of Inertia and Variety-Seeking With Marketing Variables. *International Journal of Research in Marketing*, 1-17.

Seetharaman, P. B., Ainslie, A., & Chintagunta, P. K. (1999). Investigating Household State Dependence Effects across Categories. *Journal of Marketing Research*, *36*(4), 488-

500.

Sharp, B. (2010). *How Brands Grow*. Oxford: Oxford University Press.

Sharpe, K. M., & Staelin, R. (2010). Consumption Effects of Bundling: Consumer Perceptions, Firm Actions, and Public Policy Implications. *Journal of Public Policy and Marketing*, 170-188.

Shimp, T. A. (1990). *Promotion Management and Marketing Communications.* Hinsdale: Dryden Press.

Shimp, T. A., & Kavas, A. (1984). The Theory of Reasoned Action Applied to Coupon Usage. *Journal of Consumer Research, 11*(3), 795-809.

Sinapuelas, I. C., & Robinson, W. T. (2012). Do Me-Too Brands Price Lower Than the Feature Pioneer? *Journal of Product & Brand Management*, *21*(5), 350-358.

Singh, V. P. (2000). *The Entropy Theory As A Tool for Modelling and Decision-Making in Environmental and Water Resources*. Retrieved 6 2, 2013, from South African Water Research Commission: http://www.wrc.org.za/Knowledge%20Hub%20Documents/Water%20SA%20Journals/Manuscripts/2000/01/WaterSA_2000_01_jan00_p1.pdf

Smith, R. E., & Swinyard, W. R. (1983). Attitude-Behavior Consistency: The Impact of Product Trial Versus Advertising. *Journal of Marketing Research, 20*(3), 257–267.

Song, I., & Chintagunta, P. K. (2007). A Discrete: Continuous Model for Multicategory Purchase Behavior of Households. *Journal of Marketing Research, 44*(4), 595-612.

Statista. (2016). *Snack Dollar Sales in the United States in 2005, 2010 and 2015, by Category (in Billion U.S. Dollars)*. Retrieved 3 28, 2016, from Statista: http://www.statista.com/statistics/257994/snack-dollar-sales-in-the-us-by-category/

Statista. (2016). *Statistics and Facts on the Snack Foods Industry in the U.S.* Retrieved 3 28, 2016, from Statista: http://www.statista.com/topics/1496/snack-foods/

Statista. (2016). *Statistics and Facts on the Yogurt Market in the U.S.* Retrieved 3 28, 2016, from Statista: http://www.statista.com/topics/1739/yogurt/

Strang, R. A., Harris, B. F., & Hernande, A. L. (1979). Consumer Trial of Generic Products in Supermarkets: An Exploratory Study. *Educators'ConferenceProceeding* (pp. 386-388). Chicago: American Marketing Association.

Straughan, R. D., & Albers-Miller, N. D. (2001). An International Investigation of Cultural and Demographic Effects on Domestic Retail Loyalty. *International Marketing Review, 18*(5), 521 - 541.

Stremersch, S., & Tellis, G. J. (2002). Strategic Bundling of Products and Prices: A New Synthesis for Marketing. *Journal of Marketing, 66*(72), 55-72.

Stüttgen, P., Boatwright, P., & Monroe, R. T. (2012). A Satisficing Choice Model. *Marketing Science, 31*(6), 878-899.

Tate, R. S. (1961). The Supermarket Battle for Store Loyalty. *Journal of Marketing, 25*(6), 8-13.

Teel, J. E., Williams, R. H., & Bearden, W. O. (1980). Correlates of Consumer Susceptibility to Coupons in New Grocery Product Introductions. *Journal of Advertising, 9*(3), 31-46.

Teunter, L. H. (2002). *Analysis of Sales Promotion Effects on Household Purchase Behavior.* Rotterdam: Erasmus University Rotterdam.

The Chartered Institute of Marketing. (2009). *How to Achieve An Effective Promotional Mix.* Maidenhead: The Chartered Institute of Marketing.

Thomas, S. G. (2007). *Buy, Buy Baby: How Consumer Culture Manipulates Parents and Harms Young Minds.* New York: Houghton Mifflin Company.

Toubia, O., & Stephen, A. T. (2013). Intrinsic vs. Image-Related Utility in Social Media: Why Do People Contribute Content to Twitter? *Marketing Science, 32*(3), 368-392.

Trefis Team. (2014, 6 27). *Frito-Lay Dominates U.S. Salty Snacks, But Rising Cracker Sales Could Stall Growth*. Retrieved 3 28, 2016, from Forbes: http://www.forbes.com/sites/greatspeculations/2014/06/27/frito-lay-dominates-u-s-salty-snacks-but-rising-cracker-sales-could-stall-growth/#2d7caa57274a

Tushman, M. L., & O'Reilly, C. A. (1996). Ambidextrous Organization: Managing Evolutionary and Revolutionary Change. *California Management Review, 38*(4), 8-30.

U.S. Bureau of Labor Statistics. (2016, 2 10). *Labor Force Statistics from the Current Population Survey*. Retrieved 5 8, 2016, from U.S. Bureau of Labor Statistics: http://www.bls.gov/cps/cpsaat08.htm

U.S. Census Bureau. (2007, August 1). *Age and Sex Composition in the United States: 2004*. Retrieved from United States Census Bureau: https://www.census.gov/population/age/data/2004comp.html

U.S. Census Bureau. (2007, August 1). *Age and Sex Composition in the United States: 2005*. Retrieved from United States Census Bureau: https://www.census.gov/population/age/data/2005comp.html

U.S. Census Bureau. (2009, May). *Age and Sex Composition in the United States: 2006*. Retrieved from United States Census Bureau: https://www.census.gov/population/age/data/2006comp.html

U.S. Census Bureau. (2009, June). *Age and Sex Composition in the United States: 2007*. Retrieved from United States Census Bureau: https://www.census.gov/population/age/data/2007comp.html

Umesh, U. N., Pettit, K. L., & Bozman, C. S. (1989). Shopping Model of the Time-Sensitive Consumer. *Decision Sciences*, *20*(4), 715-729.

Uncles, M. D., & Ehrenderg, A. S. (1990). Brand Choice Among Older Consumers. *Journal of Advertising Research*, 19-22.

Uncles, M., Ehrenberg, A., & Hammond, K. (1995). Patterns of Buyer Behavior:

Regularities, Models, and Extensions. *Marketing Science, 14*(3), G71-G78.

United States Census Bureau. (2010). *Geographic Identifiers 2010 Demographic Profile Data*. Retrieved 3 28, 2016, from United States Census Bureau: http://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=bkmk

United States Census Bureau. (n.d.). *Demographic Data*. Retrieved 7 21, 2016, from United States Census Bureau: https://www.census.gov/ces/dataproducts/demographicdata.html

Urbany, J. E., Dickson, P. R., & Kalapurakal, R. (1996). Price Search in the Retail Grocery Market. *Journal of Marketing, 60*, 91-104.

US Department of Agriculture and Economic Research Service. (2016). *Per Capita Consumption of Yogurt in the United States from 2000 to 2013 (in 1/2 Pints)**. Retrieved 3 28, 2016, from Statista: http://www.statista.com/statistics/184309/per-capita-consumption-of-yogurt-in-the-us-since-2000/

USDEC. (2016). *Yogurt Volume Sales in the United States from 2012 to 2015 (in Billion Pints)**. Retrieved 3 28, 2016, from Statista: http://www.statista.com/statistics/466150/us-yogurt-volume-sales/

Vaishnani, H. B. (2011). *Effects of Sales Promotions on Consumer Preferences and Brand Equity Perception: with specific reference to FMCG Products.* Rajkot: Saurashtra University.

van Heerde, H. J., & Bijmolt, T. H. (2005). Decomposing the Promotional Revenue Bump for Loyalty Program Members versus Nonmembers. *Journal of Marketing Research, 42*(4), 443-457.

Varadarajan, P. R. (1985). Joint Sales Promotion: An Emerging Marketing Tool. *Business Horizons*, 43-49.

Varadarajan, P. R. (1986). Horizontal Cooperative Sales Promotion: A Framework for Classification and Additional Perspectives. *Journal of Marketing*, *50*(2), 61-73.

Vassolo, R. S., Anand, J., & Folta, T. B. (2004). Non-Additivity in Portfolios of Exploration Activities: A Real Options-Based Analysis of Equity Alliances in Biotechnology. *Strategic Management Journal, 25*(11), 1045–1061.

Vermeulen, F., & Barkema, H. (2001). Learning Through Acquisitions. *Academy of Management Journal, 44*(3), 457-476.

Vermorel, J., & Mohri, M. (2005). Multi-Armed Bandit Algorithms and Empirical Evaluation. *ECML*, 437-448.

Viswanathan, M., Rosa, J. A., & Ruth, J. A. (2010). Exchanges in Marketing Systems: The Case of Subsistence Consumer-Merchants in Chennai, India. *Journal of Marketing, 74*, 1-17.

Vyas, P. H. (2005). *Measuring Consumer Preference for Sales Promotion Schemes Through Conjoint Design in FMCG Sector.* Ahmedabad: Indian Institute of Management.

Wakefield, K. L., & Barnes, J. H. (1996). Retailing Hedonic Consumption: A Model of Sales Promotion of A Leisure Service. *Journal of Retailing*, *72*(4), 409-427.

Walters, R. G., & MacKenzie, S. B. (1988). A Structural Equations Analysis of the Impact of Price Promotions on Store Performance. *Journal of Marketing Research, 25*(1), 51-63.

Wardman, M. (1988). A Comparison of Revealed Preferences and Stated Preference Models of Travel Behaviour. *Journal of Transport Economics and Policy, 22*(1), 71-91.

Waterschoot, W. v., & Bulte, C. V. (1992). The 4P Classification of The Marketing Mix Revisited. *Journal of Marketing, 56*, 83-93.

Webster, F. E. (1965). The "Deal-Prone" Consumer. *Journal of Marketing Research, 2*(2), 186-189.

Wernerfelt, B. (1986). A Special Case of Dynamic Pricing Policy. *Management Science, 32*(12), 1562-1566.

Wernerfelt, B. (1991). Brand Loyalty and Market Equilibrium. *Marketing Science, 10*(3), 229-245.

Wierenga, B. (1974). *An Investigation of Brand Choice Processes.* Rotterdam University.

Wirtz, J., & Chew, P. (2002). The effects of incentives, deal proneness, satisfaction and tie strength on word - of - mouth behaviour. *International Journal of Service Industry Management, 13*(2), 141-162.

Wood, L. M. (2004). Dimensions of Brand Purchasing Behaviour: Consumers in the 18–24 Age Group. *Journal of Consumer Behaviour, 4*(1), 9-24.

Wright, C., & Sparks, L. (1999). Loyalty Saturation in Retailing: Exploring the End of Retail Loyalty Cards? *International Journal of Retail & Distribution Management*, *27*(10), 429-440.

Yang, L., Toubia, O., & Jong, M. G. (2015). A Bounded Rationality Model of Information Search and Choice in Preference Measurement. *Journal of Marketing Research, LII*(April 2015), 166-183.

Yang, T.-C., & Lai, H. (2006). Comparison of Product Bundling Strategies on Different Online Shopping Behaviors. *Electronic Commerce Research and Applications, 5*, 295–304.

Yao, S., & Mela, C. F. (2011). A Dynamic Model of Sponsored Search Advertising. *Marketing Science, 30*(3), 447-468.

Yavas, U. (1983). Deal Prone Consumers: A Comparative Profile of Coupon Users and Nonusers. *Proceedings of the 1983 Academy of Marketing Science (AMS) Annual Conference* (pp. 139-142). Miami: Springer, 2015.

Yeshin, T. (2006). *Sales Promotion.* London: Thomson Learning.

Yoon, K., & Tran, T. V. (2011). Revisiting the Relationship Between Consumer Loyalty and Price Sensitivity: The Moderating Role of Deal-Proneness. *Journal of Marketing*

Theory and Practice, *19*(3), 293-306.

Zeitharnl, V. A. (1985). The New Demographics and Market Fragmentation. *Journal of Marketing*, *49*, 64-75.

APPENDICES

Appendix A: Brand Selection Conditions in Product Markets

- Salty snack market

Since consumers can make purchases freely across retailers in Pittsfield, the brands of salty snack available in Pittsfield thus are accessible to all the consumers. In other words, the selected 839 consumers have opportunities to buy 79 brands in 2004, 87 brands in 2005, 98 brands in 2006 and 106 brands in 2007 in their purchase lifecycles. Facing such a large number of brands available for selection, none of the selected consumers explored all the brands available in Pittsfield. The average number of brands tried by a consumer in Pittsfield was 5.76 in 2004, 7.9 in 2005, 9.32 in 2006, and 10.58 in 2007, which is less than 10% of total number of brands available in the market in the associated year. In addition, none of the consumer explored more than 25% of brands available in the market. In 2004 and 2005, the maximum number of brands tried by a consumer was 19. This number increased to 21 in 2006 while the number of brands available by 2007 is 98. In 2007, 24 out of 106 brands are tried by a consumer to increase the market knowledge. In general, the salty snack market in Pittsfield is a dynamic product market with a large number of brands for selection. Consumers in the salty snack market have limited market knowledge and an increased tendency to explore the market via trying alternative brands.

- Yogurt market

In yogurt market, the selected 707 consumers can access to any brands that available for purchase in Pittsfield in their purchase lifecycles. Consumers in Pittsfield thus have opportunities to buy yogurt from 16 brands in 2004, 18 brands by 2006, 21 brands by 2007, and 24 brands by 2008. Differs from salty snack market, the yogurt market has less number of brands available for purchase. Less efforts thus is needed for a consumer to obtain sufficient knowledge about the yogurt market. In this market, the average number of brands tried by a consumer is 4 in 2004, 5.21 in 2005, 5.95 in 2006 and 6.5 in 2007, which accounts for at least 25% of total number of brands available in Pittsfield yogurt market.

On the basis of the quantified exploration tendency, when a consumer explored around 40% of brands available in a product market, the Value of Information from Purchases reaches maximum. The further exploration activities provide consumers a decreased perceived Value of Information from Purchases. In yogurt market, 154 consumer tried no less than 6 out of 16 brands (i.e. when a consumer tried 6 brands in 2004, the Value of Information from Purchases reaches maximum) in 2004. Among those 154 consumers, 4 consumers explored 9 brands in 2004, which is the maximum brands explored by a consumer in 2004. By 2006, 197 consumers explored no less than 7 brands out of 18 brands (i.e. when a consumer tried 7 brands from 2004 to 2005, the Value of Information from Purchases reaches maximum). The maximum number of brands tried by a consumer from 2004 to 2005 is 10. Two consumers tried 10 brands from 2004 to 2005 in Pittsfield yogurt market. By 2007, 157 consumers tried no less than 8 out of 21 brands in Pittsfield yogurt market (i.e. when a consumer tried 8 brands from 2004 to 2006, the Value of Information from Purchases reaches maximum). The largest number of brands tried by a consumer by 2007 is 11. Among those 157 consumers, 4 consumers tried 11 brands from 2004 to 2006. From 2004 to 2007, 24 brands are available in the Pittsfield yogurt market. When a consumer tried 9 out of 24 brands by 2008, the Value of Information from Purchases reaches maximum. From 2004 to 2007, 102 consumers tried no less than 9 brands in Pittsfield market. 10 out of the 102 consumers tried 11 brands. Two out of the 102 consumers tried 12 brands and 13 brands, respectively.

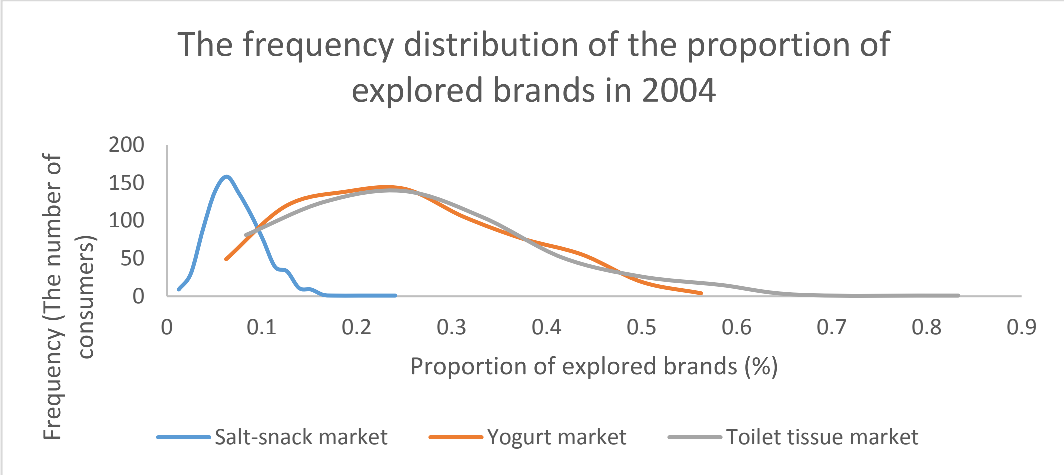
The slightly increased maximum number of brands tried by a consumer over years suggests that consumers' exploration activities tend to be decreased after they obtain a certain amount of market knowledge via trying different brands. The preference to a sub-set of brands will gradually be developed in consumer's purchase lifecycle. Even though new brands are introduced to a dynamic market over years, consumers' brand choices are suggested to be not significantly influenced by the dynamics of the market in the later stage of their purchase lifecycles.

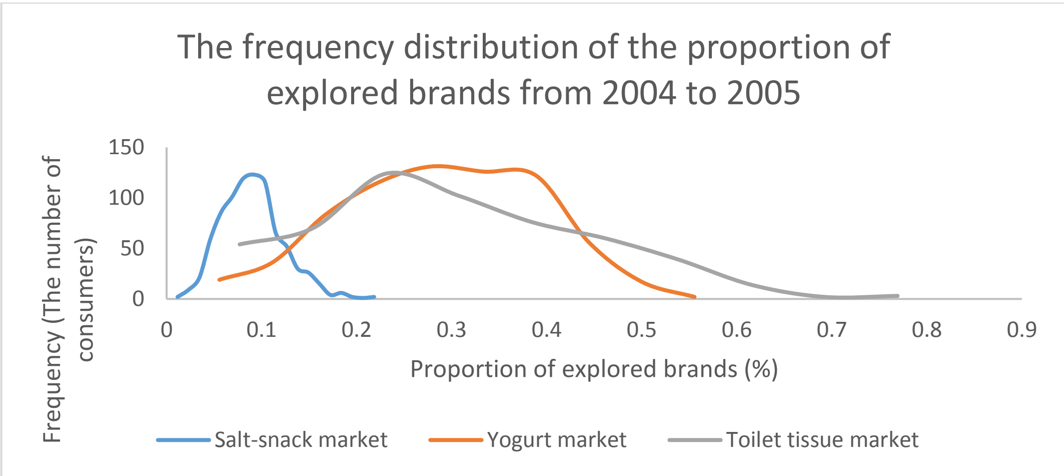
- Toilet tissue market

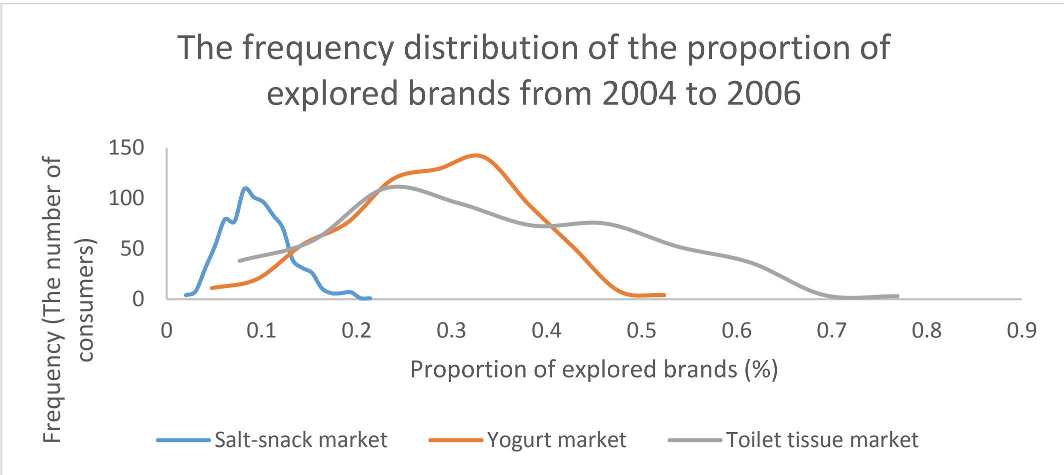
In Pittsfield, 12 brands of toilet tissue are available for purchase in 2004. The average number of brands tried by a consumer in Pittsfield in 2004 is 3.14, which accounts for around 26% of total number of brands available in the market. When consumers purchase four out of 12 brands in the Pittsfield toilet market, their Value of Information from Purchases reach maximum. In 2004, 199 consumers tried at least 4 brands in toilet tissue market. Among the 199 consumers, one consumer tried 10 out of 12 brands in 2004, which is the maximum number of brands tried by a consumer in 2004. In 2005, one new brand was introduced to the toilet market and in total 13 brands are available for purchase in Pittsfield. The average number of brands explored by a consumer in 2005 increased to 3.95, which accounts for around 30% of total number of brands available in the product market in 2005. In 2006, the number of toilet tissue brands available for purchase in Pittsfield market remains unchanged. However, the average number of brands tried by a consumer increased to 4.41, which is around 34% of total number of brands available in the market in 2006. By both of 2006 and 2007, when consumers tried 5 brands in toilet tissue market, their Value of Information from Purchases reach maximum. The number of consumers who tried at least five brands in toilet tissue market increased from 194 by 2006 to 243 by 2007. In 2007, one new brand was introduced to the toilet tissue market again and in total 14 brands are available for consumers to purchase. Consumers' Value of Information from Purchases reach maximum when they tried five brands in the toilet tissue market by 2008. 279 consumers tried at least five brands in the market by 2008. From 2005 to 2007, the maximum number of brands tried by a consumer remains to be 10 even though one new brands was introduced to the market in 2007. Three consumers tried 10 brands in Pittsfield toilet tissue market by 2006. Those three consumers then continuously purchase a sub-set of their preferred brands from 2006. Even though the maximum number of brands tried by a consumer in Pittsfield toilet tissue market remained unchanged from 2004 to 2007, the average number of brands tried by a consumer in the market increased from 3.14 to 4.71 during those four years. In 2007, the average number of brands tried by a consumer accounts for around 34% of total number of brands available in the market.

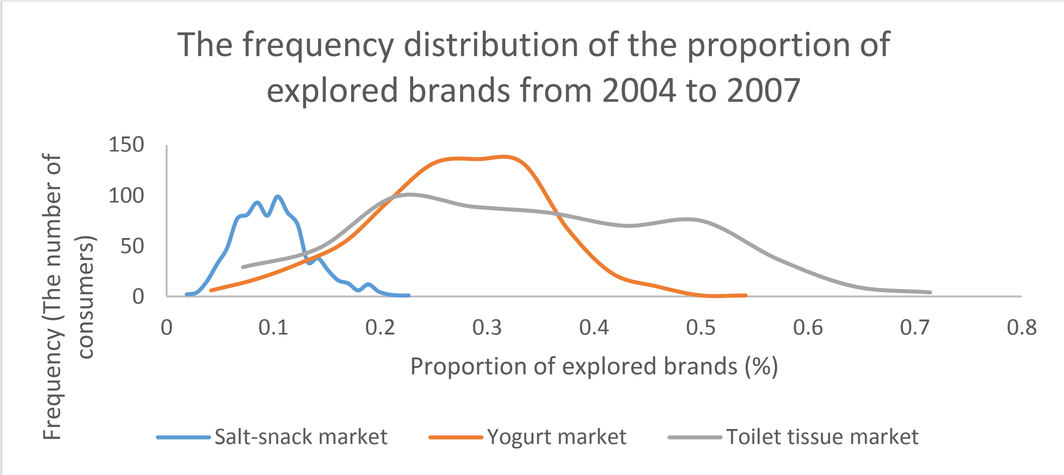
In general, toilet tissue market in Pittsfield is a relatively stable market with a smaller number of brands available for purchases. The increased number of consumers who tried the number of brands to reach maximum Value of Information from Purchases suggests that consumers have the same trend in market exploration but differ in their exploration rates. The same maximum number of brands tried by a consumers regardless of the introduction of new brands to the market over years suggests that consumers might stop their exploration activities and become brand loyal when they obtain sufficient market knowledge.

Appendix B: The Comparison of the Proportion of Explored Brands in Salty snack, Yogurt, and Toilet Tissue Markets in Each Consecutive Years from 2004 to 2007








The frequency distribution of the proportion of explored brands from 2004 to 2007
Frequency (The number of consumers)
150
100
50
0
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Proportion of explored brands (%)
Salt-snack market
Yogurt market
Toilet tissue market

Appendix C: VBA Program for Calculating the Prevalence of Promotion

```
Sub SheetCount()

Dim totalRow As Integer

totalRow = Sheet1.Rows.End(xlDown).Row

Dim dict

Set dict = CreateObject("Scripting.Dictionary")

Dim i As Integer

For i = 2 To totalRow

    If Not dict.exists(Trim(Sheet1.Range("A" & i))) Then

        dict.Add Trim(Sheet1.Range("A" & i)), ""

    End If

Next i

Dim panidCount As Integer

panidCount = dict.Count

Dim dictKeys()

dictKeys = dict.keys

For i = 0 To UBound(dictKeys)

    dict.Item(dictKeys(i)) = WorksheetFunction.CountIf(Sheet1.Range("A:A"),
dictKeys(i))

Next i

Dim j As Integer, k As Integer

Dim panID

Dim panIDNumber As Integer

Dim panIDRow As Integer

Dim Number1ShowCount As Integer

Dim BORowCount As Integer

For i = 0 To UBound(dictKeys)

    panID = dictKeys(i)

    panIDNumber = dict.Item(panID)
```

```
        Number1ShowCount = 0
        BORowCount = 0
         For j = 2 To totalRow
              If CStr(Sheet1.Cells(j, 1).Value) = panID Then
                   panIDRow = Sheet1.Cells(j, 1).Row
                            For k = 0 To panIDNumber - 1
                        BORowCount = BORowCount + 1
                        If Sheet1.Cells(j + k, 28).Value = 1 Then    '28 represents the column of "Promotion Acceptance"
                            Number1ShowCount = Number1ShowCount + 1
                        End If
                        Sheet1.Cells(j + k, 29) = Number1ShowCount    '29 represents the column of "The number of promotional purchases"
                        Sheet1.Cells(j + k, 30) = BORowCount    '30 represents the column of "The number of transactions"
                        If (Number1ShowCount <> 0) Then
                            Sheet1.Cells(j + k, 31) =  Number1ShowCount / BORowCount '31 represents the column of "The prevalence of promotion"
                        End If
                   Next k
                   Exit For
              End If
        Next j
Next i
Set dict = Nothing
End Sub
```

Appendix D: VBA Program for Calculating the Value of Information from Purchases

```
Sub SheetCount()

Dim totalRow As Integer

totalRow = Sheet1.Rows.End(xlDown).Row

Dim dict

Set dict = CreateObject("Scripting.Dictionary")

Dim dictForDisplayedValue

Set dictForDisplayedValue = CreateObject("Scripting.Dictionary")

Dim i As Integer

For i = 2 To totalRow

    If Not dict.exists(Trim(Sheet1.Range("A" & i))) Then

        dict.Add Trim(Sheet1.Range("A" & i)), ""

    End If

Next i

Dim panidCount As Integer

panidCount = dict.Count

Dim dictKeys()

dictKeys = dict.keys

For i = 0 To UBound(dictKeys)

    dict.Item(dictKeys(i)) = WorksheetFunction.CountIf(Sheet1.Range("A:A"), dictKeys(i))

Next i

Dim j As Integer, k As Integer

Dim panID

Dim panIDNumber As Integer

Dim panIDRow As Integer

Dim newResult As Integer

Dim p As Double

Dim newLogResult As Double
```

```
Dim newPLogResult As Double

For i = 0 To UBound(dictKeys)

    panID = dictKeys(i)

    panIDNumber = dict.Item(panID)

    newResult = 0

    For j = 2 To totalRow

        If CStr(Sheet1.Cells(j, 1).Value) = panID Then

            panIDRow = Sheet1.Cells(j, 1).Row

            For m = 0 To panIDNumber - 1

            If Not dictForDisplayedValue.exists(Trim(Sheet1.Cells(panIDRow + m, 8))) Then '8 represents the column of “VEND”

                dictForDisplayedValue.Add Trim(Sheet1.Cells(panIDRow + m, 8)), ""

                newResult = newResult + 1

            End If

            Sheet1.Cells(panIDRow + m, 32) = newResult '32 represents the column of “n” (i.e. the number of brands tried by a consumer)

            p = newResult / 24 '24 represents the number of brands available in a product market

            Sheet1.Cells(panIDRow + m, 33) = p '33 represents the column of “Market knowledge”

            newLogResult = WorksheetFunction.Log(p, 2)

            Sheet1.Cells(panIDRow + m, 34) = -newLogResult '34 represents the column of “Obtainable value of information from purchase”

            newPLogResult = WorksheetFunction.Log(p, 2) * p

            Sheet1.Cells(panIDRow + m, 35) = -newPLogResult '35 represents the column of “Value of information from purchase”

            Next m

        Exit For

        End If

    Next j

    dictForDisplayedValue.RemoveAll
```

```
Next i

Set dict = Nothing

End Sub
```

Appendix E: VBA Program for Calculating the Normalized Brand Switching

The calculation of the normalized brand switching consists of three steps.

Step1: For calculating the normalized brand switching, the information about the brand switch type in transactional records need to be generated. The following program is used to generating the information of brand switch type in transactional records.

```
Sub SheetCount()

Dim totalRow As Integer

totalRow = Sheet1.Rows.End(xlDown).Row

Dim dict

Set dict = CreateObject("Scripting.Dictionary")

Dim i As Integer

For i = 2 To totalRow

    If Not dict.exists(Trim(Sheet1.Range("A" & i))) Then

        dict.Add Trim(Sheet1.Range("A" & i)), ""

    End If

Next i

Dim panidCount As Integer

panidCount = dict.Count

Dim dictKeys()

dictKeys = dict.keys

For i = 0 To UBound(dictKeys)

    dict.Item(dictKeys(i)) = WorksheetFunction.CountIf(Sheet1.Range("A:A"), dictKeys(i))

Next i

Dim j As Integer, k As Integer

Dim panID

Dim panIDNumber As Integer

Dim panIDRow As Integer

For i = 0 To UBound(dictKeys)

    panID = dictKeys(i)
```

```
        panIDNumber = dict.Item(panID)

        For j = 2 To totalRow

                If CStr(Sheet1.Cells(j, 1).Value) = panID Then

                        panIDRow = Sheet1.Cells(j, 1).Row

                        For k = 0 To panIDNumber - 2
Sheet1.Cells(panIDRow + k + 1, 18) = Sheet1.Cells(panIDRow + k, 11) & "#" &
Sheet1.Cells(panIDRow + k + 1, 11)        '11 represents the column of "VEND"; 18
represents the column of brand switch type

                        Next k

  Exit For

                End If

        Next j

Next i

Set dict = Nothing

End Sub
```

Step 2: The calculation of brand switching

```
Sub SheetCount()

Dim totalRow As Integer

totalRow = Sheet2.Rows.End(xlDown).Row

Dim dict

Set dict = CreateObject("Scripting.Dictionary")

Dim i As Integer

For i = 2 To totalRow

        If Not dict.exists(Trim(Sheet2.Range("A" & i))) Then

                dict.Add Trim(Sheet2.Range("A" & i)), ""

        End If

Next i

Dim panidCount As Integer

panidCount = dict.Count

Dim dictKeys()
```

```
dictKeys = dict.keys
For i = 0 To UBound(dictKeys)
    dict.Item(dictKeys(i)) = WorksheetFunction.CountIf(Sheet2.Range("A:A"), dictKeys(i))
Next i
Dim j As Integer, k As Integer
Dim panID
Dim panIDNumber As Integer
Dim panIDRow As Integer
Dim dictRrow
Set dictRrow = CreateObject("Scripting.Dictionary")
For i = 0 To UBound(dictKeys)
    panID = dictKeys(i)
    panIDNumber = dict.Item(panID)
    For j = 2 To totalRow
        If CStr(Sheet2.Cells(j, 1).Value) = panID Then
            panIDRow = Sheet2.Cells(j, 1).Row
                dictRrow.RemoveAll
            Dim dataStr
            Dim showCount As Integer
            showCount = 0
            For k = 1 To panIDNumber - 1
                showCount = showCount + 1
                dataStr = Sheet2.Cells(panIDRow + k, 18)        '18 represents the column of brand switch type
                If dictRrow.exists(dataStr) = True Then
                    dictRrow.Item(dataStr) = dictRrow.Item(dataStr) + 1
                Else
                    dictRrow.Add dataStr, 1
```

```
End If
Dim dictRKey()
dictRKey = dictRrow.keys
Dim resultStr As String
  Dim m As Integer
For m = 0 To UBound(dictRKey)
        resultStr = Sheet2.Cells(panIDRow + k, 19)      '19 represents the column of the transitional probability P(Xn)
        resultStr = resultStr & dictRrow.Item(dictRKey(m)) & "/" & showCount
        If m <> UBound(dictRKey) Then
                resultStr = resultStr & ","
        End If
        Sheet2.Cells(panIDRow + k, 19) = resultStr      '19 represents the column of the transitional probability P(Xn)
Next m
Dim LogdataArray() As String
Dim LogdataArraySub() As String
Dim resultLogStr As String
resultLogStr = ""
Dim resultPLogStr As String
resultPLogStr = ""
Dim Plog As Double
Dim SumPlog As Double
SumPlog = 0
Dim Numerator As Double
Dim Denominator As Double
LogdataArray = Split(Sheet2.Cells(panIDRow + k, 19), ",")       '19 represents the column of the transitional probability P(Xn)
If UBound(LogdataArray) = 0 Then
```

```
                    LogdataArraySub = Split(LogdataArray(0), "/")
                    Numerator = CDbl(LogdataArraySub(0))
                    Denominator = CDbl(LogdataArraySub(1))
                    resultLogStr = WorksheetFunction.Log(Numerator / Denominator, 2)
                    Plog = WorksheetFunction.Log(Numerator / Denominator, 2) * (Numerator / Denominator)
                    SumPlog = SumPlog + Plog
                    resultPLogStr = Plog
                Else
                    For m = 0 To UBound(LogdataArray)
                        LogdataArraySub = Split(LogdataArray(m), "/")
                        Numerator = LogdataArraySub(0)
                        Denominator = LogdataArraySub(1)
                        resultLogStr = resultLogStr & WorksheetFunction.Log(Numerator / Denominator, 2) & ","
                        Plog = WorksheetFunction.Log(Numerator / Denominator, 2) * (Numerator / Denominator)
                        SumPlog = SumPlog + Plog
                        resultPLogStr = resultPLogStr & Plog & ","
                    Next m
                End If
                Sheet2.Cells(panIDRow + k, 20) = resultLogStr     '20 represents the column of the log_2 P(Xn)
                Sheet2.Cells(panIDRow + k, 21) = resultPLogStr '21 represents the column of the P(Xn) * log_2 P(Xn)
                Sheet2.Cells(panIDRow + k, 22) = -SumPlog    '22 represents the column of the brand switching
            Next k
            Exit For
        End If
```

```
        Next j
Next i
Set dict = Nothing
End Sub
```

Step 3: The calculation of the normalized brand switching

```
Sub SheetCount()
Dim totalRow As Integer
totalRow = Sheet1.Rows.End(xlDown).Row
Dim dict
Set dict = CreateObject("Scripting.Dictionary")
Dim i As Integer
For i = 2 To totalRow
        If Not dict.exists(Trim(Sheet1.Range("A" & i))) Then
                dict.Add Trim(Sheet1.Range("A" & i)), ""
        End If
Next i
Dim panidCount As Integer
panidCount = dict.Count
Dim dictKeys()
dictKeys = dict.keys
For i = 0 To UBound(dictKeys)
        dict.Item(dictKeys(i)) = WorksheetFunction.CountIf(Sheet1.Range("A:A"), dictKeys(i))
Next i
Dim j As Integer, k As Integer
Dim panID
Dim panIDNumber As Integer
Dim panIDRow As Integer
For i = 0 To UBound(dictKeys)
```

```
        panID = dictKeys(i)

        panIDNumber = dict.Item(panID)

        For j = 2 To totalRow

            If CStr(Sheet1.Cells(j, 1).Value) = panID Then

                panIDRow = Sheet1.Cells(j, 1).Row

                For m = 0 To panIDNumber – 2

Sheet1.Cells(panIDRow + m + 1, 23) = Sheet1.Cells(panIDRow + m + 1, 22) / 6.83289

'22 represents the column of the brand switching; 23 represents the column of the normalized brand switching; 6.83289 is the −∑_{i=0}^{n}(1/n)log_2(1/n) where n is the number of brands available in a retail market

                Next m

Exit For

            End If

        Next j

Next i

Set dict = Nothing

End Sub
```

Appendix F: Results of Correlation Analysis in Variable Selection

Salty snack market in 2004

Correlations

		Value of information from purchases	Prevalence of promotion	Prevalence of advertising	Prevalence of point-of-display	Prevalence of price-reduction	Normalized brand switching
Value of information from purchases	Pearson Correlation	1	.025	-.014	-.043	.031	.797**
	Sig. (2-tailed)		.463	.678	.210	.368	.000
	N	839	839	839	839	839	839
Prevalence of promotion	Pearson Correlation	.025	1	.756**	.883**	.705**	.044
	Sig. (2-tailed)	.463		.000	.000	.000	.203
	N	839	839	839	839	839	839
Prevalence of advertising	Pearson Correlation	-.014	.756**	1	.600**	.814**	-.011
	Sig. (2-tailed)	.678	.000		.000	.000	.743
	N	839	839	839	839	839	839
Prevalence of point-of-display	Pearson Correlation	-.043	.883**	.600**	1	.457**	-.092**
	Sig. (2-tailed)	.210	.000	.000		.000	.008
	N	839	839	839	839	839	839
Prevalence of price-reduction	Pearson Correlation	.031	.705**	.814**	.457**	1	.096**
	Sig. (2-tailed)	.368	.000	.000	.000		.006
	N	839	839	839	839	839	839
Normalized brand switching	Pearson Correlation	.797**	.044	-.011	-.092**	.096**	1
	Sig. (2-tailed)	.000	.203	.743	.008	.006	
	N	839	839	839	839	839	839

**. Correlation is significant at the 0.01 level (2-tailed).

Salty snack market in 2005

Correlations

		Value of information from purchases	Prevalence of promotion	Prevalence of advertising	Prevalence of point-of-display	Prevalence of price-reduction	Normalized brand switching
Value of information from purchases	Pearson Correlation	1	-.024	-.045	-.085*	.027	.727**
	Sig. (2-tailed)		.482	.189	.013	.430	.000
	N	839	839	839	839	839	839
Prevalence of promotion	Pearson Correlation	-.024	1	.759**	.899**	.746**	.005
	Sig. (2-tailed)	.482		.000	.000	.000	.880
	N	839	839	839	839	839	839
Prevalence of advertising	Pearson Correlation	-.045	.759**	1	.616**	.836**	-.008
	Sig. (2-tailed)	.189	.000		.000	.000	.816
	N	839	839	839	839	839	839
Prevalence of point-of-display	Pearson Correlation	-.085*	.899**	.616**	1	.516**	-.150**
	Sig. (2-tailed)	.013	.000	.000		.000	.000
	N	839	839	839	839	839	839
Prevalence of price-reduction	Pearson Correlation	.027	.746**	.836**	.516**	1	.113**
	Sig. (2-tailed)	.430	.000	.000	.000		.001
	N	839	839	839	839	839	839
Normalized brand switching	Pearson Correlation	.727**	.005	-.008	-.150**	.113**	1
	Sig. (2-tailed)	.000	.880	.816	.000	.001	
	N	839	839	839	839	839	839

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Salty snack market in 2006

Correlations

		Value of information from purchases	Prevalence of promotion	Prevalence of advertising	Prevalence of point-of-display	Prevalence of price-reduction	Normalized brand switching
Value of information from purchases	Pearson Correlation	1	-.040	-.066	-.099**	.020	.688**
	Sig. (2-tailed)		.247	.056	.004	.566	.000
	N	839	839	839	839	839	839
Prevalence of promotion	Pearson Correlation	-.040	1	.742**	.911**	.749**	.009
	Sig. (2-tailed)	.247		.000	0.000	.000	.790
	N	839	839	839	839	839	839
Prevalence of advertising	Pearson Correlation	-.066	.742**	1	.588**	.858**	-.015
	Sig. (2-tailed)	.056	.000		.000	.000	.663
	N	839	839	839	839	839	839
Prevalence of point-of-display	Pearson Correlation	-.099**	.911**	.588**	1	.526**	-.147**
	Sig. (2-tailed)	.004	0.000	.000		.000	.000
	N	839	839	839	839	839	839
Prevalence of price-reduction	Pearson Correlation	.020	.749**	.858**	.526**	1	.114**
	Sig. (2-tailed)	.566	.000	.000	.000		.001
	N	839	839	839	839	839	839
Normalized brand switching	Pearson Correlation	.688**	.009	-.015	-.147**	.114**	1
	Sig. (2-tailed)	.000	.790	.663	.000	.001	
	N	839	839	839	839	839	839

**. Correlation is significant at the 0.01 level (2-tailed).

Salty snack market in 2007

Correlations

		Value of information from purchases	Prevalence of promotion	Prevalence of advertising	Prevalence of point-of-display	Prevalence of price-reduction	Normalized brand switching
Value of information from purchases	Pearson Correlation	1	-.039	-.084*	-.095**	.017	.669**
	Sig. (2-tailed)		.262	.015	.006	.626	.000
	N	839	839	839	839	839	839
Prevalence of promotion	Pearson Correlation	-.039	1	.741**	.916**	.770**	.013
	Sig. (2-tailed)	.262		.000	0.000	.000	.714
	N	839	839	839	839	839	839
Prevalence of advertising	Pearson Correlation	-.084*	.741**	1	.597**	.864**	-.046
	Sig. (2-tailed)	.015	.000		.000	.000	.179
	N	839	839	839	839	839	839
Prevalence of point-of-display	Pearson Correlation	-.095**	.916**	.597**	1	.555**	-.140**
	Sig. (2-tailed)	.006	0.000	.000		.000	.000
	N	839	839	839	839	839	839
Prevalence of price-reduction	Pearson Correlation	.017	.770**	.864**	.555**	1	.102**
	Sig. (2-tailed)	.626	.000	.000	.000		.003
	N	839	839	839	839	839	839
Normalized brand switching	Pearson Correlation	.669**	.013	-.046	-.140**	.102**	1
	Sig. (2-tailed)	.000	.714	.179	.000	.003	
	N	839	839	839	839	839	839

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Yogurt market in 2004

Correlations

		Prevalence of promotion	Value of information from purchases	Prevalence of advertising	Prevalence of point-of-display	Prevalence of price-reduction	Normalized brand switching
Prevalence of promotion	Pearson Correlation	1	.084*	.969**	.388**	.973**	.142**
	Sig. (2-tailed)		.026	0.000	.000	0.000	.000
	N	707	707	707	707	707	707
Value of information from purchases	Pearson Correlation	.084*	1	.089*	.013	.094*	.840**
	Sig. (2-tailed)	.026		.018	.733	.013	.000
	N	707	707	707	707	707	707
Prevalence of advertising	Pearson Correlation	.969**	.089*	1	.385**	.948**	.149**
	Sig. (2-tailed)	0.000	.018		.000	0.000	.000
	N	707	707	707	707	707	707
Prevalence of point-of-display	Pearson Correlation	.388**	.013	.385**	1	.392**	-.009
	Sig. (2-tailed)	.000	.733	.000		.000	.816
	N	707	707	707	707	707	707
Prevalence of price-reduction	Pearson Correlation	.973**	.094*	.948**	.392**	1	.149**
	Sig. (2-tailed)	0.000	.013	0.000	.000		.000
	N	707	707	707	707	707	707
Normalized brand switching	Pearson Correlation	.142**	.840**	.149**	-.009	.149**	1
	Sig. (2-tailed)	.000	.000	.000	.816	.000	
	N	707	707	707	707	707	707

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Yogurt market in 2005

Correlations

		Prevalence of promotion	Value of information from purchases	Prevalence of advertising	Prevalence of point-of-display	Prevalence of price-reduction	Normalized brand switching
Prevalence of promotion	Pearson Correlation	1	.171**	.962**	.473**	.983**	.257**
	Sig. (2-tailed)		.000	0.000	.000	0.000	.000
	N	707	707	707	707	707	707
Value of information from purchases	Pearson Correlation	.171**	1	.188**	.095*	.162**	.753**
	Sig. (2-tailed)	.000		.000	.011	.000	.000
	N	707	707	707	707	707	707
Prevalence of advertising	Pearson Correlation	.962**	.188**	1	.498**	.944**	.267**
	Sig. (2-tailed)	0.000	.000		.000	0.000	.000
	N	707	707	707	707	707	707
Prevalence of point-of-display	Pearson Correlation	.473**	.095*	.498**	1	.450**	.113**
	Sig. (2-tailed)	.000	.011	.000		.000	.003
	N	707	707	707	707	707	707
Prevalence of price-reduction	Pearson Correlation	.983**	.162**	.944**	.450**	1	.247**
	Sig. (2-tailed)	0.000	.000	0.000	.000		.000
	N	707	707	707	707	707	707
Normalized brand switching	Pearson Correlation	.257**	.753**	.267**	.113**	.247**	1
	Sig. (2-tailed)	.000	.000	.000	.003	.000	
	N	707	707	707	707	707	707

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Yogurt market in 2006

Correlations

		Prevalence of promotion	Value of information from purchases	Prevalence of advertising	Prevalence of point-of-display	Prevalence of price-reduction	Normalized brand switching
Prevalence of promotion	Pearson Correlation	1	.221**	.969**	.459**	.988**	.269**
	Sig. (2-tailed)		.000	0.000	.000	0.000	.000
	N	707	707	707	707	707	707
Value of information from purchases	Pearson Correlation	.221**	1	.215**	.121**	.207**	.740**
	Sig. (2-tailed)	.000		.000	.001	.000	.000
	N	707	707	707	707	707	707
Prevalence of advertising	Pearson Correlation	.969**	.215**	1	.488**	.957**	.254**
	Sig. (2-tailed)	0.000	.000		.000	0.000	.000
	N	707	707	707	707	707	707
Prevalence of point-of-display	Pearson Correlation	.459**	.121**	.488**	1	.429**	.120**
	Sig. (2-tailed)	.000	.001	.000		.000	.001
	N	707	707	707	707	707	707
Prevalence of price-reduction	Pearson Correlation	.988**	.207**	.957**	.429**	1	.250**
	Sig. (2-tailed)	0.000	.000	0.000	.000		.000
	N	707	707	707	707	707	707
Normalized brand switching	Pearson Correlation	.269**	.740**	.254**	.120**	.250**	1
	Sig. (2-tailed)	.000	.000	.000	.001	.000	
	N	707	707	707	707	707	707

**. Correlation is significant at the 0.01 level (2-tailed).

Yogurt market in 2007

Correlations

		Prevalence of promotion	Value of information from purchases	Prevalence of advertising	Prevalence of point-of-display	Prevalence of price-reduction	Normalized brand switching
Prevalence of promotion	Pearson Correlation	1	.225**	.965**	.454**	.989**	.259**
	Sig. (2-tailed)		.000	0.000	.000	0.000	.000
	N	707	707	707	707	707	707
Value of information from purchases	Pearson Correlation	.225**	1	.223**	.116**	.210**	.737**
	Sig. (2-tailed)	.000		.000	.002	.000	.000
	N	707	707	707	707	707	707
Prevalence of advertising	Pearson Correlation	.965**	.223**	1	.484**	.953**	.245**
	Sig. (2-tailed)	0.000	.000		.000	0.000	.000
	N	707	707	707	707	707	707
Prevalence of point-of-display	Pearson Correlation	.454**	.116**	.484**	1	.416**	.080*
	Sig. (2-tailed)	.000	.002	.000		.000	.034
	N	707	707	707	707	707	707
Prevalence of price-reduction	Pearson Correlation	.989**	.210**	.953**	.416**	1	.241**
	Sig. (2-tailed)	0.000	.000	0.000	.000		.000
	N	707	707	707	707	707	707
Normalized brand switching	Pearson Correlation	.259**	.737**	.245**	.080*	.241**	1
	Sig. (2-tailed)	.000	.000	.000	.034	.000	
	N	707	707	707	707	707	707

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Toilet tissue market in 2004

Correlations

		Prevalence of promotion	Value of information from purchases	Prevalence of advertising	Prevalence of point-of-display	Prevalence of price-reduction	Normalized brand switching
Prevalence of promotion	Pearson Correlation	1	.016	.936**	.852**	.974**	.068
	Sig. (2-tailed)		.709	.000	.000	0.000	.111
	N	544	544	544	544	544	544
Value of information from purchases	Pearson Correlation	.016	1	-.003	-.006	-.011	.799**
	Sig. (2-tailed)	.709		.942	.894	.793	.000
	N	544	544	544	544	544	544
Prevalence of advertising	Pearson Correlation	.936**	-.003	1	.845**	.940**	.040
	Sig. (2-tailed)	.000	.942		.000	.000	.346
	N	544	544	544	544	544	544
Prevalence of point-of-display	Pearson Correlation	.852**	-.006	.845**	1	.818**	.031
	Sig. (2-tailed)	.000	.894	.000		.000	.467
	N	544	544	544	544	544	544
Prevalence of price-reduction	Pearson Correlation	.974**	-.011	.940**	.818**	1	.034
	Sig. (2-tailed)	0.000	.793	.000	.000		.423
	N	544	544	544	544	544	544
Normalized brand switching	Pearson Correlation	.068	.799**	.040	.031	.034	1
	Sig. (2-tailed)	.111	.000	.346	.467	.423	
	N	544	544	544	544	544	544

**. Correlation is significant at the 0.01 level (2-tailed).

Toilet tissue market 2005

Correlations

		Prevalence of promotion	Value of information from purchases	Prevalence of advertising	Prevalence of point-of-display	Prevalence of price-reduction	Normalized brand switching
Prevalence of promotion	Pearson Correlation	1	.052	.974**	.897**	.984**	.172**
	Sig. (2-tailed)		.228	0.000	.000	0.000	.000
	N	544	544	544	544	544	544
Value of information from purchases	Pearson Correlation	.052	1	.031	.018	.030	.674**
	Sig. (2-tailed)	.228		.473	.678	.478	.000
	N	544	544	544	544	544	544
Prevalence of advertising	Pearson Correlation	.974**	.031	1	.895**	.971**	.139**
	Sig. (2-tailed)	0.000	.473		.000	0.000	.001
	N	544	544	544	544	544	544
Prevalence of point-of-display	Pearson Correlation	.897**	.018	.895**	1	.887**	.089*
	Sig. (2-tailed)	.000	.678	.000		.000	.037
	N	544	544	544	544	544	544
Prevalence of price-reduction	Pearson Correlation	.984**	.030	.971**	.887**	1	.139**
	Sig. (2-tailed)	0.000	.478	0.000	.000		.001
	N	544	544	544	544	544	544
Normalized brand switching	Pearson Correlation	.172**	.674**	.139**	.089*	.139**	1
	Sig. (2-tailed)	.000	.000	.001	.037	.001	
	N	544	544	544	544	544	544

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Toilet tissue market 2006

Correlations

		Prevalence of promotion	Value of information from purchases	Prevalence of advertising	Prevalence of point-of-display	Prevalence of price-reduction	Normalized brand switching
Prevalence of promotion	Pearson Correlation	1	.015	.972**	.914**	.985**	.216**
	Sig. (2-tailed)		.735	0.000	.000	0.000	.000
	N	544	544	544	544	544	544
Value of information from purchases	Pearson Correlation	.015	1	.003	.001	-.004	.490**
	Sig. (2-tailed)	.735		.941	.976	.933	.000
	N	544	544	544	544	544	544
Prevalence of advertising	Pearson Correlation	.972**	.003	1	.909**	.972**	.171**
	Sig. (2-tailed)	0.000	.941		.000	0.000	.000
	N	544	544	544	544	544	544
Prevalence of point-of-display	Pearson Correlation	.914**	.001	.909**	1	.900**	.136**
	Sig. (2-tailed)	.000	.976	.000		.000	.002
	N	544	544	544	544	544	544
Prevalence of price-reduction	Pearson Correlation	.985**	-.004	.972**	.900**	1	.176**
	Sig. (2-tailed)	0.000	.933	0.000	.000		.000
	N	544	544	544	544	544	544
Normalized brand switching	Pearson Correlation	.216**	.490**	.171**	.136**	.176**	1
	Sig. (2-tailed)	.000	.000	.000	.002	.000	
	N	544	544	544	544	544	544

**. Correlation is significant at the 0.01 level (2-tailed).

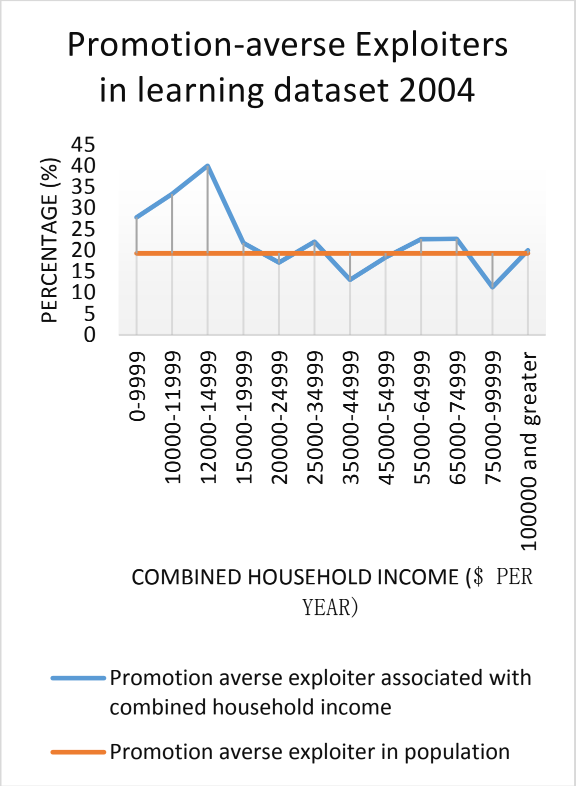
Toilet tissue market 2007

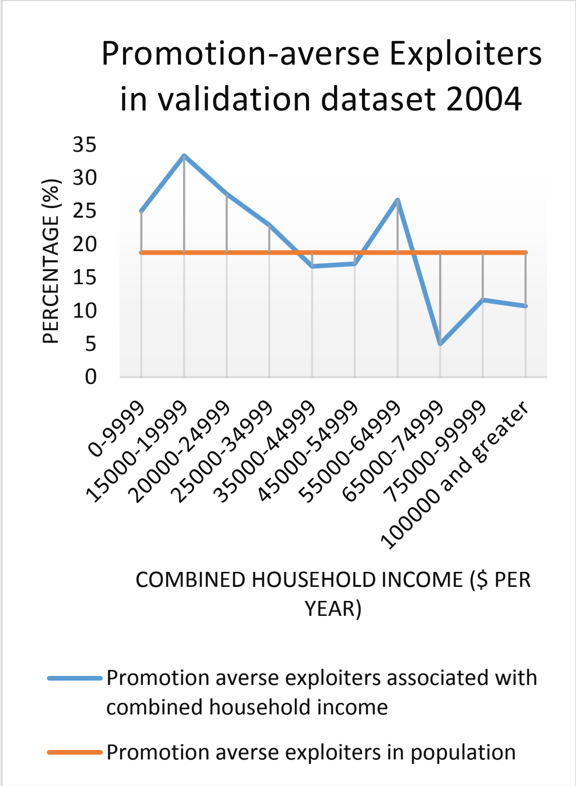
Correlations

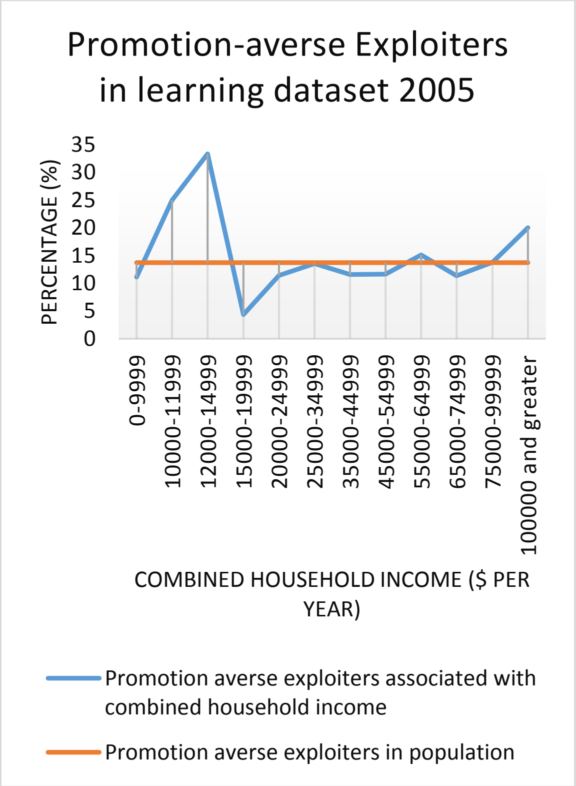
		Prevalence of promotion	Value of information from purchases	Prevalence of advertising	Prevalence of point-of-display	Prevalence of price-reduction	Normalized brand switching
Prevalence of promotion	Pearson Correlation	1	.021	.974**	.930**	.985**	.218**
	Sig. (2-tailed)		.633	0.000	.000	0.000	.000
	N	544	544	544	544	544	544
Value of information from purchases	Pearson Correlation	.021	1	-.001	-.007	-.013	.522**
	Sig. (2-tailed)	.633		.988	.880	.767	.000
	N	544	544	544	544	544	544
Prevalence of advertising	Pearson Correlation	.974**	-.001	1	.926**	.973**	.168**
	Sig. (2-tailed)	0.000	.988		.000	0.000	.000
	N	544	544	544	544	544	544
Prevalence of point-of-display	Pearson Correlation	.930**	-.007	.926**	1	.916**	.138**
	Sig. (2-tailed)	.000	.880	.000		.000	.001
	N	544	544	544	544	544	544
Prevalence of price-reduction	Pearson Correlation	.985**	-.013	.973**	.916**	1	.173**
	Sig. (2-tailed)	0.000	.767	0.000	.000		.000
	N	544	544	544	544	544	544
Normalized brand switching	Pearson Correlation	.218**	.522**	.168**	.138**	.173**	1
	Sig. (2-tailed)	.000	.000	.000	.001	.000	
	N	544	544	544	544	544	544

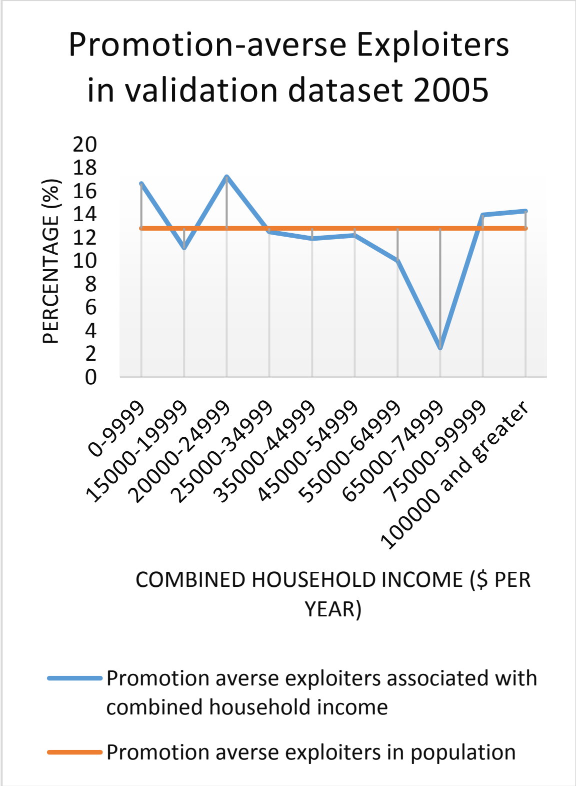
**. Correlation is significant at the 0.01 level (2-tailed).

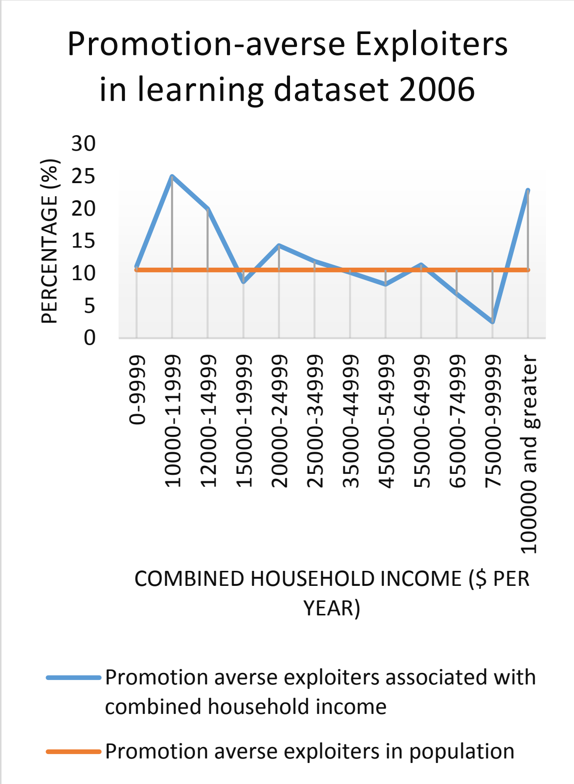
Appendix G: The Improved Performance of Targeting Promotion-averse Exploiters via Using the Combined Household Income in Pittsfield Salty Snack Market

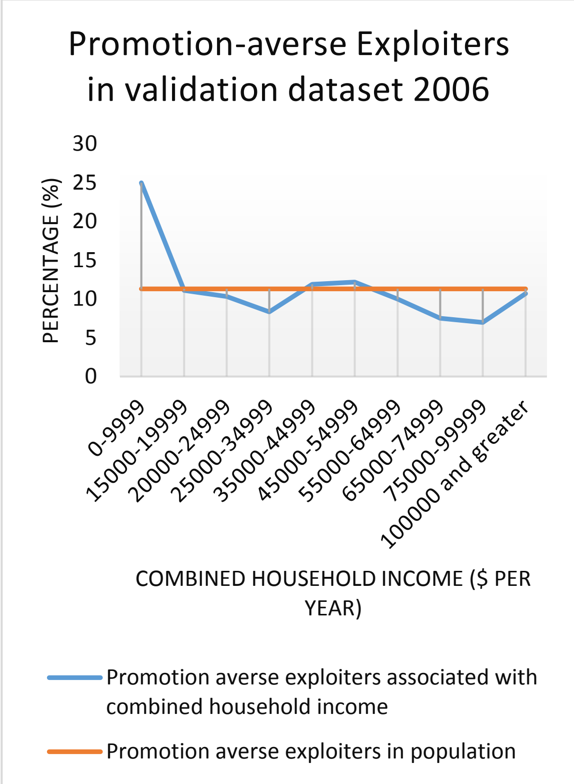


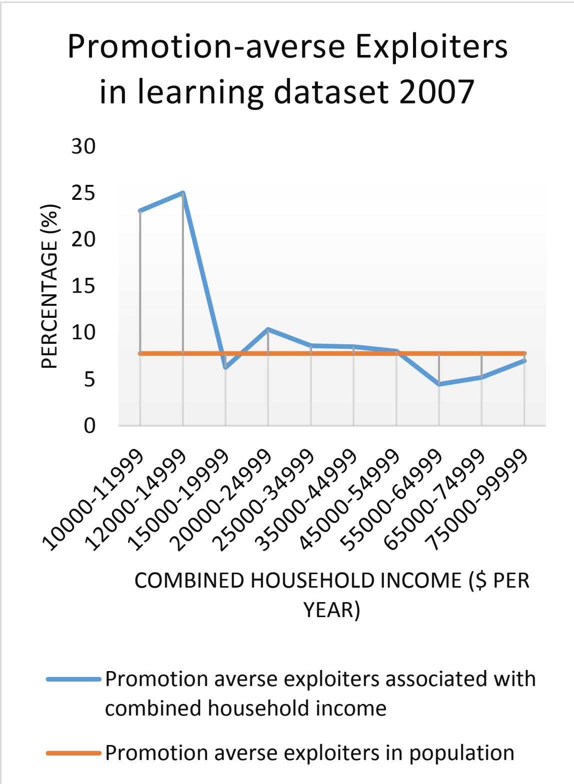


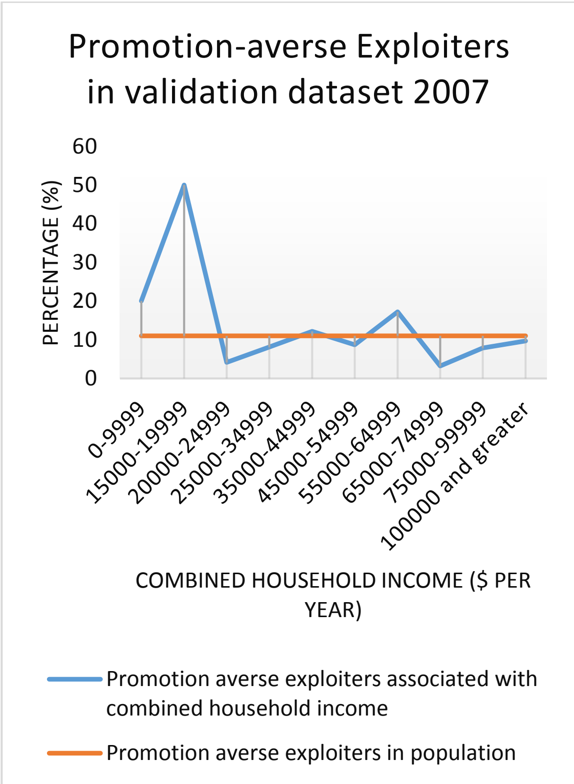




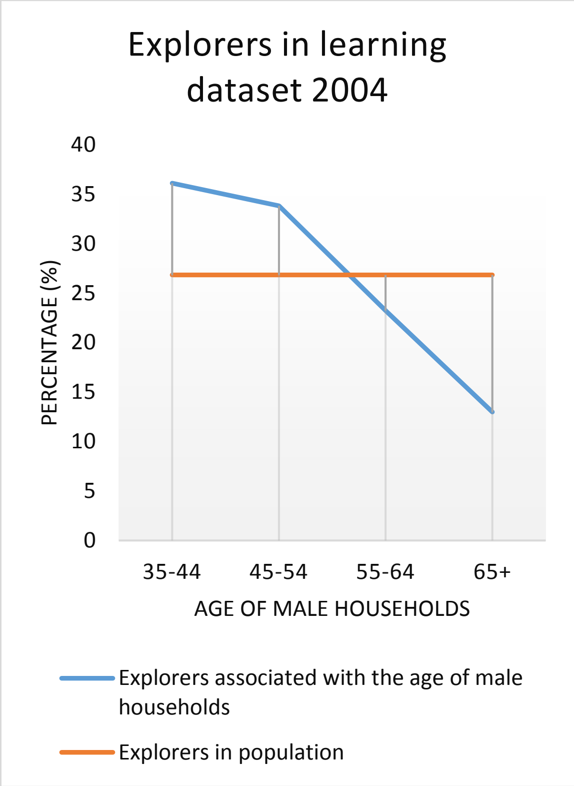

Promotion-averse Exploiters in learning dataset 2006
PERCENTAGE (%)
30
25
20
15
10
5
0
0-9999
10000-11999
12000-14999
15000-19999
20000-24999
25000-34999
35000-44999
45000-54999
55000-64999
65000-74999
75000-99999
100000 and greater
COMBINED HOUSEHOLD INCOME ($ PER YEAR)
Promotion averse exploiters associated with combined household income
Promotion averse exploiters in population

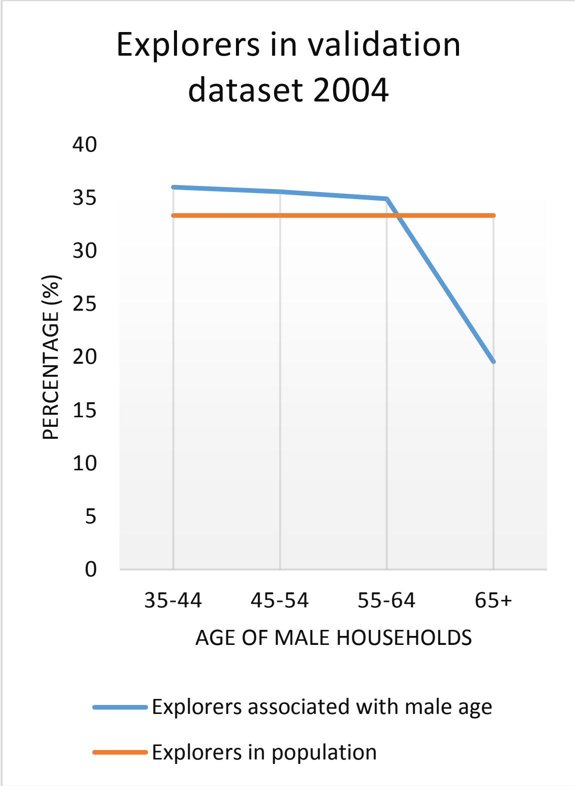

Promotion-averse Exploiters in validation dataset 2006
PERCENTAGE (%)
30
25
20
15
10
5
0
0-9999
15000-19999
20000-24999
25000-34999
35000-44999
45000-54999
55000-64999
65000-74999
75000-99999
100000 and greater
COMBINED HOUSEHOLD INCOME ($ PER YEAR)
Promotion averse exploiters associated with combined household income
Promotion averse exploiters in population

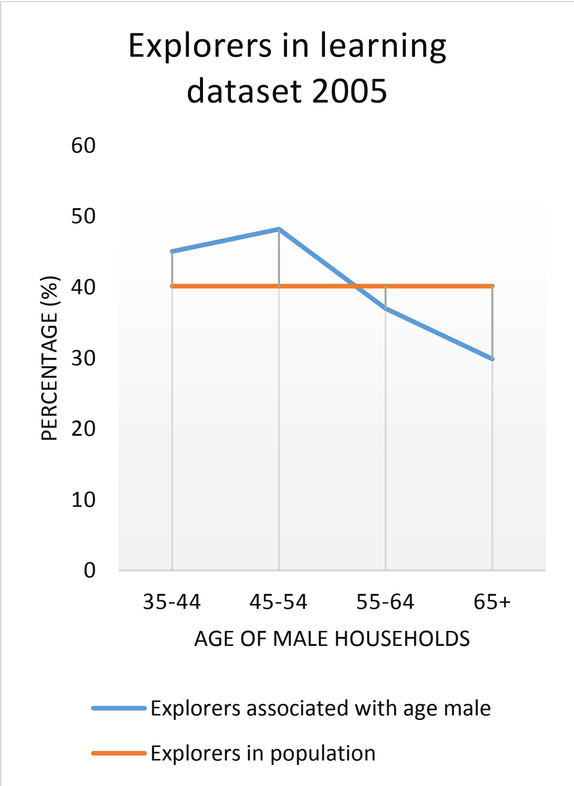

Promotion-averse Exploiters in learning dataset 2007
PERCENTAGE (%)
30
25
20
15
10
5
0
10000-11999
12000-14999
15000-19999
20000-24999
25000-34999
35000-44999
45000-54999
55000-64999
65000-74999
75000-99999
COMBINED HOUSEHOLD INCOME ($ PER YEAR)
Promotion averse exploiters associated with combined household income
Promotion averse exploiters in population

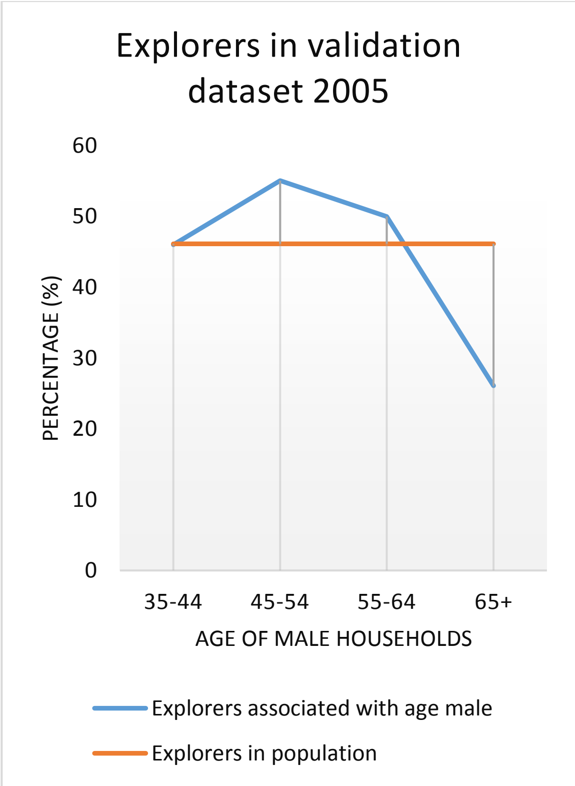

Promotion-averse Exploiters in validation dataset 2007
PERCENTAGE (%)
60
50
40
30
20
10
0
0-9999
15000-19999
20000-24999
25000-34999
35000-44999
45000-54999
55000-64999
65000-74999
75000-99999
100000 and greater
COMBINED HOUSEHOLD INCOME ($ PER YEAR)
Promotion averse exploiters associated with combined household income
Promotion averse exploiters in population

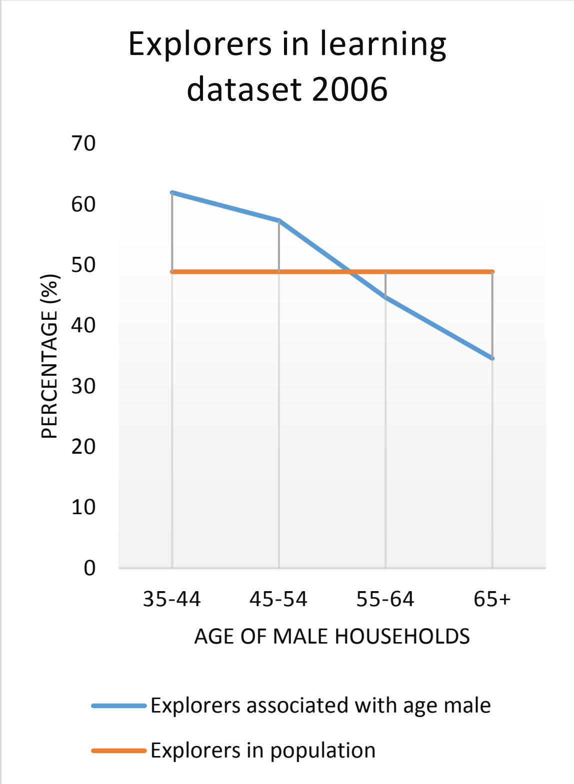
Appendix H: The Improved Performance of Targeting Explorers via Using the Age of Male Households in Pittsfield Salty Snack Market



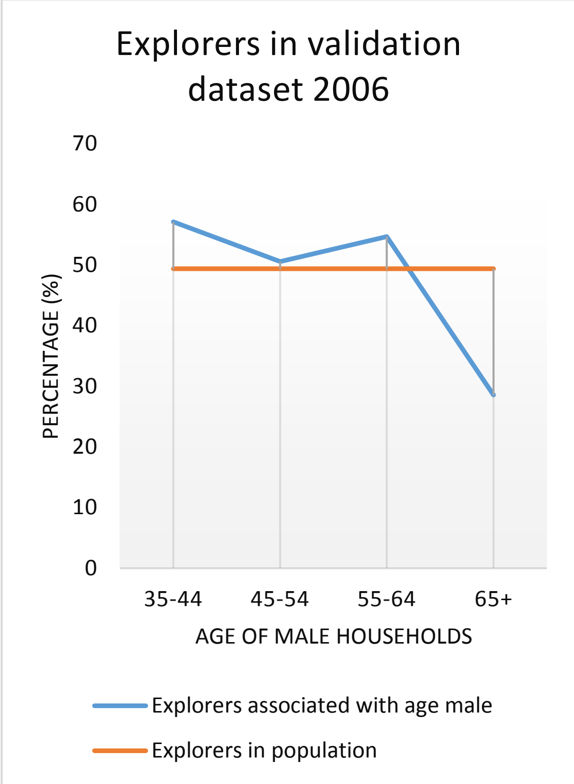




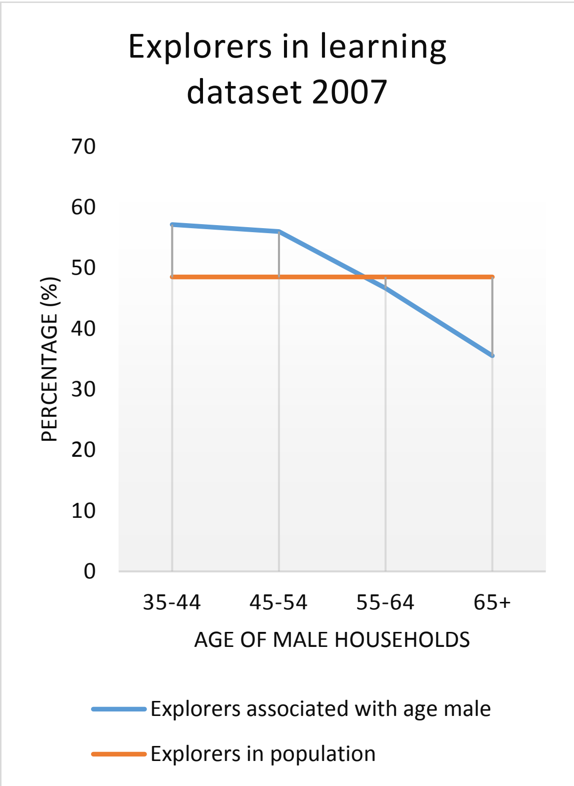




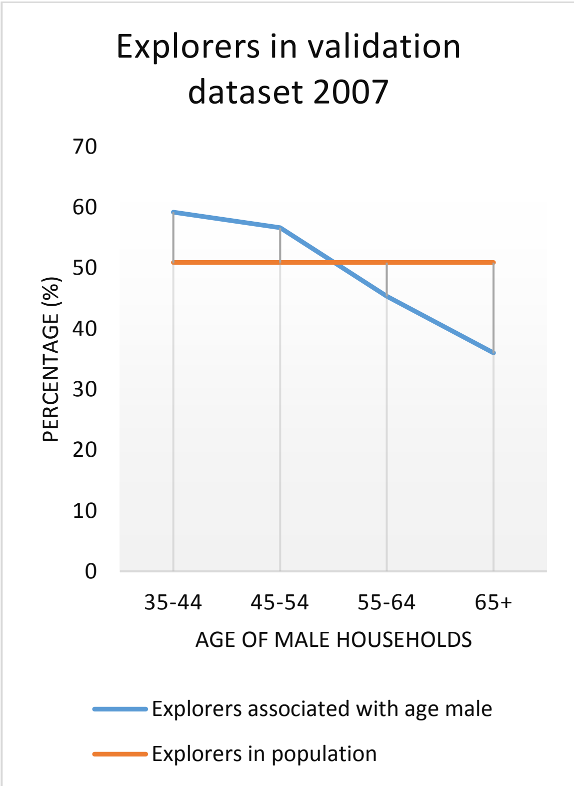
Explorers in learning dataset 2006
PERCENTAGE (%)
70
60
50
40
30
20
10
0
35-44
45-54
55-64
65+
AGE OF MALE HOUSEHOLDS
Explorers associated with age male
Explorers in population



Explorers in validation dataset 2006
PERCENTAGE (%)
70
60
50
40
30
20
10
0
35-44
45-54
55-64
65+
AGE OF MALE HOUSEHOLDS
Explorers associated with age male
Explorers in population

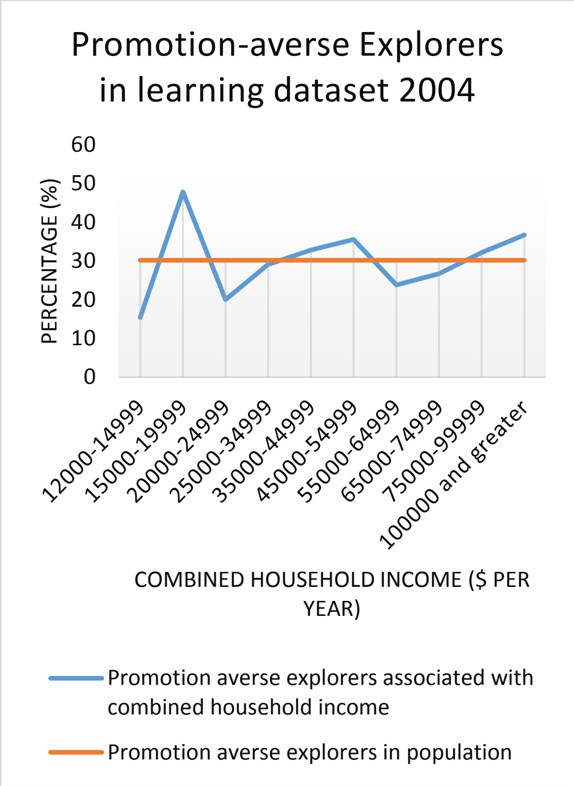


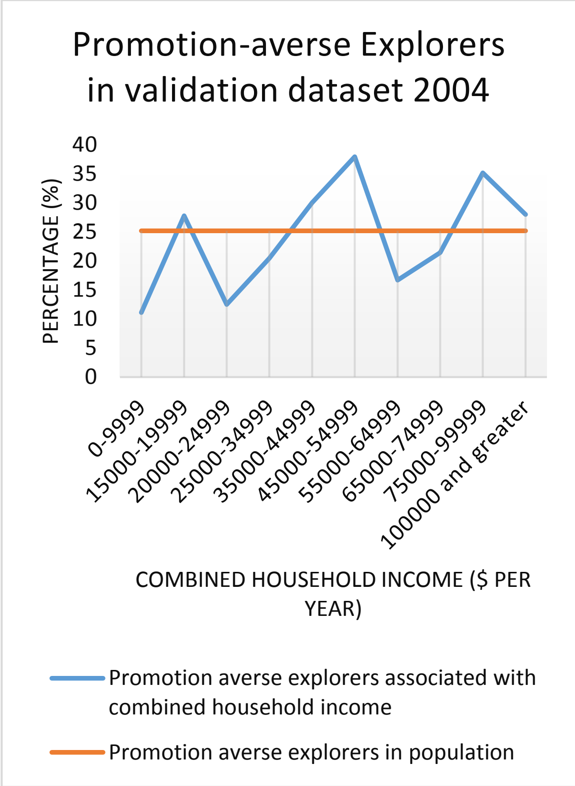
Explorers in learning dataset 2007
PERCENTAGE (%)
70
60
50
40
30
20
10
0
35-44
45-54
55-64
65+
AGE OF MALE HOUSEHOLDS
Explorers associated with age male
Explorers in population

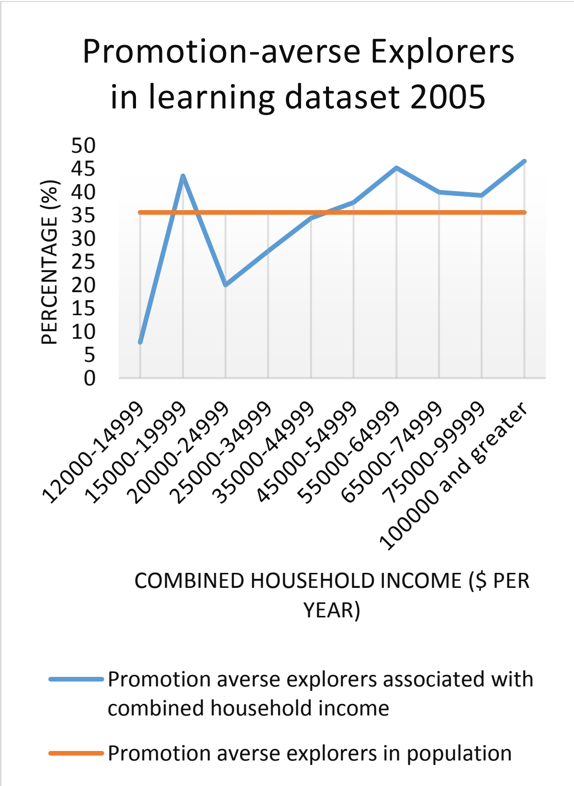


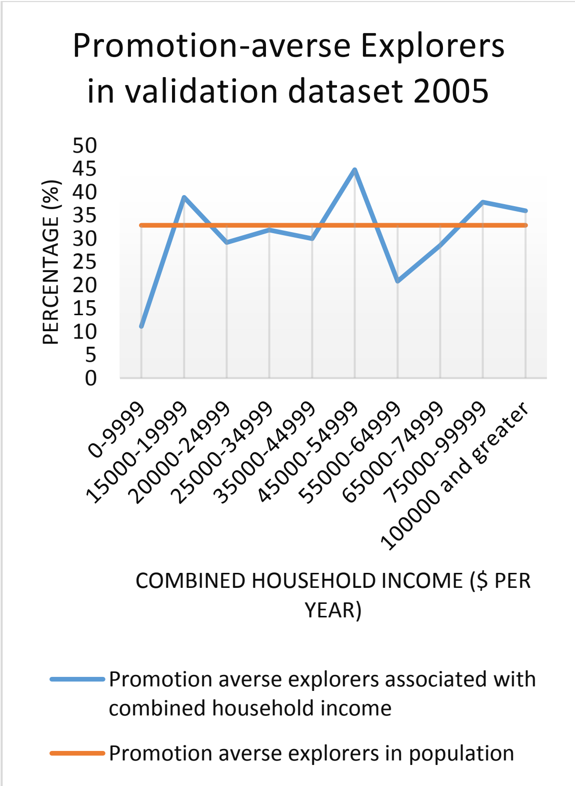
Explorers in validation dataset 2007
PERCENTAGE (%)
70
60
50
40
30
20
10
0
35-44
45-54
55-64
65+
AGE OF MALE HOUSEHOLDS
Explorers associated with age male
Explorers in population

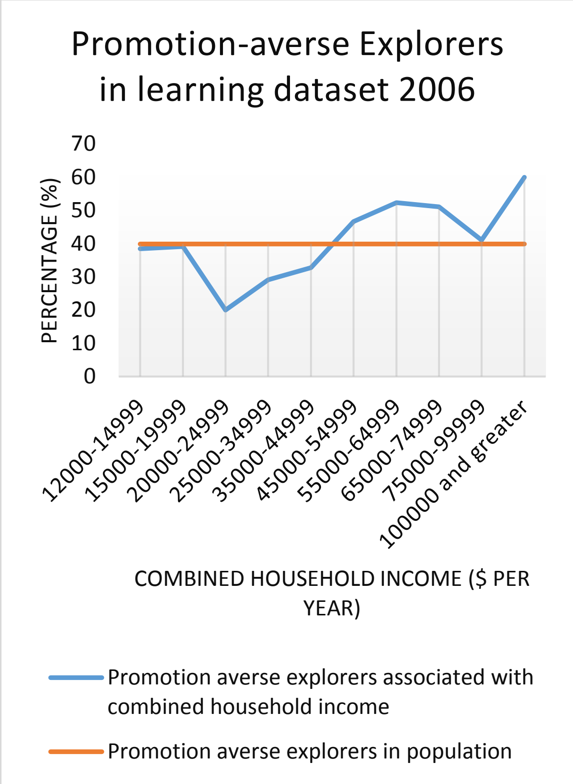
Appendix I: The Improved Performance of Targeting Promotion-averse Explorers via Using the Combined Household Income in Pittsfield Yogurt Market

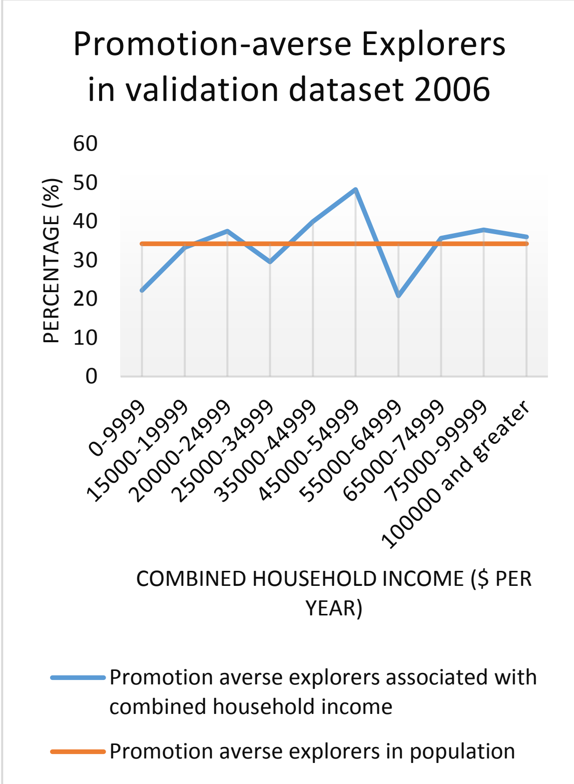


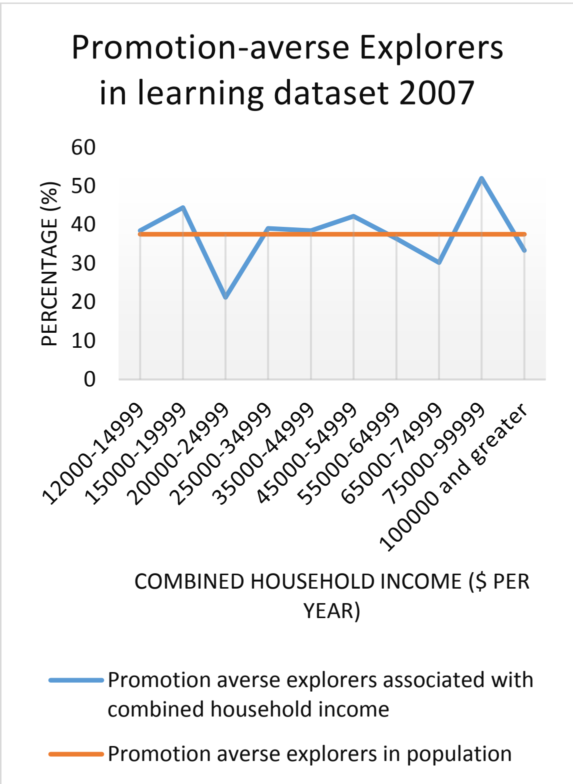


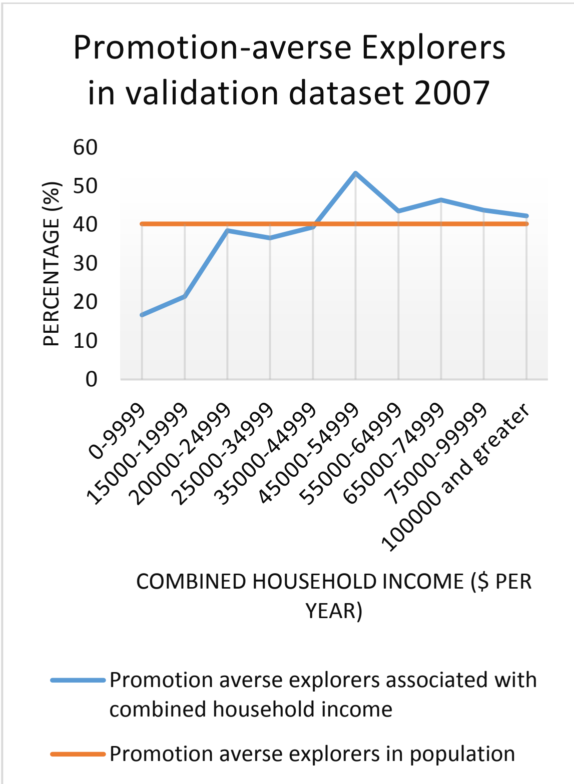




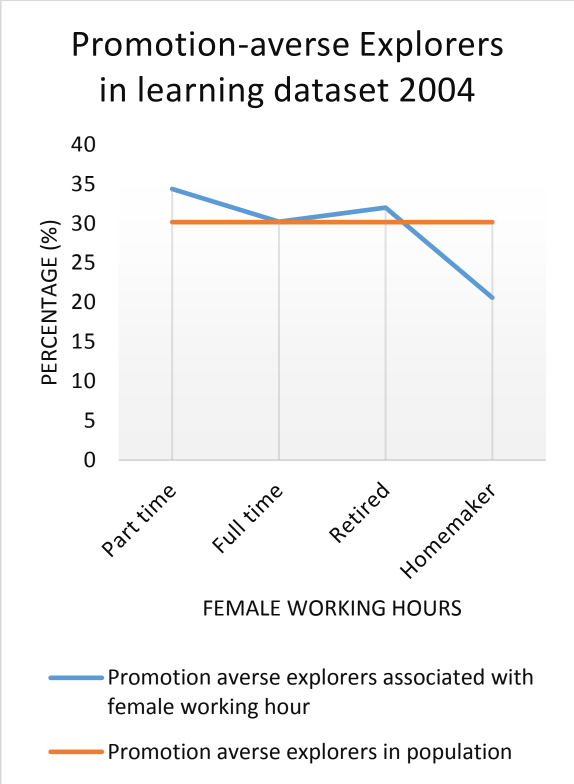

Promotion-averse Explorers in learning dataset 2006
PERCENTAGE (%)
70
60
50
40
30
20
10
0
12000-14999
15000-19999
20000-24999
25000-34999
35000-44999
45000-54999
55000-64999
65000-74999
75000-99999
100000 and greater
COMBINED HOUSEHOLD INCOME ($ PER YEAR)
Promotion averse explorers associated with combined household income
Promotion averse explorers in population

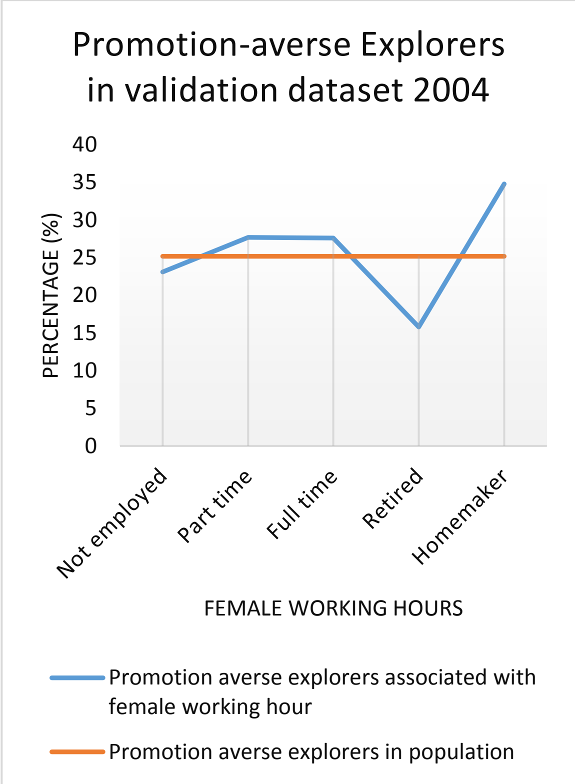

Promotion-averse Explorers in validation dataset 2006
PERCENTAGE (%)
60
50
40
30
20
10
0
0-9999
15000-19999
20000-24999
25000-34999
35000-44999
45000-54999
55000-64999
65000-74999
75000-99999
100000 and greater
COMBINED HOUSEHOLD INCOME ($ PER YEAR)
Promotion averse explorers associated with combined household income
Promotion averse explorers in population

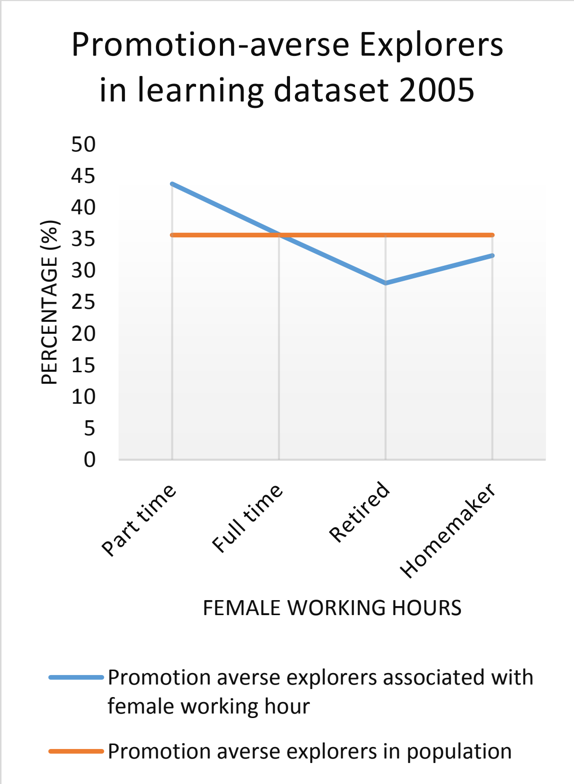

Promotion-averse Explorers in learning dataset 2007
PERCENTAGE (%)
60
50
40
30
20
10
0
12000-14999
15000-19999
20000-24999
25000-34999
35000-44999
45000-54999
55000-64999
65000-74999
75000-99999
100000 and greater
COMBINED HOUSEHOLD INCOME ($ PER YEAR)
Promotion averse explorers associated with combined household income
Promotion averse explorers in population

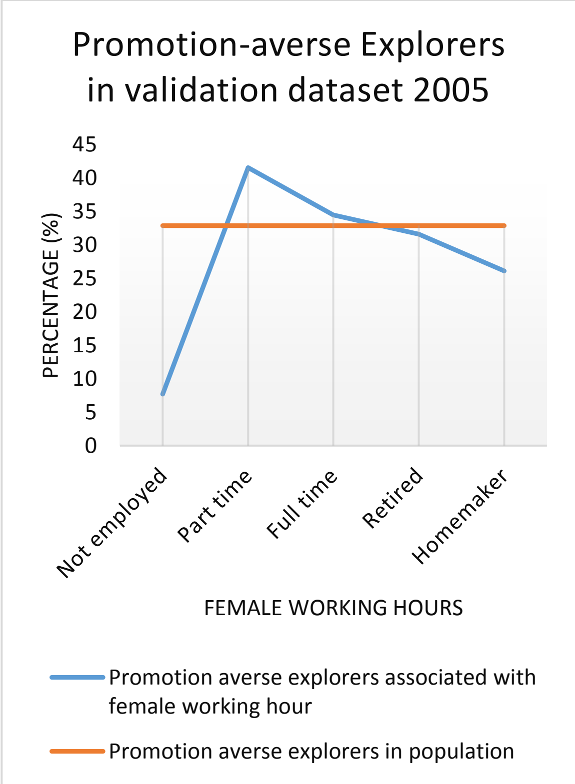

Promotion-averse Explorers in validation dataset 2007
PERCENTAGE (%)
60
50
40
30
20
10
0
0-9999
15000-19999
20000-24999
25000-34999
35000-44999
45000-54999
55000-64999
65000-74999
75000-99999
100000 and greater
COMBINED HOUSEHOLD INCOME ($ PER YEAR)
Promotion averse explorers associated with combined household income
Promotion averse explorers in population

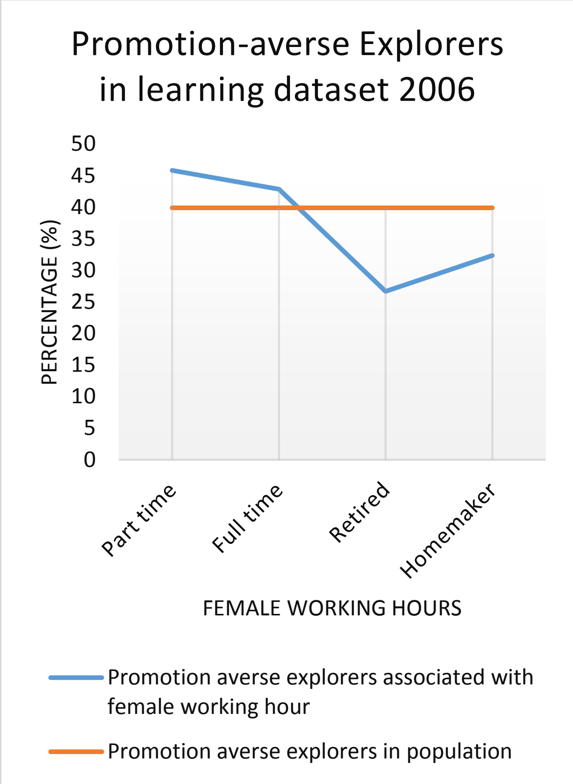
Appendix J: The Improved Performance of Targeting Promotion-averse Explorers via Using the Female Working Hours in Pittsfield Yogurt Market

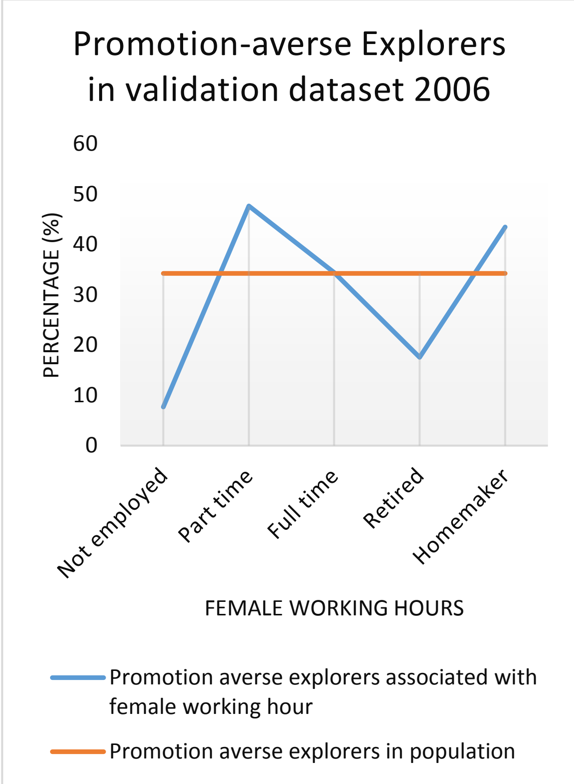


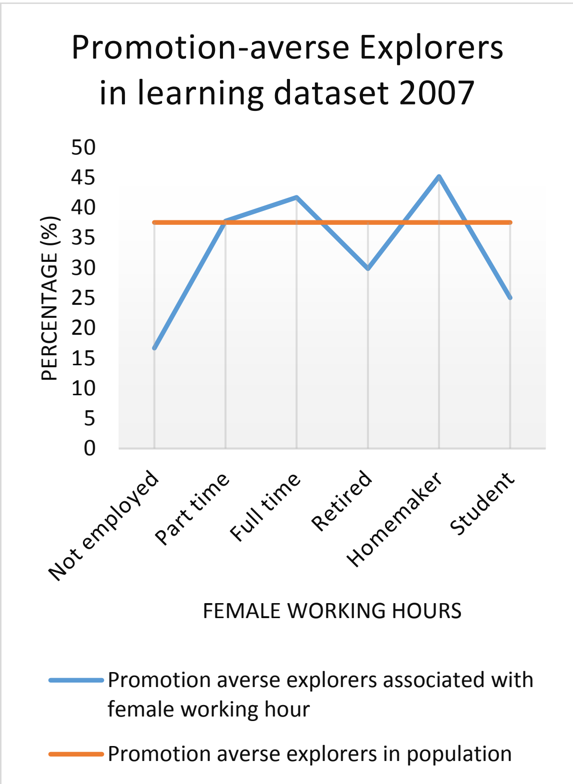


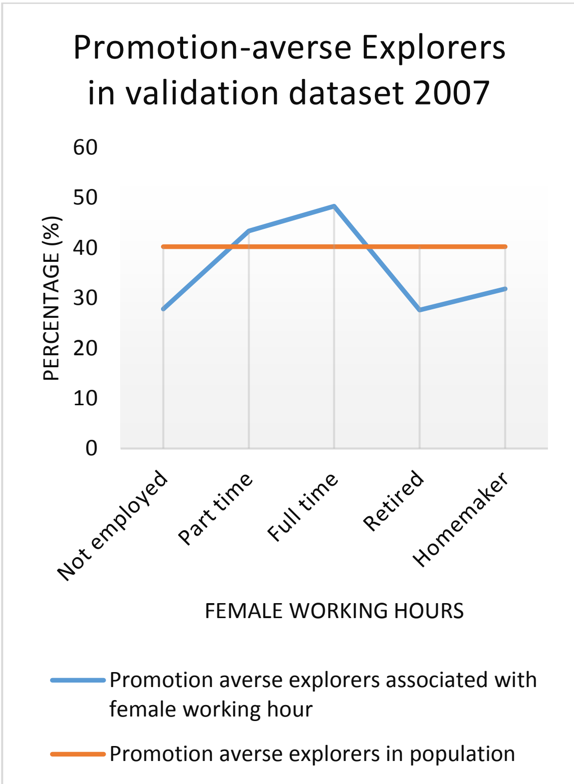





Promotion-averse Explorers in learning dataset 2006
PERCENTAGE (%)
50
45
40
35
30
25
20
15
10
5
0
Part time
Full time
Retired
Homemaker
FEMALE WORKING HOURS
Promotion averse explorers associated with female working hour
Promotion averse explorers in population

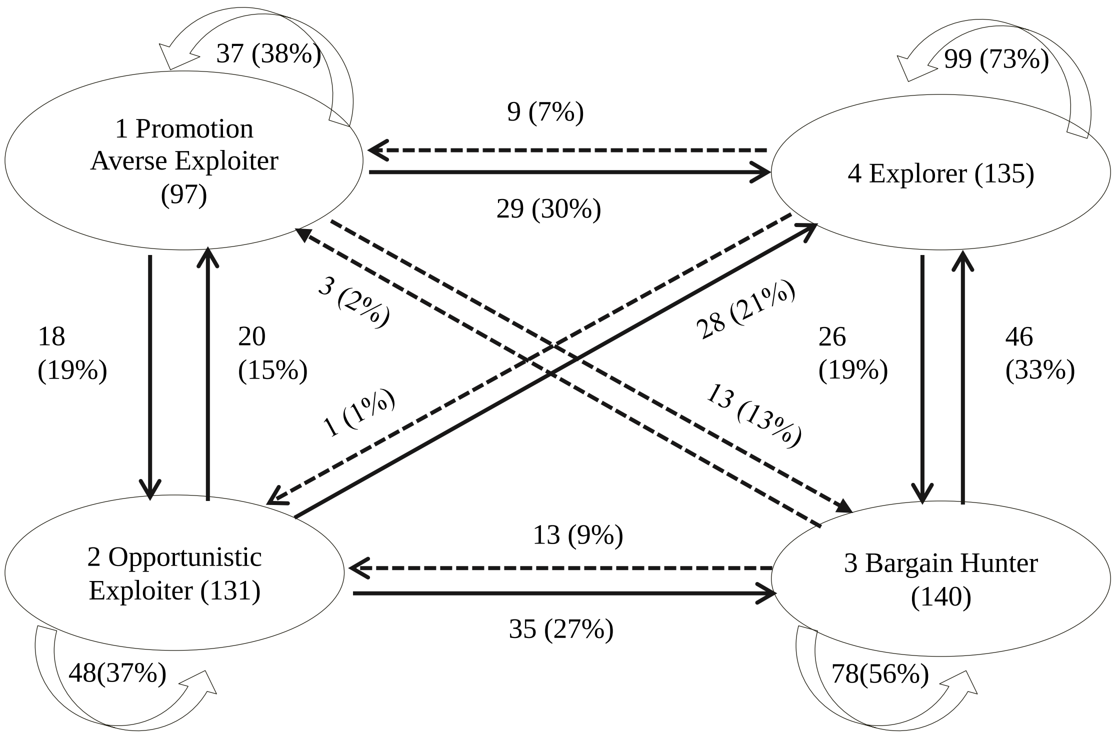

Promotion-averse Explorers in validation dataset 2006
PERCENTAGE (%)
60
50
40
30
20
10
0
Not employed
Part time
Full time
Retired
Homemaker
FEMALE WORKING HOURS
Promotion averse explorers associated with female working hour
Promotion averse explorers in population


Promotion-averse Explorers in learning dataset 2007
PERCENTAGE (%)
50
45
40
35
30
25
20
15
10
5
0
Not employed
Part time
Full time
Retired
Homemaker
Student
FEMALE WORKING HOURS
Promotion averse explorers associated with female working hour
Promotion averse explorers in population

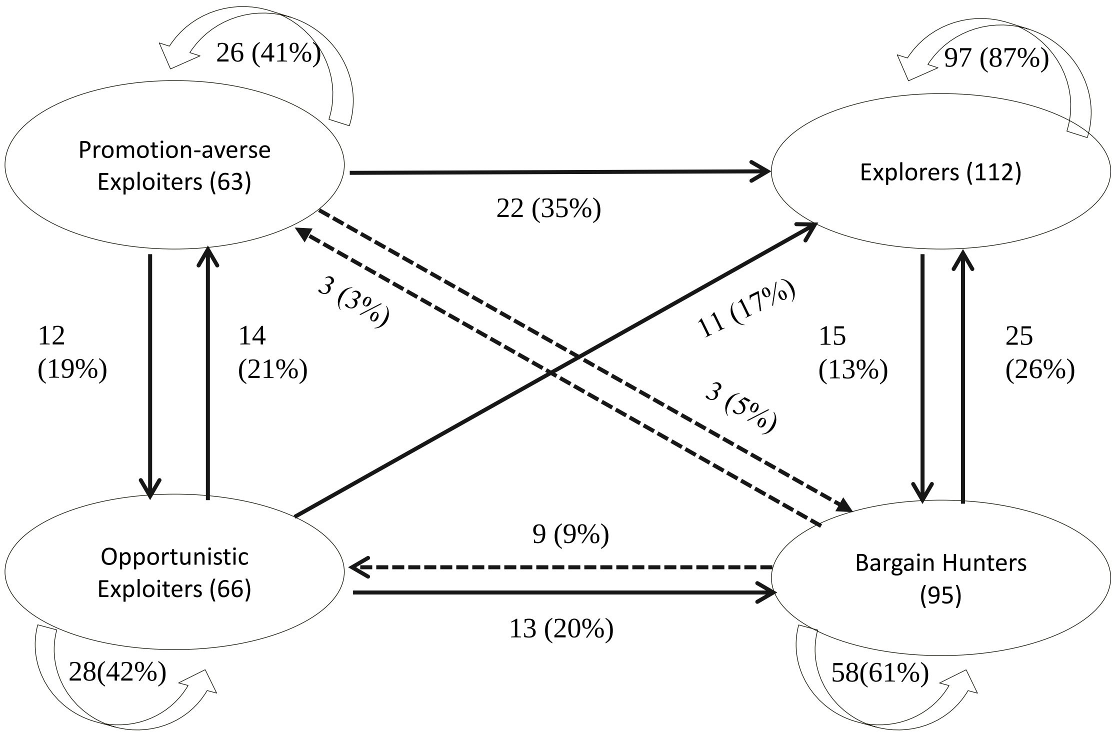

Promotion-averse Explorers in validation dataset 2007
PERCENTAGE (%)
60
50
40
30
20
10
0
Not employed
Part time
Full time
Retired
Homemaker
FEMALE WORKING HOURS
Promotion averse explorers associated with female working hour
Promotion averse explorers in population

Appendix K: The Dynamic Behavioural Evolvement Patterns in Salty Snack Market

- The dynamic behavioural evolvement pattern in the first stage of consumer purchase lifecycles from 2004 to 2005

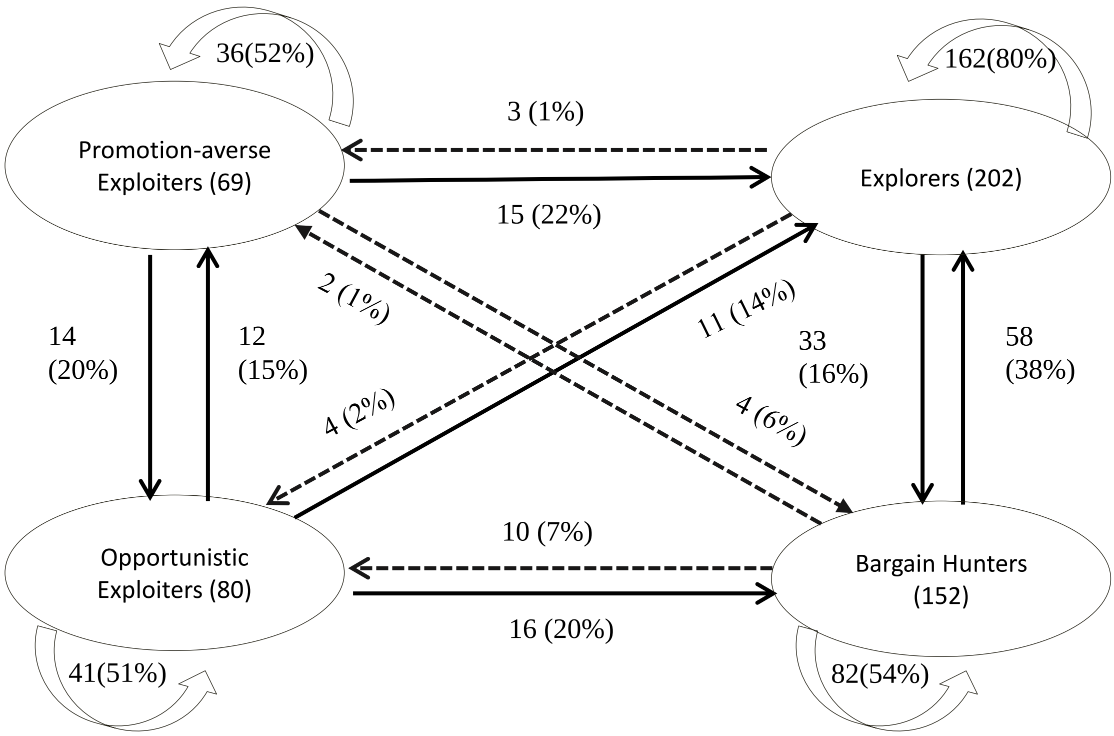


Learning datasets from 2004 to 2005

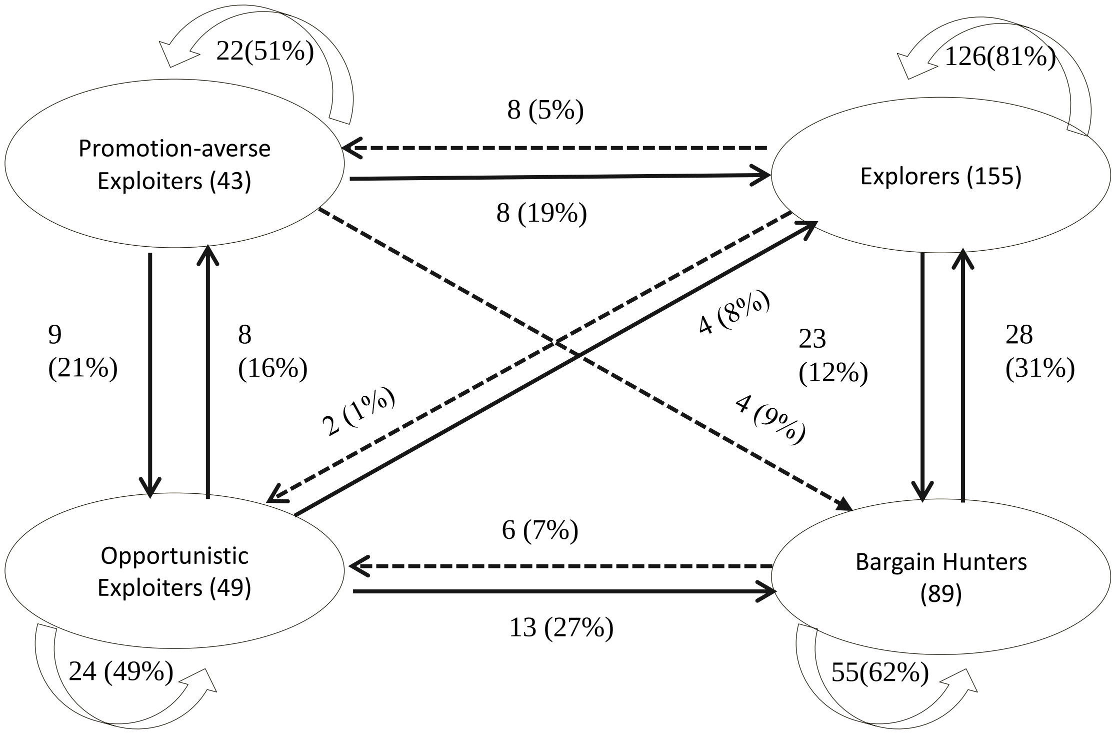


Validation datasets from 2004 to 2005

- The dynamic behavioural evolvement pattern in the second stage of consumer purchase lifecycles from 2005 to 2006

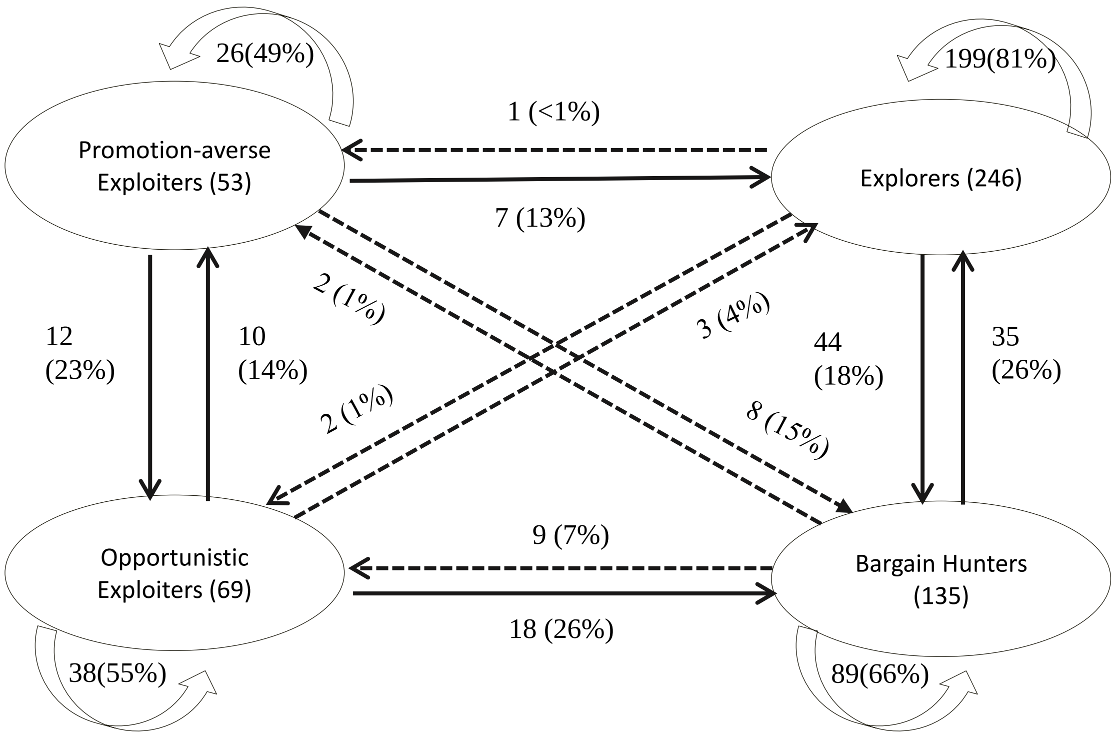


Learning datasets from 2005 to 2006

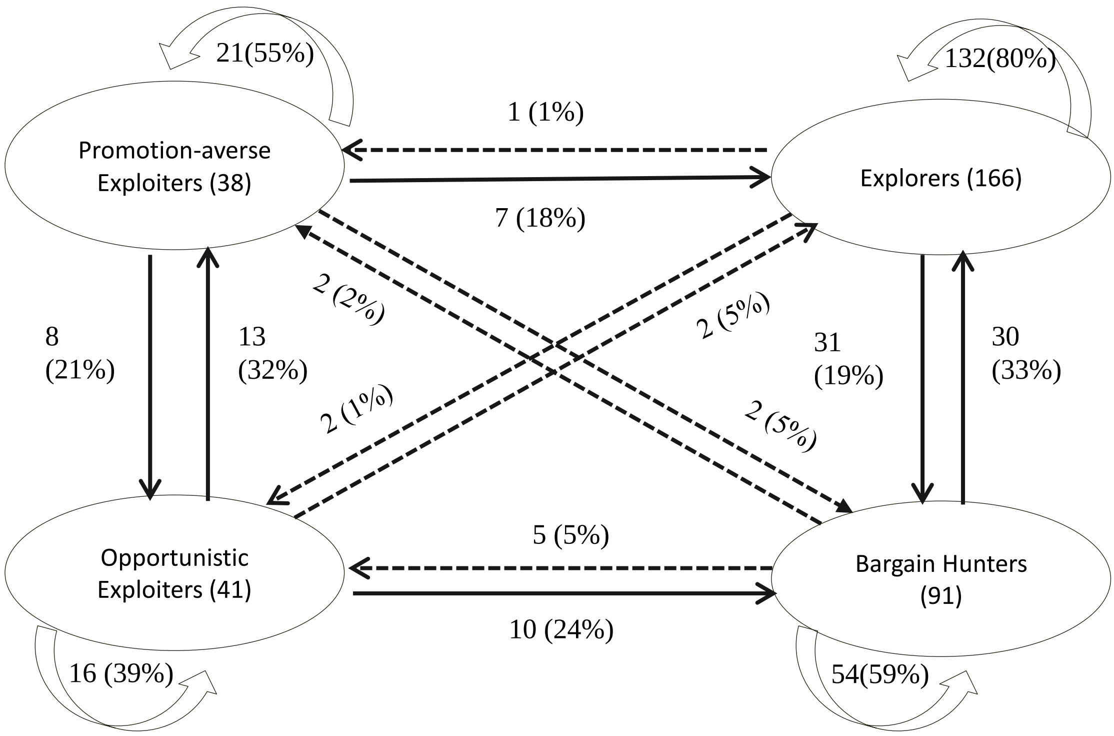


Validation datasets from 2005 to 2006

- The dynamic behavioural evolvement pattern in the third stage of consumer purchase lifecycles from 2006 to 2007



Learning datasets from 2006 to 2007



Validation datasets from 2006 to 2007

The dynamic behavioural evolvement pattern in a dynamic behavioural evolvement stage consisted of behavioural evolvement types that had high transitional probability. In the above figures, the dynamic behavioural evolvement pattern in each dynamic behavioural evolvement stage was represented by solid lines. Those behavioural evolvement patterns were similar across behavioural evolvement stages. It suggested that consumers with different amount of purchase experiences in salty snack market evolved in a similar pattern with the increase of purchase experiences over years.

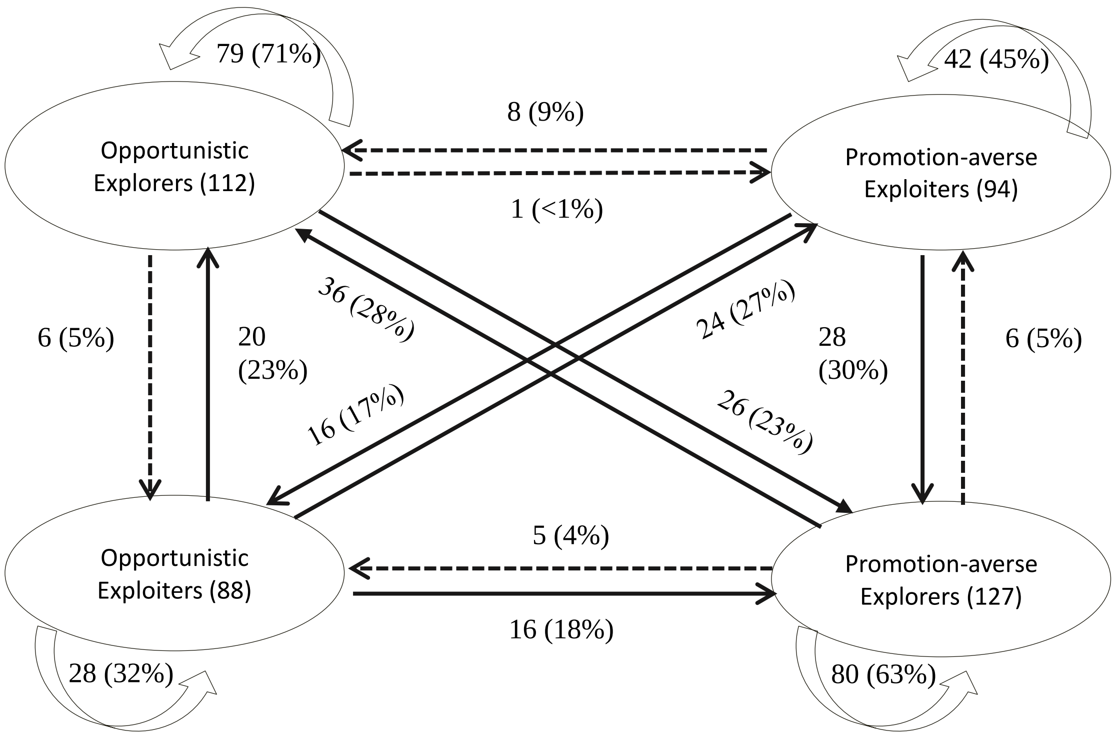
As can be seen from those figures, the transitional probability of the evolvement from Promotion-averse Exploiters to Bargain Hunters was normally much lower than that to Opportunistic Exploiters and Explorers. It indicated that those Promotion-averse Exploiters were likely to evolve to be either Opportunistic Exploiters or Explorers with the increase of purchase experiences.

The transitional probability of the evolvement from Opportunistic Exploiters to the other three behavioural segments were similar in the first and the second behavioural evolvement stages. It indicated that those Opportunistic Exploiters evolved to be Promotion-averse Exploiters, Explorers, and Bargain Hunters at the similar possibility in those two behavioural evolvement stages. However, in the third behavioural evolvement stage, the transitional probability of the evolvement from Opportunistic Exploiters to Explorers were much lower than that to Promotion-averse Exploiters and Bargain Hunters. It indicated that those Opportunistic Exploiters became less likely to directly evolve to be Explorers than to be Promotion-averse Exploiters and Bargain Hunters in the third behavioural evolvement stage. It suggested that the Opportunistic Exploiters with rich purchase experiences were less likely to evolve to be Explorers than those Opportunistic Exploiters with some market knowledge.

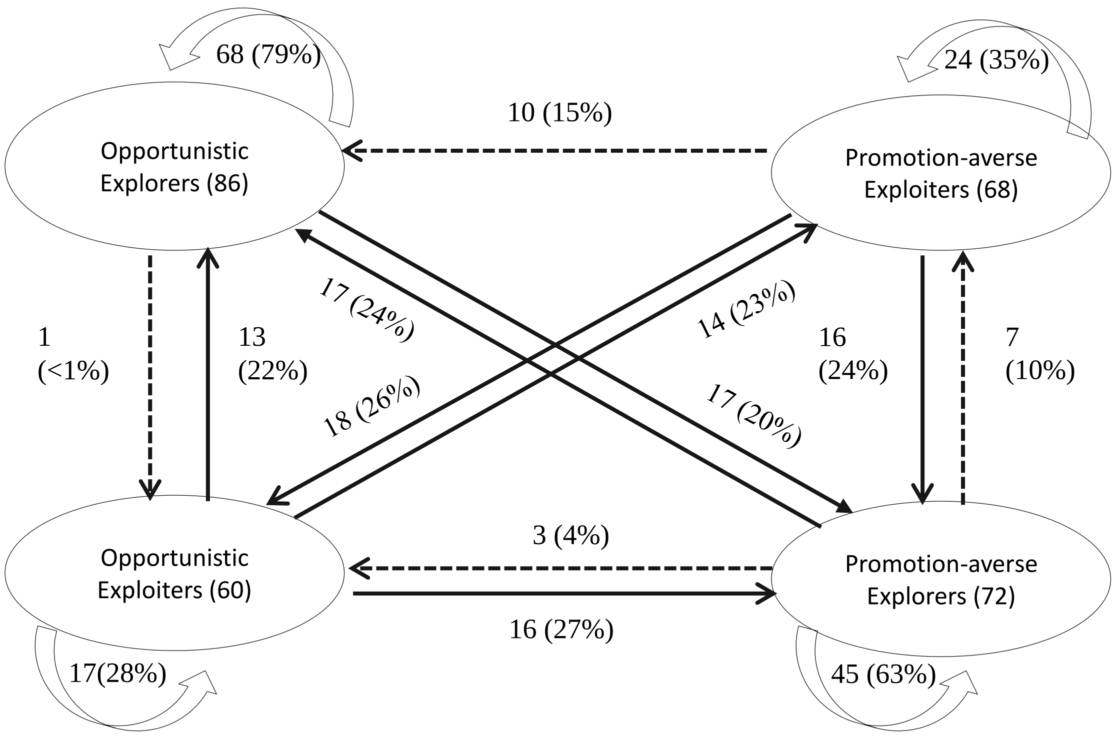
The high transitional probability of the evolvement between Explorers and Bargain Hunters indicated that those Explorers and Bargain Hunters were likely to evolve between themselves with the increase of purchase experiences over years. The transitional probability of the evolvement from Bargain Hunters to Explorers was higher than that from Explorers to Bargain Hunters. It indicated that the proportion of the evolved Explorers from Bargain Hunters was higher than the proportion of the evolved Bargain Hunters from Explorers. It thus suggested that consumers might be more likely to evolve to be Explorers than to be Bargain Hunters in the end of their purchase lifecycles in salty snack market.

Appendix L: The Dynamic Behavioural Evolvement Patterns in Yogurt Market

- The dynamic behavioural evolvement pattern in the first stage of consumer purchase lifecycles from 2004 to 2005

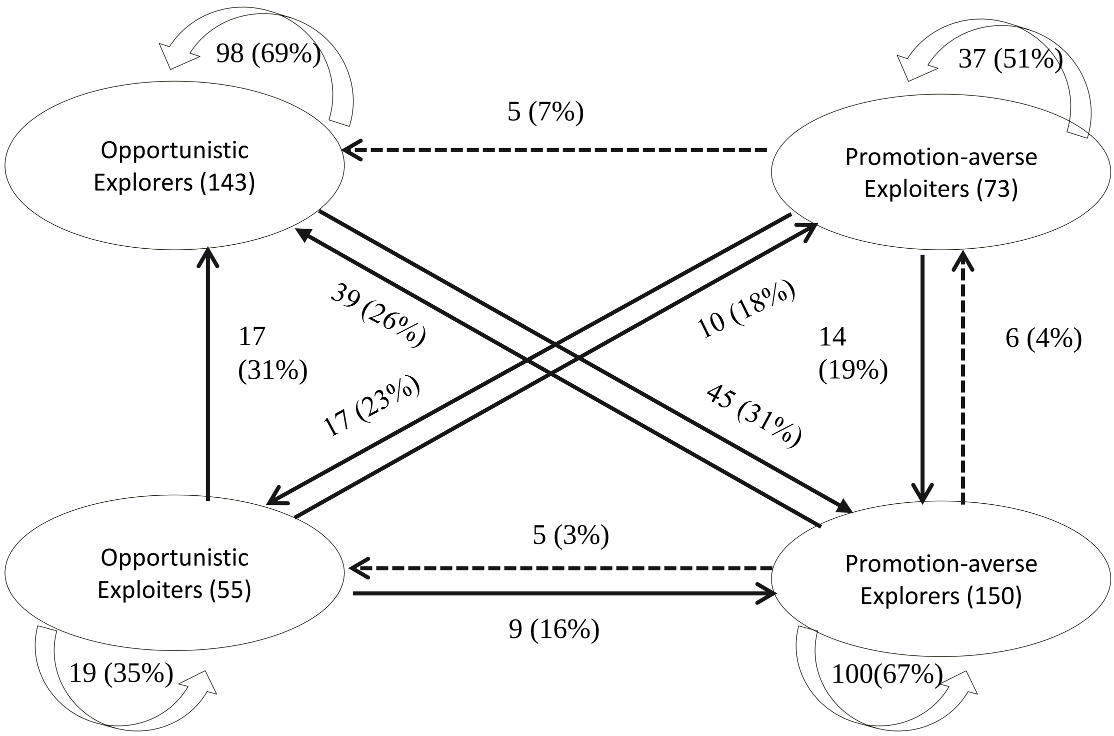


Learning datasets from 2004 to 2005

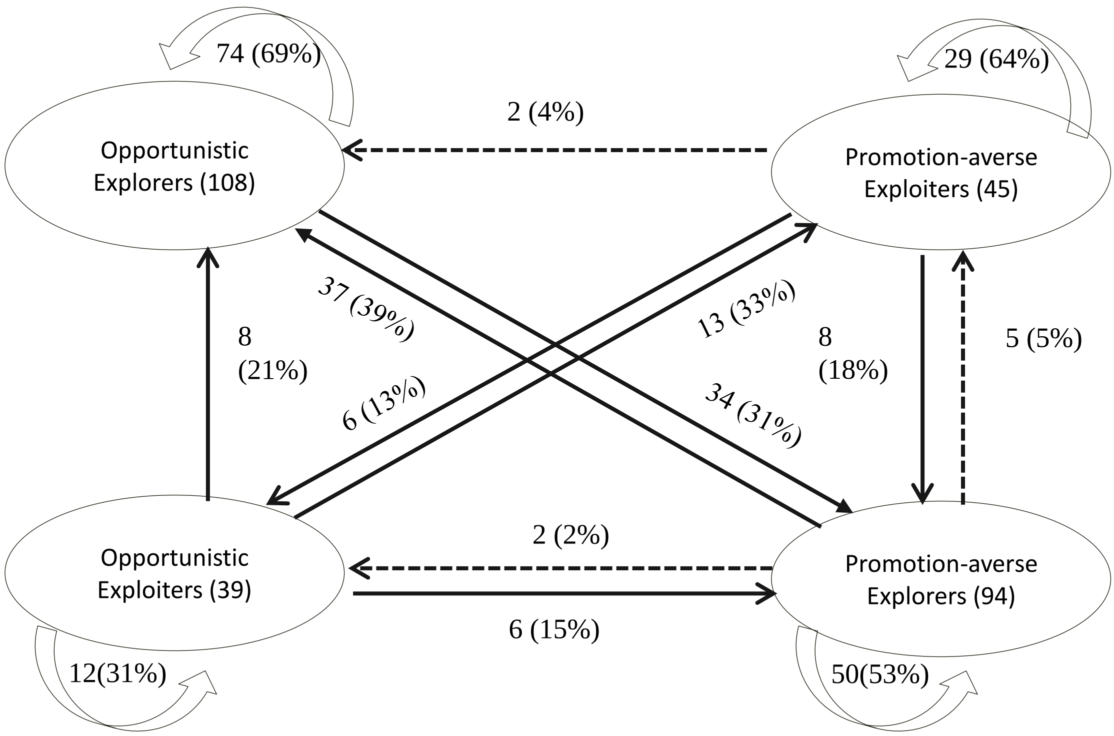


Validation datasets from 2004 to 2005

- The dynamic behavioural evolvement pattern in the second stage of consumer purchase lifecycles from 2005 to 2006

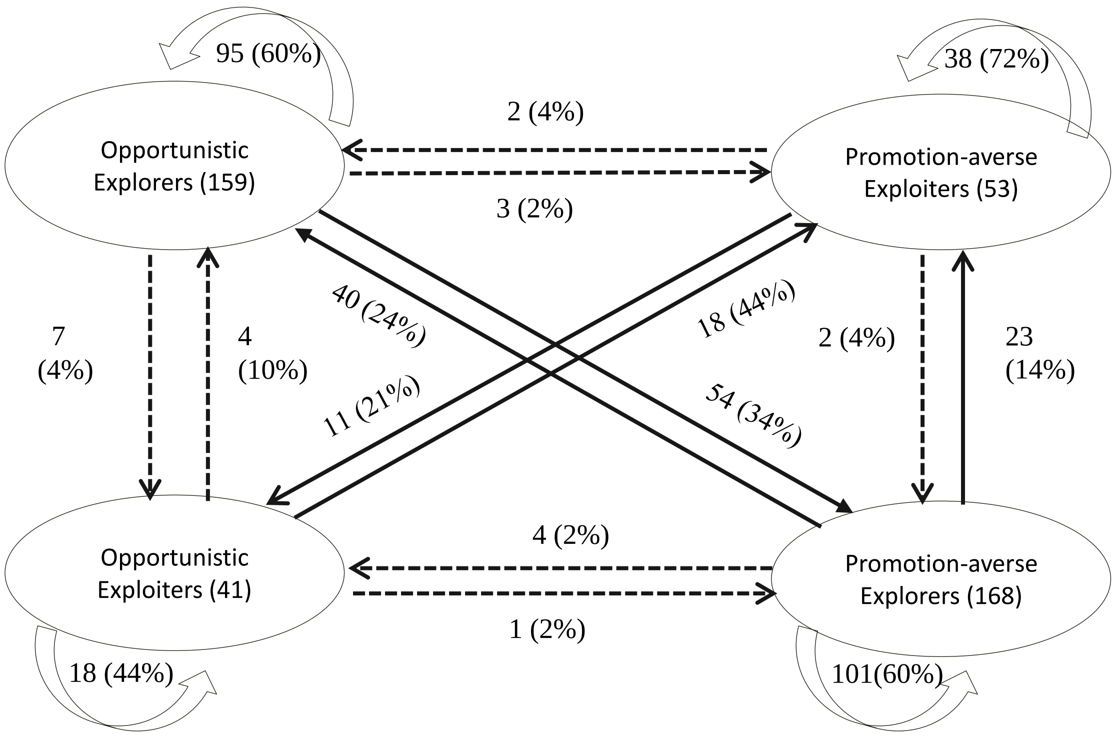


Learning datasets from 2005 to 2006

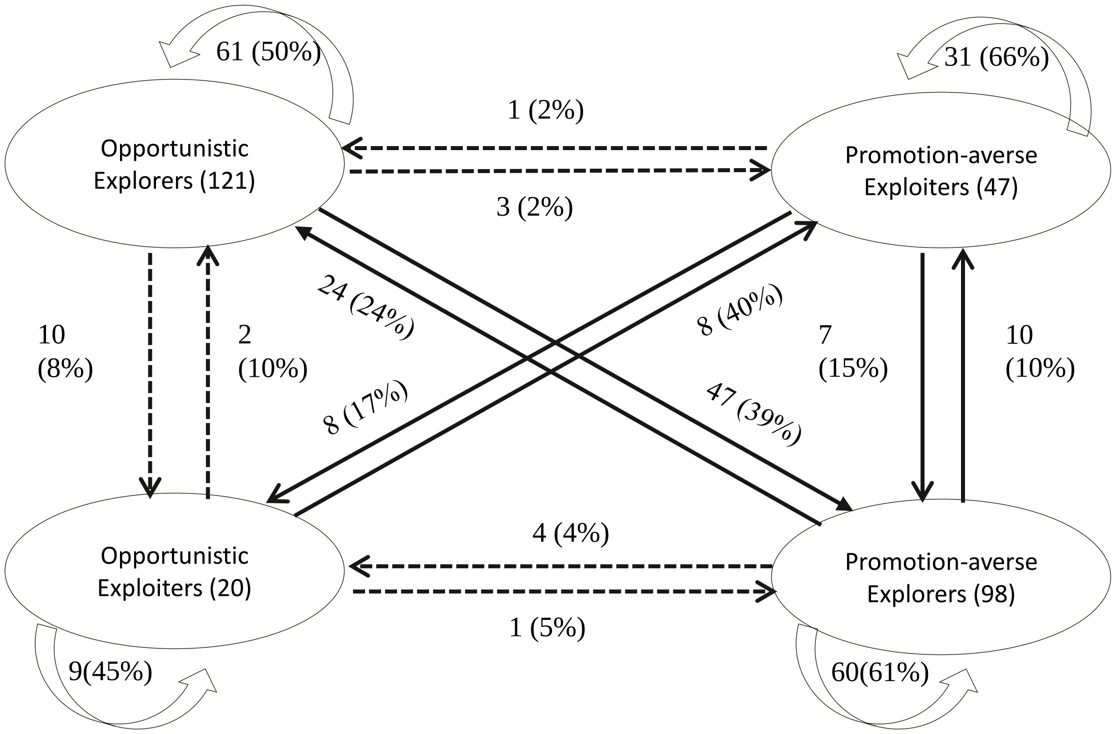


Validation datasets from 2005 to 2006

- The dynamic behavioural evolvement pattern in the third stage of consumer purchase lifecycles from 2006 to 2007



Learning datasets from 2006 to 2007



Validation datasets from 2006 to 2007

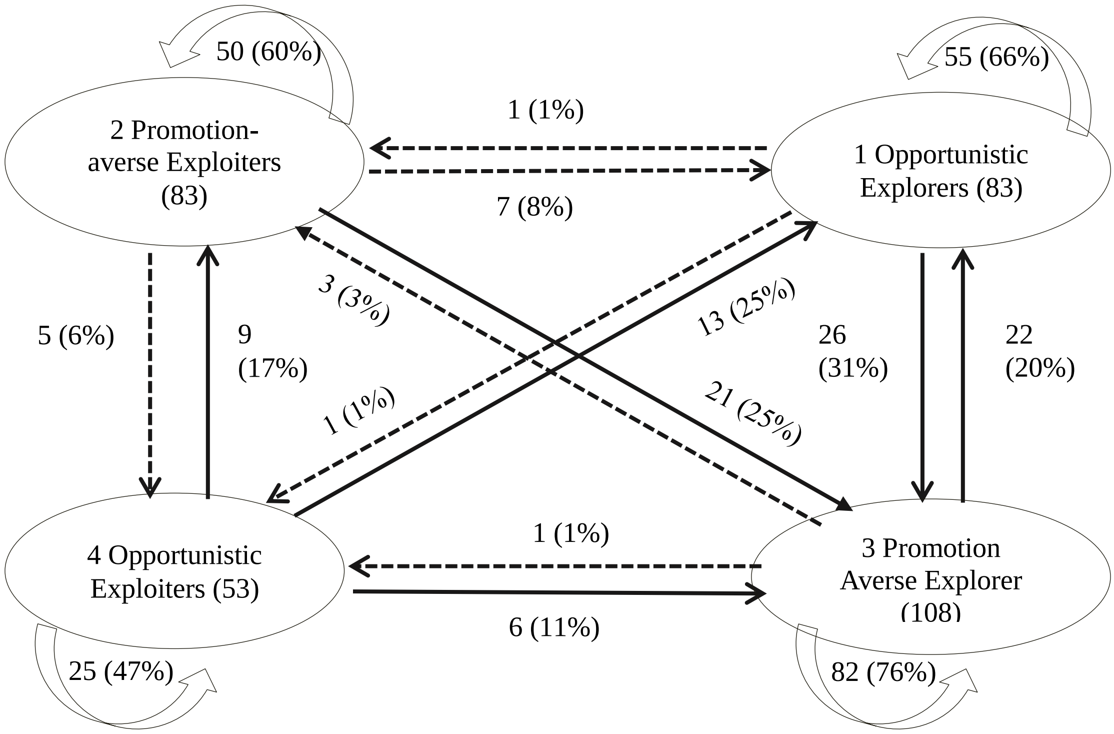
The dynamic behavioural evolvement pattern in a dynamic behavioural evolvement stage consisted of behavioural evolvement types that had high transitional probability. In the above figures, the dynamic behavioural evolvement pattern in each dynamic behavioural evolvement stage was represented by solid lines. The dynamic behavioural evolvement patterns in the first and the second dynamic behavioural evolvement stages were similar even though the transitional probabilities of behavioural evolvement types slightly changed across those two behavioural evolvement stages. It indicated that the consumers in the first and second behavioural evolvement stages evolved in a similar pattern with the increase of purchase experiences over years.

In the first and second dynamic behavioural evolvement stages, the transitional probabilities of the evolvements from Opportunistic Exploiters to the other behavioural segments were similar. It indicated that those Opportunistic Exploiters had the similar likelihood to evolve to be Promotion-averse Exploiters, Promotion-averse Explorers, and Opportunistic Explorers in both of the first and second behavioural evolvement stages. The transitional probability of the evolvement from Promotion-averse Explorers to Opportunistic Explorers was higher than that to exploiters. It indicated that those Promotion-averse Explorers were likely to evolve to be Opportunistic Explorers in those two stages. By the same token, the higher transitional probability of the evolvement from Opportunistic Explorers to Promotion-averse Explorers than that to exploiters indicated that those Opportunistic Explorers were likely to evolve to be Promotion-averse Explorers with the increase of purchase experiences in those two stages. The transitional probabilities of those two behavioural evolvement types suggested that Opportunistic Explorers and Promotion-averse Explorers were likely to evolve between themselves in those two behavioural evolvement stage. The transitional probability of the evolvement from Promotion-averse Exploiters to Opportunistic Explorers was much lower than that to either Opportunistic Exploiters or Promotion-averse Explorers. It indicated that those Promotion-averse Exploiters were likely to evolve to be either Opportunistic Exploiters or Promotion-averse Explorers in those two behavioural evolvement stage.

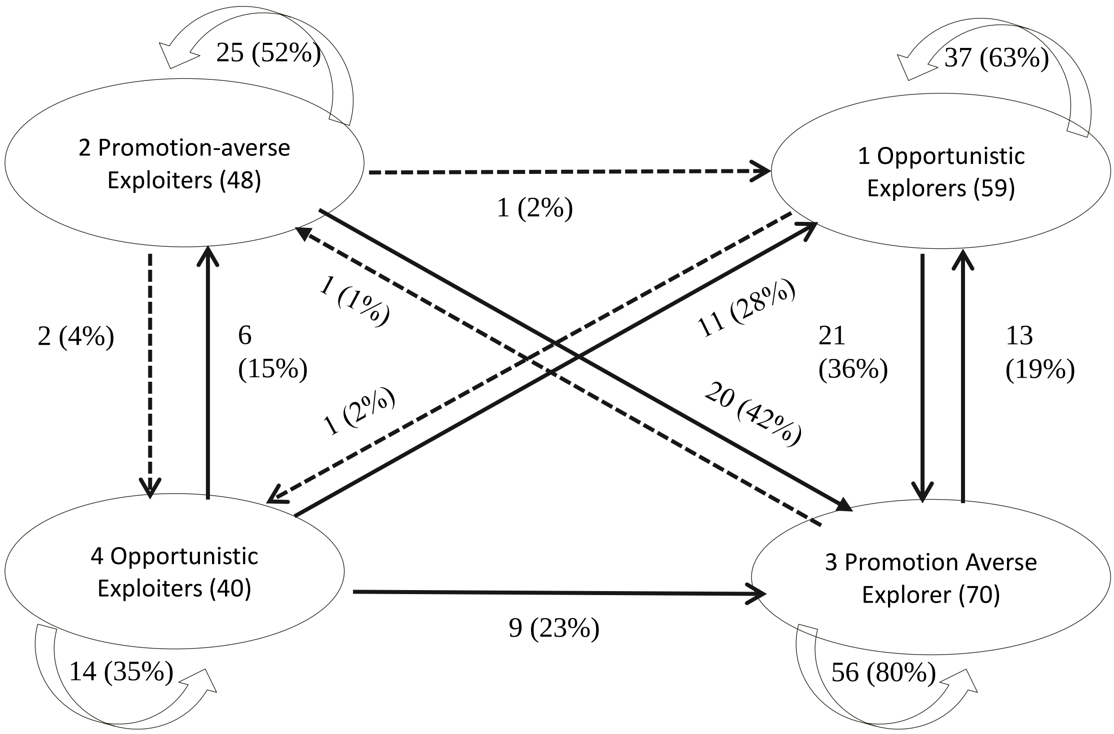
Compared to the dynamic behavioural evolvement pattern in the first and second dynamic behavioural evolvement stages, the transitional probabilities of the evolvement from Opportunistic Exploiters to Explorers were significantly decreased in the third dynamic behavioural evolvement stage. It indicated that those Opportunistic Exploiters became not likely to evolve to be Explorers in the third dynamic behavioural evolvement stage. On the contrary, the significantly increased transitional probability of the evolvement from Opportunistic Exploiters to Promotion-averse Exploiters suggested that those Opportunistic Exploiters became more likely to evolve to be Promotion-averse Exploiters when they had rich purchase experiences. By the same token, the decreased transitional probability of the evolvement from Promotion-averse Exploiters to Promotion-averse Explorers indicated that those Promotion-averse Exploiters became less likely to evolve to be Promotion-averse Explorers in the third behavioural evolvement stage. On the contrary, the transitional probability of the evolvement from Promotion-averse Explorers to Promotion-averse Exploiters significantly increased in the third stage. It indicated that those Promotion-averse Explorers became more likely to evolve to be Promotion-averse Exploiters in this behavioural evolvement stage. It suggested that those Promotion-averse Explorers gradually became inclined to consistently purchase a sub-set of their preferred brands when they obtained sufficient purchase experiences. In general, compared to the dynamic behavioural evolvement pattern in the first and second dynamic behavioural evolvement stages, consumers in the third stage were more likely to evolve to be exploiters.

Appendix M: The Dynamic Behavioural Evolvement Patterns in Toilet Tissue Market

- The dynamic behavioural evolvement pattern in the first stage of consumer purchase lifecycles from 2004 to 2005

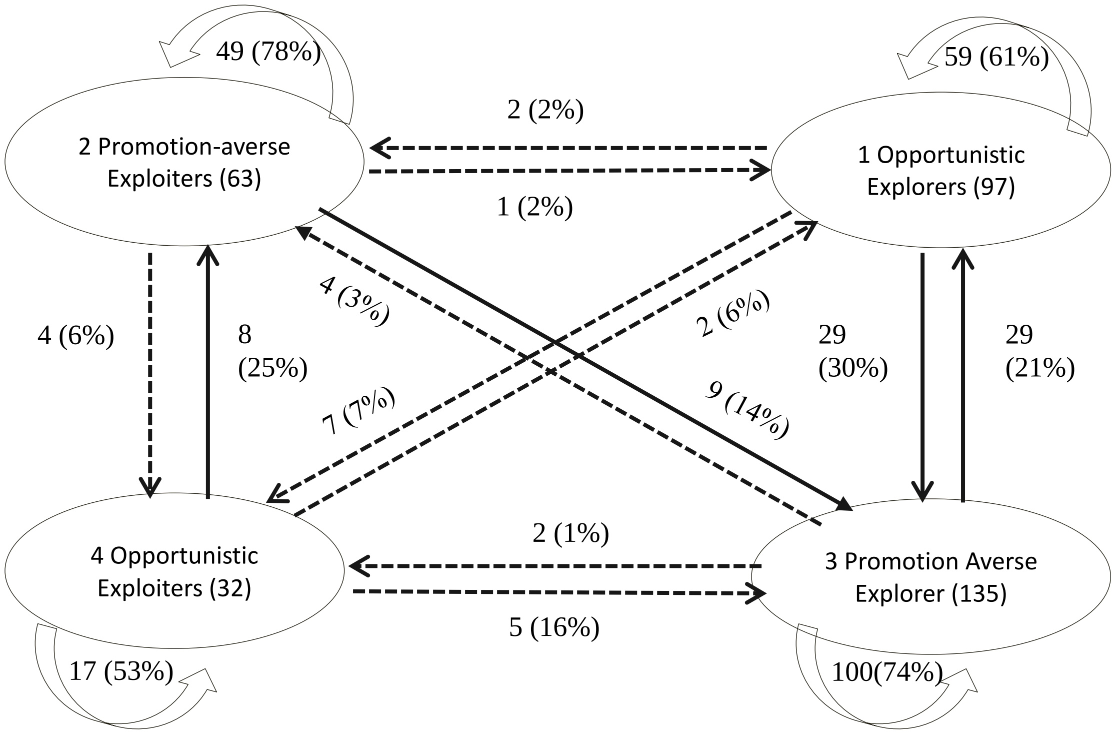


Learning datasets from 2004 to 2005

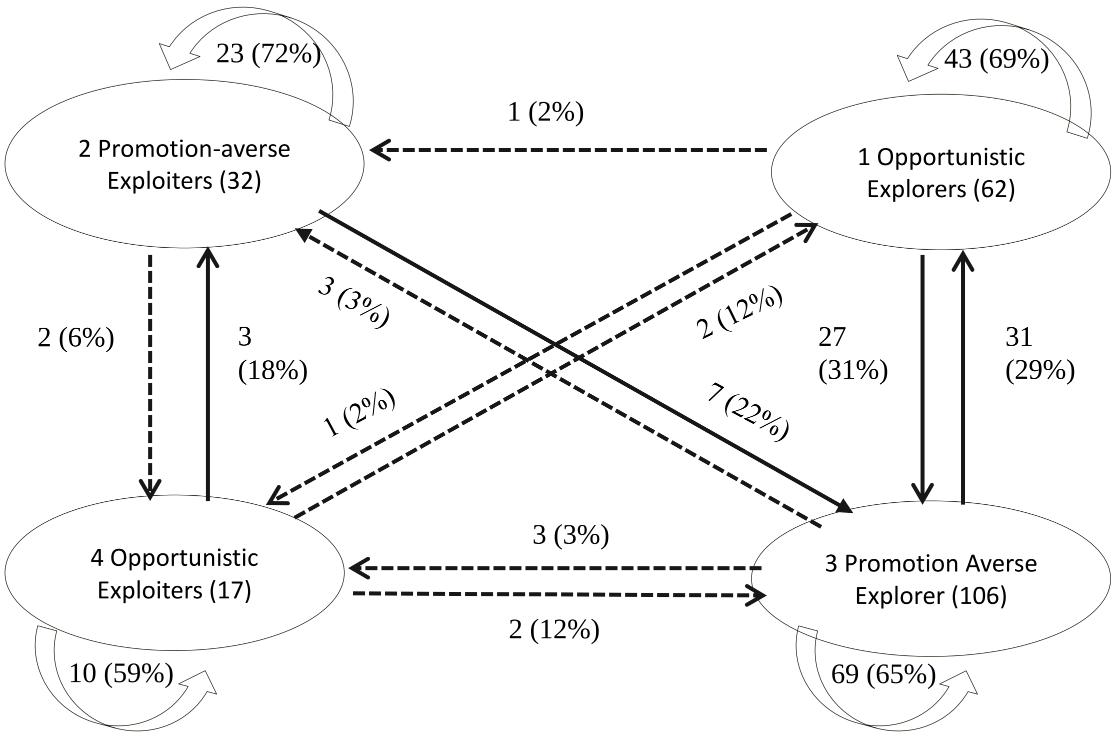


Validation datasets from 2004 to 2005

- The dynamic behavioural evolvement pattern in the first stage of consumer purchase lifecycles from 2005 to 2006

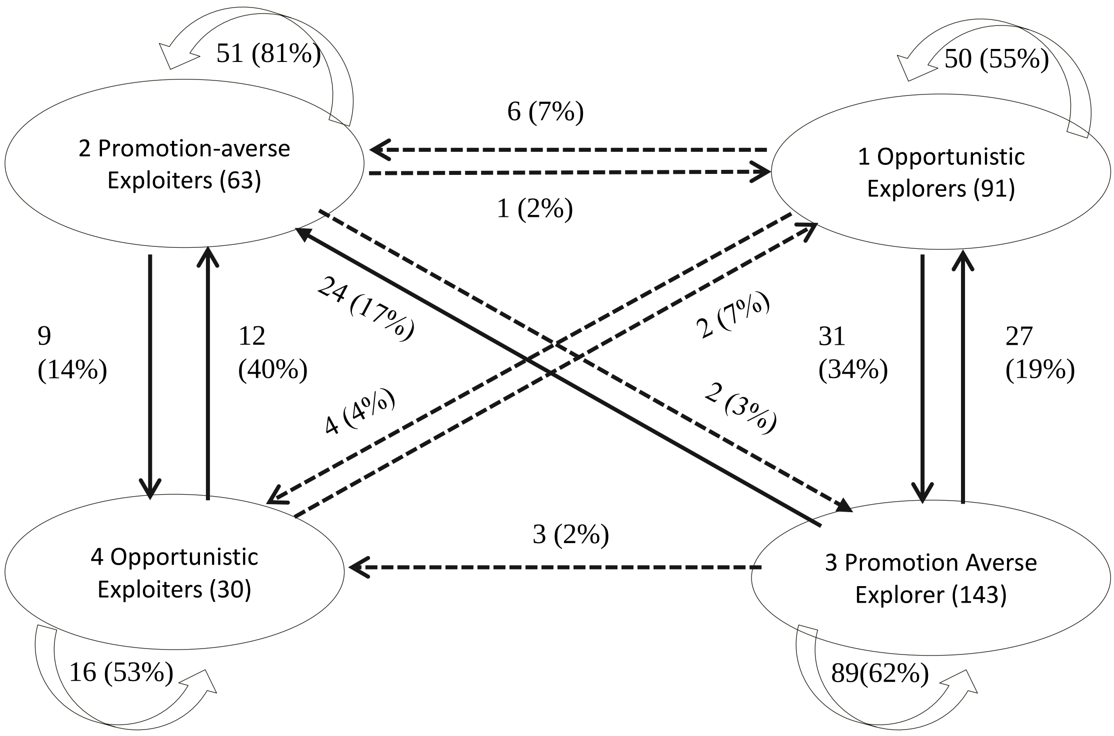


Learning datasets from 2005 to 2006

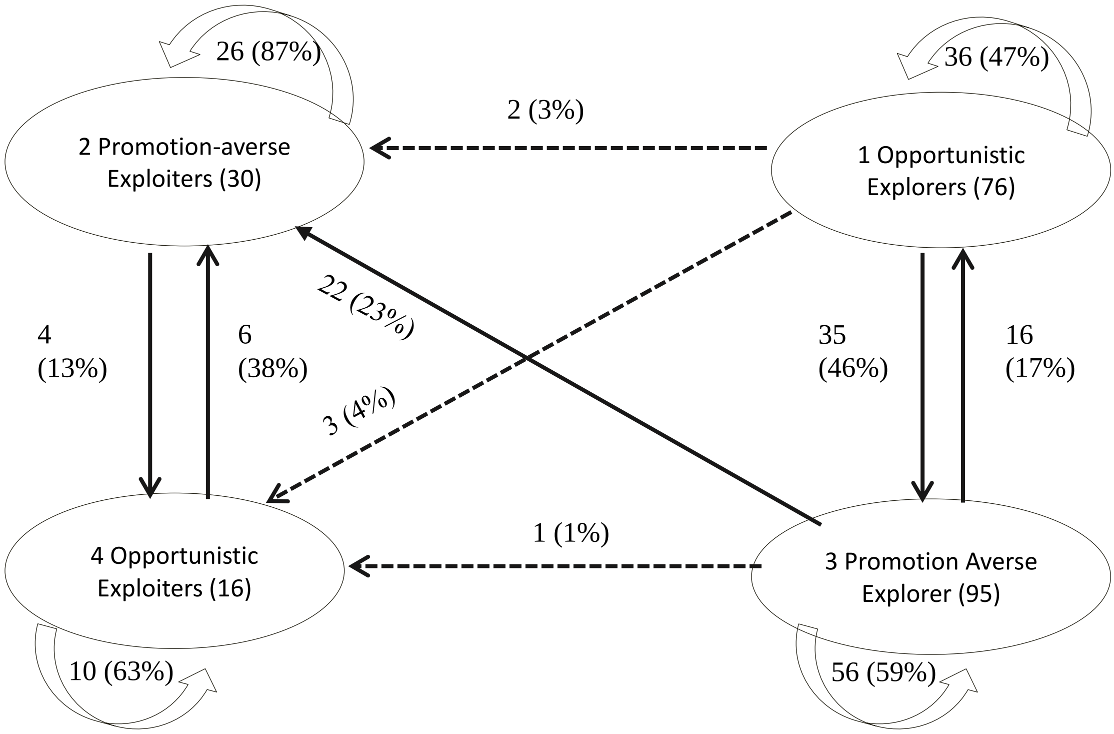


Validation datasets from 2005 to 2006

- The dynamic behavioural evolvement pattern in the first stage of consumer purchase lifecycles from 2006 to 2007



Learning datasets from 2006 to 2007



Validation datasets from 2006 to 2007

The dynamic behavioural evolvement pattern in a dynamic behavioural evolvement stage consisted of behavioural evolvement types that had high transitional probability. In the above figures, the dynamic behavioural evolvement pattern in each dynamic behavioural evolvement stage was represented by solid lines. The identified three behavioural evolvement patterns in behavioural evolvement stages were different from each other. It indicated that consumers with different amount of purchase experiences evolved in different behavioural evolvement patterns with the further increase of purchase experiences over years. It suggested that the purchase experiences of consumers had significant influences on the current purchase behaviour of those consumers in toilet tissue market.

In the first behavioural evolvement stage, the transitional probabilities of the evolvements from Opportunistic Exploiters to the other behavioural segments were similar. It indicated that those Opportunistic Exploiters had the similar likelihood to evolve to be Opportunistic Explorers, Promotion-averse Exploiters, and Promotion-averse Explorers in this evolvement stage. The transitional probability of the evolvement from Promotion-averse Exploiters to Promotion-averse Explorers was much higher than that to opportunists. It indicated that those Promotion-averse Exploiters were most likely to evolve to be Promotion-averse Explorers with the increase of purchase experiences in this stage. The high transitional probabilities of the evolvement between Promotion-averse Explorers and Opportunistic Explorers indicated that Promotion-averse Explorers and Opportunistic Explorers were likely to evolve between themselves in this stage. The transitional probability of the evolvement from Opportunistic Explorers to Promotion-averse Explorers was higher than that of the evolvement from Promotion-averse Explorers to Opportunistic Explorers. It indicated that the proportion of the evolved Promotion-averse Explorers from Opportunistic Explorers was higher than the proportion of the evolved Opportunistic Explorers from Promotion-averse Explorers. It thus suggested that consumers might be more likely to evolve to be Promotion-averse Explorers than to be Opportunistic Explorers in the end of the first behavioural evolvement stage.

Compared to the behavioural evolvement pattern in the first behavioural evolvement stage, the transitional probability of the evolvement from Opportunistic Exploiters to Promotion-averse Exploiters was higher in the second behavioural evolvement stage. It indicated that those Opportunistic Exploiters were more likely to evolve to be Promotion-averse Exploiters in the second evolvement stage than that in the first evolvement stage. It suggested that those Opportunistic Exploiters in the second stage became more inclined to consistently purchase a sub-set of their preferred brands regardless of promotions than those in the first stage. In the first and second behavioural evolvement stages, Promotion-averse Exploiters were likely to evolve to be Promotion-averse Explorers. However, the decreased transitional probability of this type of behavioural evolvement across behavioural evolvement stages indicated that Promotion-averse Exploiters in the second stage were less likely to evolve to be Promotion-averse Explorers than those consumers in the first stage. It suggested that Promotion-averse Exploiters with some purchase experiences were less inclined to further extend their market knowledge regardless of promotions than those consumers with limited purchase experiences. The transitional probability of the evolvement between Opportunistic Explorers and Promotion-averse Explorers did not significantly change from the first stage to the second stage. It suggested that those Opportunistic Explorers and Promotion-averse Explorers with different amount of purchase experiences evolved in the similar behavioural evolvement pattern with the further increase of purchase experiences in the first and second stages.

Compared to the behavioural evolvement pattern in the second behavioural evolvement stage, the transitional probability from Opportunistic Exploiters to Promotion-averse Exploiters was higher in the third behavioural evolvement stage. The change of the transitional probability of this evolvement type across behavioural evolvement stages suggested that those Opportunistic Exploiters with rich purchase experiences were more likely to evolve to be Promotion-averse Exploiters than those with less purchase experiences. The behavioural evolvement pattern of Promotion-averse Exploiters in the third behavioural evolvement stage was different from that in the first and second behavioural evolvement stage. In the third behavioural evolvement stage, the transitional probability of the evolvement from Promotion-averse Exploiters to Opportunistic Exploiters was much higher than that to the other behavioural segments. It indicated that those Promotion-averse Exploiters were likely to evolve to be Opportunistic Exploiters in the third behavioural evolvement stage. It suggested that those Promotion-averse Exploiters with rich purchase experiences were likely to evolve to be Opportunistic Exploiters rather than Promotion-averse Explorers. In the third behavioural evolvement stage, the Opportunistic Explorers and Promotion-averse Explorers also evolved between themselves. Besides, a high and significantly increased transitional probability of the evolvement from Promotion-averse Explorers to Promotion-averse Exploiters in the third behavioural evolvement stage indicated that those Promotion-averse Explorers were also likely to evolve to be Promotion-averse Exploiters in this stage. It suggested that Promotion-averse Explorers with rich purchase experiences became inclined to consistently purchase a sub-set of their preferred brands regardless of promotions.